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The organization of scientific knowledge: the structural characteristics of keyword networks

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Abstract The understanding of scientific knowledge itself may promote further advances in science and research on the organization of knowledge may be an initiative to this effort. This stream of research, however, has been mainly driven by the analysis of citation networks. This study uses, as an alternative knowledge element, information on the keywords of papers published in business research and examines how they are associated with each other to constitute a body of scientific knowledge. The results show that, unlike most citation networks, keyword networks are not small-word networks but, rather, locally clustered scale-free networks with a hierarchic structure. These structural patterns are robust against the scope of scientific fields involved. In addition, this paper discusses the origins and implications of the identified structural characteristics of keyword networks.

Keywords Organization of knowledge · Keyword network · Small-world network · Power-law distribution · Hierarchy

Introduction

Scientific knowledge, which results from the collective efforts of many researchers across regions and scientific fields, has helped people understand the world better and enabled the dramatic development of human society and standards of living. However, scientific knowledge itself has attracted less attention than its outcomes. A better understanding of the organization and evolution of scientific knowledge can accelerate future advances. This study contributes to answering the fundamental question of how scientific knowledge is organized. We view knowledge as a complex system of many associated concepts that

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adapt to the real world over time. This perspective is consistent with Hume's associationism, which emphasizes the association of ideas once they have entered our minds via our experiences (Plotkin 1997).

Research on the organization of scientific knowledge has been largely driven by the analysis of scientific citations, in which researchers construct and examine the citation networks of papers and patents (e.g., Barnett et al. 2011; Hung and Wang 2010; Li et al. 2007; Newman 2005; Price 1965). This stream of research has discovered a number of structural patterns in scientific/technological citations that may serve as a foundation to understand the organization of knowledge.

Structural characteristics of citation networks

The first feature observed in citation networks is their small-world network structure, which is characterized by a high degree of clustering and a short average distance between nodes (Watts and Strogatz 1998). This structure has been observed in a wide range of citation networks (Newman 2005; Watts 1999), such as academic paper citations (Barnett et al. 2011; Newman 2005; Price 1965) and radio frequency identification (RFID) patent citations (Hung and Wang 2010; Watts 1999). A high degree of clustering implies the existence of modularity, that is, within-group connections are stronger and denser than between-group connections (Watts 1999). This modular structure is consistent with our traditional belief that groups of researchers with a coherent scientific and intellectual world view and a shared set of questions and methodologies are a fundamental part of intellectual thought and rigor (Kuhn 1962). The small-world structure provides the evolutionary advantages of both between-group heterogeneity and efficiency in the flow of information and resources across the network (Watts 1999). Between-group connections play an important bridging role to reduce the average distances in the network. The citation network of RFID patents (Hung and Wang 2010), for example, identifies patents with a high degree of betweenness centrality, with whom 81% of patent citation activities are related. The emergence of the small-world structure seems natural, since advances in scientific knowledge are driven by communities of researchers with shared interests and knowledge building on each other's ideas (Crane 1972). More generally, the small-world structure can emerge through local network interactions, such as transitive linking (Granovetter 1973; Ebel et al. 2002).

The second structural feature observed in citation networks is the power-law degree distribution (Barabasi and Albert 1999; Price 1965; Valverde et al. 2007). A well-known cause of this phenomenon is "preferential attachment" (Barabasi and Albert 1999), or, more generally, the "rich get richer" mechanism: A paper/patent has more chances of being cited as it becomes increasingly famous through more citations. For example, papers at the forefront of research are more highly visible and thus actively cited, which makes them increasingly noticed (Crane 1972). The process may be facilitated by the function of researcher communities (Crane 1972) and the strategic positioning of developers of new knowledge or technologies to acquire attention and resources (Upham et al. 2010). This positive feedback, however, loses its momentum as papers or patents become older, and this aging effect is captured by the dropping tail of the power-law distribution (Valverde et al. 2007).

