Neural Embeddings of Scholarly Periodicals Reveal Complex Disciplinary Organizations

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Abstract

Understanding the structure of knowledge domains has been one of the foundational challenges in the science of science [19, 44]. Although there have been a series of studies on the self-organized structure of knowledge domains and their relationships [39, 45, 40, 8, 7], creating rich, coherent, and quantitative representation frameworks is still an open challenge. Meanwhile, neural embedding methods, which learn continuous vector representations of entities by using neural networks and contextual information, are emerging as a powerful representation framework that can encode nuanced semantic relationships into geometric ones [33, 26, 49]. Here, we propose a neural embedding technique that leverages the information contained in the paper citation network to obtain continuous representations of scientific periodicals. We demonstrate that our embeddings encode nuanced relationships between periodicals as well as the complex disciplinary structure of science, even allowing us to make cross-disciplinary analogies between periodicals. Furthermore, we show that the embeddings capture meaningful “axes” that encompass all disciplines in the knowledge domains, such as an axis from “soft” to “hard” sciences or from “social” to “biological” sciences, which allow us to quantitatively ground a periodical on a given spectrum. Using this new capacity, we test the hypothesis of the hierarchy of the sciences, showing that, in most disciplines such as Social Sciences and Life Sciences, most widely cited papers tend to appear in “harder” periodicals. Our framework may offer novel quantification methods in science of science, which may in turn facilitate the study of how knowledge is created and organized.
Since the formalization of science, scholarly periodicals, such as academic journals and proceedings, have become the primary loci of scientific activities [20, 18, 4, 15]. Periodicals are not only the conduits of scientific communication, but also distributed repositories of scientific knowledge organized around topical niches and disciplines [32, 15]. Therefore, scholarly periodicals have been considered the fundamental units for investigating the structure and evolution of science [40, 5, 8, 50]. Here, we propose a network embedding method to learn vector-space representations of periodicals and show that the periodical embeddings can effectively encode the complex and nuanced organization of knowledge in science.

Neural embedding is a set of techniques for obtaining vector-space representations of entities that efficiently encode multi-faceted relationships between the entities, and has become a core ingredient in modern machine learning [29]. Although its precursor, the vector-space model, was developed many decades ago [43], the combination of the flexibility of neural network approach and the availability of large training data has recently produced many breakthroughs [33, 34].

Since it was demonstrated that word embeddings can encode rich semantic relationships between words as geometrical ones in low-dimensional vector-space [33, 34, 35, 3], the embedding models have offered novel opportunities and solutions to challenging problems, including language evolution [23, 42], gender and stereotypes [6, 21], culture and identities [9, 26], and even the prediction of material properties [49]. Furthermore, the idea of vector-space embedding using neural networks is not limited to words and language; it has been adopted to many other domains and to other entity types, including sentences, paragraphs, documents, images, and networks [28, 25, 22].

Here, we propose a method for learning embeddings of scholarly periodicals, and use them to quantify relationships between periodicals and to study the structural organization of knowledge domains. Our method extends a random walk-based graph embedding method to a multi-layer network of papers and periodicals. Using the continuous vector-space representations of scholarly periodicals learnt by our method, we demonstrate that, as in the case of word embeddings, periodical embeddings geometrically capture the semantic relationships and allow us to make cross-disciplinary analogies. Harnessing the continuous nature of the learned embeddings, we conduct novel measurements on the theory of the “hierarchy of the sciences” [14], showing that there tends to be a citation hot-spot in the “harder” part of a field than its “softer” counterpart in social sciences and life sciences, whereas the opposite pattern can be seen in mathematics and physics.

Our embedding method builds on the DeepWalk model [38], which is a direct adaptation of the word2vec model in the context of networks, via the application of random walks on the network to construct “sentences”. Instead of using the network of periodicals, our method leverages the richer and higher-order citation network of papers to learn the representations of periodicals (see Methods).