The third commonly observed pattern in citation networks is hierarchy, a multilevel structure where the status or structure of a system's higher levels constrains that of lower levels (Simon 1962). Many complex systems in the real world are organized following such a structure (Ravasz and Barabasi 2003). An idea that has long persisted in a broad range of literature is that a decomposable, hierarchic structure enhances the evolvability of complex systems, such as the populations of species (Wright 1932, 1964), organizations (Simon 1962; Ethiraj and Levinthal 2004; Thompson 1967; Weick 1976), and products (Sanchez and Mahoney 1996; Baldwin and Clark 2000), and various kinds of complex real world networks (Strogatz 2001; Watts 1999). If we assume that scientific knowledge adapts to the world we live in and wish to understand (Plotkin 1997), the advantageous hierarchic structure of many complex systems should be reflected in its organization.

Keyword network analysis as an alternative approach

The structural patterns observed in citation networks can help us understand how scientific and technological knowledge is organized and evolves over time. However, the analysis of citation networks has inherent limitations. First is the issue of the level of analysis: Does a paper or patent represent an element of knowledge? One could argue that the nodes in citation networks i.e., papers or patents are a combination of knowledge elements, rather than an element of knowledge itself (Lee et al. 2010; Su and Lee 2010). In spite of this issue, the popularity of citation network analysis might be mainly due to the availability of large quantities of citation data. What constitutes knowledge, however, may be an on-going question of debate. Therefore, scientific attention to an alternative form of knowledge element should be essential and necessary to further advances in the science of knowledge. This study attempts to fill this gap by utilizing information on the keywords of scientific papers. The second limitation is that it is not straightforward to apply theories on the organization of citations to understand the organization of knowledge. This issue is also related to the first issue on the level of analysis. For theory on knowledge to advance, we need to deeply consider the elements of knowledge as the unit of analysis (McGrath 1996).

A few recent studies on knowledge networks began to recognize the usefulness of keyword information and the potential of keyword network analysis. Lee et al. (2010) calculated similarities between journal articles based on the degree of shard keywords on the assumption that "a keyword is the most basic fundamental carrier of knowledge." Su and Lee (2010) took an initiative step in constructing and visualizing a keyword network from the 556 author keywords of 181 technology foresight related papers. They provide a brief description of the keyword network and comparisons with author, institution, and country networks constructed from the same database. Although these recent studies did make a contribution to keyword network analysis, they are not dedicated to deep investigation into the nature of keyword networks. The literature is therefore still in need of a systematic approach to keyword network analysis to get substantial insight into how knowledge is organized, especially in comparison with our understanding of the structure of citation networks.

This study is our attempt to further develop the methodology of keyword network analysis and make a theoretical contribution to understanding the structure of knowledge from the network perspective. Specifically, we construct and analyze the keyword networks from three major journals in closely related fields in business research published during the 30-year period from 1980 to 2009: *MIS Quarterly, Management Science,* and *Marketing*. Two keywords are regarded as connected if they appear in a paper together. Since keywords are carefully selected by an author to identify a paper's distinctive research focus (Abrahamson 1996; McCloskey 1998), they represent the paper's key concepts and component ideas, and the way in which they are associated is linked to the novelty of the paper. The organization of keywords for a scientific field, therefore, is shaped and influenced by the thoughts and logic of its researchers, which represents the structure of the scientific knowledge of the field. Our analysis examines whether the structural patterns observed in citation networks still appear in keyword networks, and determines the differences and causes. In doing so, we attempt to determine the fundamental mechanisms underlying the observed patterns in the keyword networks from an evolutionary and network perspective, which may enable us to build an integrative theory on the organization of scientific knowledge.

The paper is organized as follows. The next section presents the construction process of keyword networks, as well as notable challenges and their solutions. The third section presents and interprets the structural patterns of keyword networks. The last section discusses the results and their implications.

The construction of keyword networks

The analysis of keyword networks faces two major challenges. The first one is the large computational burden. Because a paper usually contains multiple keywords, given a publication dataset, we have to deal with much bigger networks than citation networks, and the computational burden increases exponentially with network size. Second, identifying the list of independent keywords is not straightforward. Because keywords are mostly provided by authors, they appear in various forms, for example, singular and plural. Our first step, therefore, is to find keywords that are the same but in different forms.

The objective of this study, however, requires us to construct and analyze the keyword networks for closely related research fields during a long publication period. This requirement and the issue of computational burden necessitated a compromise, and we thus chose three closely related fields in business research: management information systems, management and organization, and marketing. For each field, we picked a major journal that represents the field with a long history: *Management Information Systems Quarterly* (MISQ: 1980 4(1)–2009 33(23), 726 papers), *Marketing Science* (MKTS: 1982 1(1)–2009 28 (5), 973 papers), and *Management Science* (MS: 1980 26(1)–2009 55(11), 3,626 papers).

For reliability in identifying the keyword list, we designed and followed the two-stage procedure specified in the Appendix. In the first stage, we identified independent keywords that represent key concepts, objects, and other methods researchers commonly use for scientific communications. This procedure applies two rules to the original keywords from the publication dataset: The uniform rule finds keywords that are considered the same and transforms them into a single form, preferably a simple and popular term; and the split rule finds keywords that consist of multiple independent keywords and splits them into separate terms. This stage is time-consuming and difficult but very important, because the resulting keyword networks directly depend on the keywords identified. To minimize errors at this stage, we implement a second stage to double-check important keywords that appear in many papers or have a high degree or betweenness centrality in the keyword network. Errors with respect to these keywords in stage 1 can have a relatively large impact on the analysis results; thus the second stage significantly reduces any potential defects in the resulting keyword networks. Table 1 summarizes the descriptive statistics for the identified keywords and the resulting keyword networks.

For robustness, we also analyzed the structural features of the keyword network at a higher level by constructing a keyword community network. We applied the clique percolation method (CPM) (Palla et al. 2005) to identify the interwoven set of overlapping keyword groups that make up the keyword community network. In a general sense, we need to allow for overlap in groups of closely associated concepts, because some concepts

Table 1 Descriptive statistics

	MIS quarterly	Marketing science	Management science	All journals
Number of papers	726	848	3,626	5,200
Number of keywords	2,247	1,864	6,575	9,523
Keywords per paper	3.10	2.20	1.81	1.83
Links per keyword	4.38	4.47	4.27	4.76
Average degree	8.82	8.86	8.21	9.38
Average path length	3.90	3.41	3.85	3.81
Clustering coefficient	0.86	0.84	0.83	0.83

are commonly related to others in constructing a body of knowledge. The CPM is a unique algorithm widely used for this purpose (Derényi et al. 2005; Palla et al. 2007). In the CPM, a community is defined as the union of all k-cliques (completely interconnected keyword groups of size k) that can be reached from each other through a series of adjacent k-cliques, where two k-cliques are adjacent if they share k–1 nodes. A challenge with this method (generally, in community analysis) is in choosing the value of the parameter k that determines what communities are identified and how they are connected. We followed a generally accepted rule of thumb: Choose a value that generates the clearest community network structure (Palla et al. 2005). Technically, as proposed (Palla et al. 2005), we adjusted the parameter to the point ($k = 8$) where the largest community becomes roughly twice as big as the second largest one.

Characteristics of the keyword networks

The structural features of the keyword networks are examined and compared with those of the citation networks noted above. The results show that, unlike most citation networks, keyword networks are not small-world networks but, rather, scale-free networks with a hierarchic structure. These results hold across the three keyword networks of each journal and the combined keyword network, implying structural equivalence in the organization of scientific knowledge across different scopes of scientific fields. The determined structural patterns, however, do not hold at a higher level of the analysis unit, the community of keywords, which implies that different underlying mechanisms may apply at different levels of knowledge elements. The following sections present each of the structural patterns observed in the keyword networks.