Let us explain the key idea of our method. Imagine reading a paper from a field that you are unfamiliar with. To understand this paper, you may need to read another paper from the reference list; which in turn may prompt you to read another earlier paper, taking you to a rabbit hole of a citation trail. We hypothesize that such citation trails, created from references between papers, capture natural sequences in the citation
network. Now, by looking at the periodicals where each of the papers in the citation trail was published, we obtain a trail of *periodicals*. Here, we consider each periodical as a “word” and each trail as a “sentence”. If we apply the *word2vec* model to these “sentences”, it lets us learn embeddings that encode the semantic relationships among periodicals, and those with similar context in the citation trails would have similar periodical embeddings. Note that, instead of using random walks on the citation network of *periodicals*, we leverage richer and higher-order trajectories from the paper citations to enrich the output embeddings (cf. information gained from higher-order trajectories [11]).

**Disciplinary structure revealed by periodical embeddings**

We applied our framework to a citation network of 53 million papers and 402 million citation pairs. We trained a 100-dimensional embedding model using 100 million citation trails generated from this network (see [Methods]). As a result, we obtained a 100-d unit vector for each of the 20,835 periodicals. Our embeddings offer natural ways—i.e. the cosine similarity between vectors—to measure similarities between periodicals, which can be used for identifying similar periodicals. For instance, the two closest periodicals to *PNAS* are *Nature* and *Science*, and the two closest periodicals to *American Sociological Review* are *Social Forces* and *American Journal of Sociology* (see SI Fig. S7 for more examples and evaluation). The similarities defined by the embeddings also correlate with the similarities estimated by experts (see SI Model validation for detail).

Fig. 1 presents a 2-d representation of the embeddings of 12,780 journals, providing an overview of the global structure of major scientific disciplines. Although our approach produces continuous—not categorical—representations of periodicals, to facilitate a comparison with a traditional journal classification system, we color each journal in Fig. 1 based on its discipline category designated in the UCSD Map of Science catalog [8]. The major disciplines defined in the UCSD map still show up as conspicuous clusters in our projection. However, it also exposes the nuanced structure as well as the limitations of the classification approach. For instance, it uncovers highly interdisciplinary micro-clusters, such as parasite research or neuroimaging, that cannot be properly captured in the disjoint categories (see Fig. 1 insets and SI Fig. S12-S24 for other examples).

**Cross-disciplinary analogies between periodicals using embeddings**

One of the primary reasons behind the fame of the *word2vec* model is its uncanny ability to capture semantic relationships geometrically in vector space [21, 3, 26]. The most famous example goes like this: $v(\text{king}) - v(\text{man}) + v(\text{woman}) \approx v(\text{queen})$. That is, the difference between *man* and *woman* (or *king* and *queen*) vectors captures the axis of “gender”, which can be generalized to other gendered nouns such as *brother* and

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1 An interactive version is available at [https://haoopeng.github.io/journals](https://haoopeng.github.io/journals)
Figure 1: **Embeddings of scholarly periodicals reveal complex disciplinary organizations.**

a. Each dot represents a journal and its color denotes its discipline designated in the UCSD map of science [8]. A dimension reduction technique, t-SNE [31], is used to obtain the 2-d projection. We show 12,780 journals with known discipline category. 

b. archaeology and anthropology journals classified as “Earth Sciences” form a distinct cluster with its center closer to “Social Sciences” than the major “Earth Sciences” cluster (verified by the cosine distance).

c. a group of medical imaging journals comes from “Brain Research”, “Medical Specialties”, and “EE & CS”, highlighting the key role of computer science and engineering in the study of brain imaging.

d. a set of parasite-focused journals spans a wide variety of disciplines, including “Social Sciences” (*Ecohealth*), “Biology” (*Parasites*), “Infectious Diseases” (*Malaria Journal*), and “Chemistry” (*Journal of Natural Toxins*), revealing the multi-faceted, highly interdisciplinary nature of parasite research.