Not a small-world network

The keyword networks have a large clustering coefficient but not a small average distance (Table 1), thus deviating from a small-world network (Granovetter 1973; Watts 1999). The U.S. movie actor network, a traditional example of a small-world network in a social context, has a high clustering coefficient of 0.79, as well as a short path length of 3.65, in spite of its size of 2,25,226 actors (Watts and Strogatz 1998). The idea of "six degrees of separation" (Milgram 1967) also implies that all the (six billion) people in the world can be reached through only six steps of social relations, on average. Here, a simple heuristic is that a network of size N with an average path length of L complies with the distance requirement for a small-world network if $L < 1 + \log_{100} N$. Given the sizes (i.e., the number of keywords) of the keyword networks, between 1,000 and 10,000, the average path length should fall between two and three to meet the requirements, but it exceeds this range.

One might conjecture that the organization of scientific knowledge has a small-world structure that is not fully captured by the keyword network from a single or few research fields. For example, research fields overlap in the sense that they share common keywords and collectively associate those words together. There may be missing links in the keyword networks that could be covered by additional information from other journals and research fields. It is difficult, however, to construct an entire keyword network from the publication information of all journals in all scientific fields, and so it is difficult to directly verify this conjecture. Instead, we may get a clue by examining how the structure of a keyword network changes as more scientific fields become involved. Here, the ratio $(1 + \log_{100} N)/L$ could be a useful measure of the extent to which a network complies with the distance requirement of the small-world network. The results show that the combined keyword network has a smaller average distance than the individual keyword networks but still exceeds the required range: 0.79 (all journals) > 0.69 (MISQ), 0.77 (MKTS), and 0.76 (MS).

A scale-free network

Figure 1 shows the log–log plot of the cumulative distribution of the node-level degree, that is, the number of connections of a keyword with others. The vertical axis represents

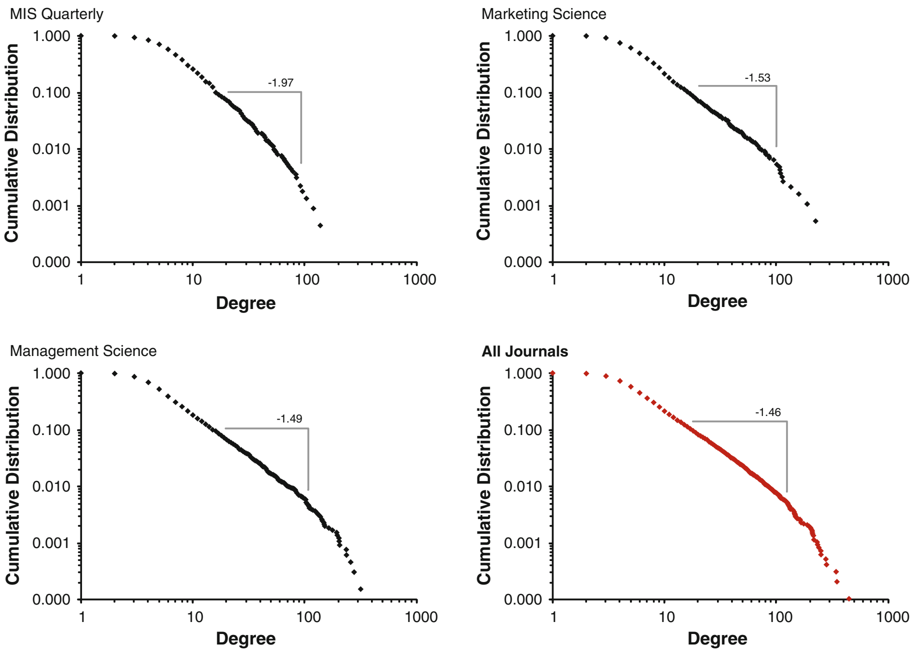

Fig. 1 Degree distribution of keyword networks

the fraction of keywords whose degree is less than the corresponding degree on the horizontal axis.

The linear relation implies that the keyword networks follow a power-law degree distribution where the probability of a keyword having x connections is proportional to $x^{-\gamma}$. In such networks, most keywords have a small number of connections, but certain keywords are associated with a large number of keywords. The same degree distribution pattern appears across the different keyword networks of each journal, as well as in the combined keyword network. Moreover, the scaling factor (γ) in the power-law degree distribution for all the keyword networks falls between two and three; that is, the scaling factor in the cumulative degree distribution falls between one and two in a network with a power-law degree distribution of the scaling exponent of γ, the cumulative degree distribution also follows a power-law distribution of γ – 1 (Newman 2005). An important implication is that that the keyword networks optimize the association of keywords at low cost (in terms of links) based on the role of hub keywords (Solé et al. 2010). Outside these bounds, the network either becomes easily disconnected ($\gamma > 3$) or too dense ($\gamma < 2$). This range of the scaling exponent therefore defines a window for the existence of scale-free networks. Commonality in the degree distribution and the scaling factor hints at the existence of a universal mechanism underlying the organization of scientific knowledge.

Hierarchic structure

Figure 2 shows the correlation between the degree of each keyword and its clustering coefficient on the log scale, as a measure of the degree of hierarchic structure. In hierarchical networks, the correlation between local clustering (connection density in a neighborhood) and degree (the number of connections) exhibits a scaling behavior; in contrast, nonhierarchical networks (such as a power grid) typically display constant clustering (Ravasz et al. 2002; Ravasz and Barabasi 2003). The results show a strong linear correlation, which implies that keyword networks have a hierarchic structure (Ravasz et al. 2002).

This structural feature provides clues about the generative mechanism underlying the organization and evolution of scientific knowledge. First, small groups of concepts are organized in a hierarchical manner into increasingly large groups, which results in two fundamental features of the network: a high degree of clustering and a scale-free topology (Ravasz and Barabasi 2003). Second, the hierarchic structure explains why the keyword networks have a longer path length than the small-world structure. A lack of direct links between top (central) groups of keywords and bottom (peripheral) groups increases the average distance in the network. In sum, the hierarchic structure of the keyword networks is coherent with their other characteristics, noted above.

Different characteristics at the community level

Given no consensus on what constitutes an element of scientific knowledge, one can argue away any gap between investigating keyword networks and studying the organization of scientific knowledge. While this debate has no clear answer, investigation into keyword association at a different level, rather than at the keyword level, may provide useful comparison and insights. Accordingly, we identify and examine communities (i.e., clusters) of keywords as an alternative element of scientific knowledge of a higher level, in our goal of determining whether the keyword network and keyword community network share similar structural characteristics.