$sister \ (i.e. \ v(brother) - v(man) + v(woman) \approx v(sister))$ [33, 34].

Can we make similar analogies between scholarly periodicals using our embeddings? For instance, given a periodical pair \((A,B)\), where \(A\) is a quintessential Computer Science periodical and \(B\) is the one for Sociology, can \((v(A) - v(B))\) capture the axis that runs between Computer Science and Sociology? If that is
the case, given a “seed” periodical, we can also explore other periodicals that are closer to Computer Science and farther away from Sociology than the seed, or vice versa.

Figure 2: Analogy graphs generated with periodical embeddings. a, We apply the analogy defined by ASR (American Sociological Review) and JMLR (Journal of Machine Learning Research) to a computational social science conference KDD (or ICWSM) iteratively to find the most similar periodical at each step. The two graphs for KDD and ICWSM are combined into one. A blue edge from $X$ to $Y$ means $v(X) - v(ASR) + v(JMLR) \approx v(Y)$. A yellow edge from $X$ to $Y$ means $v(X) - v(JMLR) + v(ASR) \approx v(Y)$. Each node has two outgoing edges. A cycle in the same color means we cannot go any farther in that direction. b, We apply (Cell, PRL (Physical Review Letters)) to ASR, and only expand periodicals that are one step away from ASR to make the graph concise. c, This analogy graph is obtained by applying (ASR, PRL) to Blood. d, Similar to c, we use the periodical pair (ASR, PRL) as two poles of the axis between “soft” and “hard” sciences, and identify “softer” and “harder” periodicals for seeds in different disciplines, including “Brain Research” (Cognition, Brain), “Earth Sciences” (Journal of Climate), “Humanities” (Mind), “Medical Specialties” (Cancer), and “Social Sciences” (Quarterly Journal of Economics).

To demonstrate the possibility of making such cross-disciplinary analogies, we visualize “analogy graphs”, which are constructed by repeatedly applying the vector analogy and taking the best candidate from each analogy task. We first choose two canonical disciplinary periodicals and consider them as the “poles” of an axis going from one discipline to the other. Using the two poles, given a seed periodical, we then iteratively make analogies to the seed and subsequently discovered periodicals. For instance, in Fig. 2a, given a computational social science conference ICWSM (The International AAAI Conference on Web and Social Media) as a seed, and JMLR (Journal of Machine Learning Research) and ASR (American Sociological Review) as the poles, we iteratively make analogies to find the most similar periodicals at each step. The two graphs for ICWSM and ICWSM are combined into one. A blue edge from $X$ to $Y$ means $v(X) - v(ASR) + v(JMLR) \approx v(Y)$. A yellow edge from $X$ to $Y$ means $v(X) - v(JMLR) + v(ASR) \approx v(Y)$. Each node has two outgoing edges. A cycle in the same color means we cannot go any farther in that direction. b, We apply (Cell, PRL (Physical Review Letters)) to ASR, and only expand periodicals that are one step away from ASR to make the graph concise. c, This analogy graph is obtained by applying (ASR, PRL) to Blood. d, Similar to c, we use the periodical pair (ASR, PRL) as two poles of the axis between “soft” and “hard” sciences, and identify “softer” and “harder” periodicals for seeds in different disciplines, including “Brain Research” (Cognition, Brain), “Earth Sciences” (Journal of Climate), “Humanities” (Mind), “Medical Specialties” (Cancer), and “Social Sciences” (Quarterly Journal of Economics).

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Sociological Review) as two poles of an axis that goes from Sociology to Machine Learning, we discover EMNLP (Conference on Empirical Methods in Natural Language Processing) via the analogy \( \mathbf{v}(ICWSM) - \mathbf{v}(ASR) + \mathbf{v}(JMLR) \approx \mathbf{v}(?) \) and identify Social Forces based on \( \mathbf{v}(ICWSM) - \mathbf{v}(JMLR) + \mathbf{v}(ASR) \approx \mathbf{v}(?) \). All identified periodicals, including the seed, can be visualized as a directed network with nodes representing periodicals and links representing the analogical relationships.