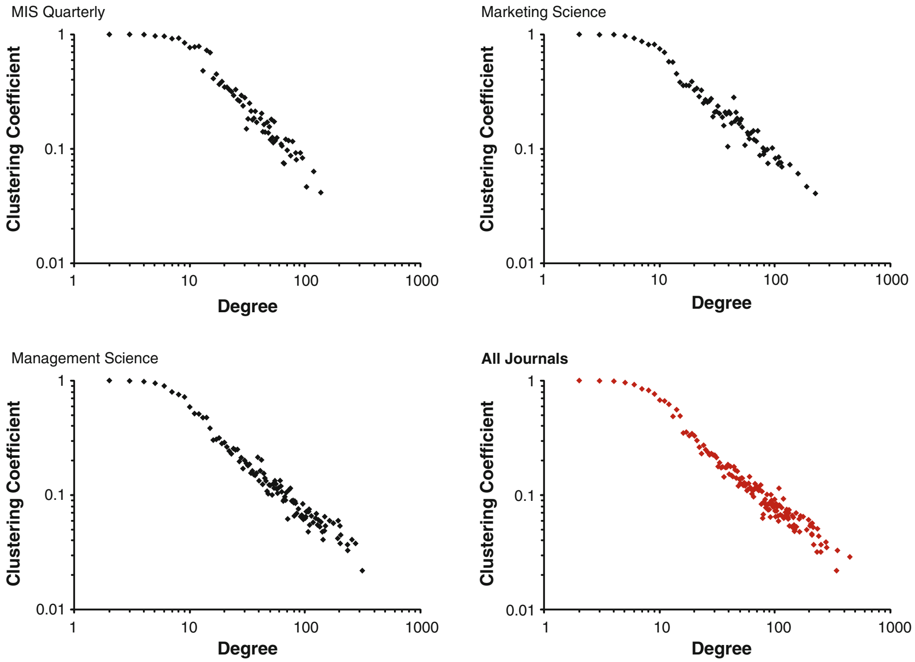

Fig. 2 Hierarchic structure of keyword networks

Figure 3 represents the degree distribution and the correlation between degree and clustering coefficient for the combined keyword network. The keyword community network, however, shows different patterns: It is not a scale-free network and does not have a clear hierarchic structure. This difference implies that different generative mechanisms apply to different levels of the scientific knowledge system. One of the reasons for this is boundaries between researcher groups. A keyword community is a group of strongly associated keywords and thus corresponds to a group of researchers familiar with them. The fact that the keyword communities are determined by modularity—that is, more within-group connections than between-group connections—implies the existence of barriers to interactions between researcher groups.

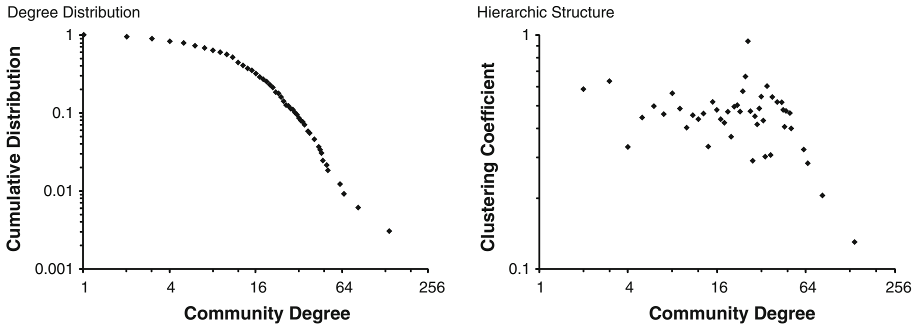

Fig. 3 Characteristics of the keyword community network

Conclusion and discussions

In this study, we attempted to make both methodological and theoretical contributions to the science of knowledge. As a methodological contribution, we demonstrated a systematic approach to constructing and analyzing keyword networks to examine the structure of scientific knowledge. Our analysis shows that keyword network analysis has a considerable potential as an alternative way to citation network analysis. The keywords of scientific papers could be a better proxy for knowledge elements, because the concepts in a scientific field are represented and communicated in the form of keywords (Lee et al. 2010; Su and Lee 2010). From this new perspective and approach, our analysis on keyword networks revealed interesting findings that have substantial implications for the understanding of knowledge structure. The most notable one is that, unlike citation networks, keyword networks are not small-world networks but, rather, scale-free networks with a modular, hierarchic structure. Moreover, this hierarchic structure seems to lie at the heart of the organization of scientific knowledge, because other structural characteristics can be understood as a byproduct of the evolutionary process that generates the hierarchic structure. The hierarchic structure of keyword networks has been hinted at in some previous studies by simple visualization (e.g., Su and Lee 2010). Our study is an initiative attempt to uncover the hierarchic structure of keyword networks in a rigorous way by using theory-based measurement and analysis (Ravasz et al. 2002; Ravasz and Barabasi 2003).

Researchers have identified the advantages of the hierarchic structure of complex systems, that is, why it is not due to chance but, rather, favored by an evolutionary selection process (Simon 1962). A hierarchy enables one to deal with the complexity a system faces as it grows up, that is, an exponential increase in the number of interactions between elements. A decomposable and hierarchic structure minimizes necessary interactions and helps the system work effectively and efficiently, thus enhancing its evolvability and survival (Simon 1962). In theories on organization and product innovations, the power of modular organizational and product architectures is well known (Sanchez and Mahoney 1996; Baldwin and Clark 2000). Our scientific knowledge, which has been developed to understand such systems, may also be organized in the same way. If so, the evolution of scientific knowledge, as a complex adaptive system itself, would also benefit from the same structural advantages so as to enhance the evolvability of human society.