Fig. 2a shows the analogy graph for ICWSM and KDD (ACM SIGKDD Conference on Knowledge Discovery and Data Mining), two major conferences that publish computational social science research. Fig. 2a reveals a spectrum of periodicals that sit between Sociology and Machine Learning, from a disciplinary sociology journal (Social Forces) to interdisciplinary computational social science conferences (e.g., EMNLP and ICDM (IEEE International Conference on Data Mining)), to more method-oriented machine learning conferences (e.g., ICML (The International Conference on Machine Learning) and NeurIPS (The Conference on Neural Information Processing Systems)). Another analogy graph is obtained by applying the periodical pair (Cell, PRL (Physical Review Letters)) that represents the axis from Biology to Physics, to the seed journal ASR, which identifies periodicals with biological flavor—NEJM (The New England Journal of Medicine)—or more physics flavor—Social Forces (Fig. 2b). We apply, in Fig. 2c-d, the pair (ASR, PRL) to periodicals across disciplines; for instance, when applied to Blood, we can discover a more physics journal (Cell) and a more sociological journal (NEJM).

Extracting conceptual dimensions in disciplinary organizations

The power of embeddings to discover analogical relationships between periodicals prompts us to explore more general conceptual dimensions in the knowledge space, because the two disciplinary “poles” (e.g., “Computer Science” and “Sociology”) of a scientific “axis” can be defined not only by a periodical pair, but also by two sets of periodicals. We first pick two general disciplinary areas and calculate their centroids by taking the average of all periodical vectors in each area. Given the two centroid vectors, we obtain an axis that runs from one disciplinary area to the other as we did in the previous examples with individual periodicals. Formally, let \( S^+ = \{ \mathbf{v}^+_1, \mathbf{v}^+_2, \ldots, \mathbf{v}^+_m \} \) and \( S^- = \{ \mathbf{v}^-_1, \mathbf{v}^-_2, \ldots, \mathbf{v}^-_n \} \) be two sets of periodical vectors, the centroid of each set is computed as: \( \mathbf{v}^+ = \frac{1}{m} \sum^m_i \mathbf{v}^+_i \) and \( \mathbf{v}^- = \frac{1}{n} \sum^n_j \mathbf{v}^-_j \). Then the axis vector is defined as: \( \mathbf{v}_{axis} = \mathbf{v}^+ - \mathbf{v}^- \). We measure the projection of a periodical \( p \) to this axis using the cosine similarity between two vectors: \( s(p, \mathbf{v}_{axis}) = \frac{\mathbf{v}(p) \cdot \mathbf{v}_{axis}}{|\mathbf{v}(p)||\mathbf{v}_{axis}|} \). Here, we examine two spectra of scholarship: (i) “soft” to “hard” sciences [1, 12, 24] and (ii) social sciences to life sciences.