We do not have a general theory on the origin of the hierarchic organization of scientific knowledge, but Simon's (1962) seminal work on the architecture of complexity provides a good foundation. The author poses a notable puzzle with respect to the direction of causality between bounded rationality and complexity. As boundedly rational actors with a limited capacity of cognition, we may be imperfect in viewing and understanding the world. Simon (1962, p. 477) states, "The fact, then, that many complex systems have a nearly decomposable, hierarchic structure is a major facilitating factor enabling us to understand, to describe, and even to 'see' such systems and their parts. Or perhaps the proposition should be put the other way round. If there are important systems in the world that are complex without being hierarchic, they may to a considerable extent escape our observation and our understanding." As Simon notes (p. 478), it is still an open question as to whether "we are able to understand the world because it is hierarchic, or whether it appears hierarchic because those aspects of it which are not elude our understanding and observation." It is an interesting conjecture that, in either case, our knowledge should be organized into a modular, hierarchic structure. Our results from the analysis of keyword networks support this conjecture.

The hierarchic structure of scientific knowledge may have emerged through a long evolutionary process in which new concepts are created, compared with existing ones in explaining the world, and established or abandoned. Thomas Kuhn's seminal work *The Structure of Scientific Revolutions*, for example, tells us about the creation of and competition between communities of researchers and corresponding bodies of knowledge (Kuhn 1962; Fleming and Sorenson 2001). In this process, being a part of a school of thought (i.e., an established and influential body of knowledge) is significantly beneficial for new knowledge, and within a school of thought new knowledge has more impact if it is on the intellectual semi-peripheries (Fleming and Sorenson 2001; Trajtenberg 1990). In this sense, the organization of scientific knowledge can reflect the history of science in terms of conceptual interactions among researchers, just as the structural patterns of scientific citations do in terms of social interactions.

Learning is essential for all living things, including human beings, to survive in daily life. Learning from direct or indirect experiences serves as the source of our knowledge, and knowledge in turn guides our decisions and experiences. In this sense, our living implies seamless interactions between our knowledge and the complex world we live in, and thus knowledge itself may be a stack of adaptations for survival. As Plotkin (1997, pp. xiv–xv) notes, "The human capacity to gain and impart knowledge is itself an adaptation or a set of adaptations… Adaptations are themselves knowledge, themselves forms of 'incorporation' of the world into the structure and organization of living things." We believe that understanding the organization of scientific/technological knowledge will help reveal the fundamental structure of the scientific/technological landscape in which innovative attempts are made; more generally, understanding the organization of knowledge helps reveal the architectural complexity of the world in which our adaptations are made.

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Appendix: Identifying independent keywords

Stage 1: Identify independent keywords.

- Uniform rule: For multiple keywords that are considered the same, transform them into a single form, preferably a simple and popular term. For example,

  Agent, Agents → Agent.
  Case study, Case study research → Case study.
  IT, Information technology → IT (other examples are CEO, E-MAIL, R&D, M&A, E-business).
  MCMC, Markov chain Monte Carlo, Markov chain Monte carlo (MCMC) → Markov chain Monte Carlo.
  CRM, Customer relationship management, Consumer relationship management → Customer relationship management.
  Technology management, Management of technology → Technology management.

- Split rule: If a keyword consists of multiple independent keywords, split them. For example,

  Efficiency and effectiveness → Efficiency, Effectiveness.
  Discrete/Continuous Choice Model → Discrete choice model, Continuous choice model.

Stage 2: Double-check important keywords.

- Identify important keywords that appear in many papers or have a high degree of betweenness centrality in the keyword network. Stage 1 errors for these keywords can have a relatively large impact on analysis results.
- Rerun important keywords through the first stage to minimize errors with these words.

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