The first axis (dimension) captures the idea of the hierarchy of the sciences—an ordering of scientific disciplines by the complexity of the subject matter and the hypothesized order of development—which places natural sciences like Mathematics and Physics at the bottom and social sciences like Sociology at the top [14, 11, 17]. Disciplines at the top of the hierarchy are argued to be “soft”—more complex, difficult to develop, and having less codified knowledge with more competing theories than disciplines at the bottom [11, 24, 30].
Figure 3: **Two spectra of scholarship.** a, The spectrum of soft and hard sciences, operationalized by defining $S^+ = \{v(p) | p \in \text{"Math & Physics"}\}$ and $S^- = \{v(p) | p \in \text{"Social Sciences"} \lor p \in \text{"Humanities"}\}$. Each journal is represented by a vertical line inside the box (12,780 in total). The color represents the discipline category and the position reflects the cosine similarity between the periodical vector and the axis $v_{\text{soft} \rightarrow \text{hard}}$. We also annotate several journals and proceedings, whose background colors are proportional to their projection values. We then show journals in each disciplinary category separately in the bottom. The black vertical line in each discipline represents the mean projection value of its journals. b, The spectrum along the axis between social sciences and life sciences (biological), operationalized by defining $S^+ = \{v(p) | p \in \text{"Biology"} \lor p \in \text{"Biotechnology"} \lor p \in \text{"Infectious Diseases"} \lor p \in \text{"Health Professionals"} \lor p \in \text{"Medical Specialties"}\}$ and $S^- = \{v(p) | p \in \text{"Social Sciences"} \lor p \in \text{"Humanities"}\}$. Note that the ordering of 13 disciplines is dramatically changed from a, reflecting the complex organization of scholarly periodicals in the embedding space along scientific axes.

We operationalize the axis from “soft” to “hard” sciences using two sets of periodicals. The pole of the “hard” sciences is defined by the centroid of all journals in “Math & Physics” and the pole of “soft” sciences is defined by the centroid of all journals in “Social Sciences” and “Humanities”. We project each journal $p$ onto $v_{\text{soft} \rightarrow \text{hard}}$ by calculating the cosine similarity $s(p, v_{\text{soft} \rightarrow \text{hard}})$. The projection in Fig. 3a forms a continuous spectrum along this axis, documenting how scholarly journals are distributed along the given axis that runs from Social Sciences & Humanities to Mathematics & Physics. Some exemplary “hard” journals include *Biophysical Journal, Journal of Theoretical Biology, Fractals, Physics Reports*, and *Physical Review E*. Some exemplary “soft” journals include *Applied Psychology, Anthropological Quarterly, Law & Society Review, Sociological Forum*, and *Politics & Society*. Several representative periodicals are annotated.
in the spectrum. We also rank 13 disciplines by the mean projection value of all journals in each category in Fig. \ref{fig:spectrum}. The break-down into each discipline provides richer insights into how major scientific branches are organized along this conceptual dimension (see SI \textit{Spectrum of journals in sub-disciplines}). Overall, this spectrum shows that the “hardness” of academic disciplines increases in the order of Sociology, Psychology, Biology, Chemistry, Physics, and Mathematics, which concurs with the common conceptual ordering based on the hierarchy of the sciences \cite{14, 11, 36}.

The second dimension we examine is the one from social sciences to life sciences, another major branch of Natural sciences. We place all “Social Sciences” and “Humanities” periodicals into social sciences group, and all journals that are classified as “Biology”, “Biotechnology”, “Infectious Diseases”, “Health Professionals”, and “Medical Specialties” into life sciences group. The spectrum of $v_{\text{social} \rightarrow \text{life}}$ is shown in Fig. \ref{fig:spectrum}. As expected, biomedical disciplines are located near the biological end of this spectrum. Most physical sciences, including “Chemistry”, “Earth Sciences”, and “Math & Physics”, are distributed in the middle of this band. Surprisingly, computer science, which was far from “Social Sciences” on the soft–hard sciences axis, is the closest to “Social Sciences” on this dimension. The same set of representative periodicals annotated in Fig. \ref{fig:spectrum} are rearranged on the axis between social sciences and life sciences (Fig. \ref{fig:spectrum}), highlighting the multifaceted nature of the disciplinary organization of periodicals and the embeddings’ ability to tease out semantic dimensions.

\textbf{Impact of “soft” and “hard” research}

As introduced earlier, August Comte’s hypothesis of the \textit{hierarchy of the sciences} argues that the “hard” sciences and “soft” sciences are fundamentally distinctive because of the complexity of the subject matters \cite{14, 11}. For instance, because human behavior is inherently more complex than the behavior of an atom, it has been hypothesized that there should be more consensus and more established facts in Physics than in Sociology \cite{27, 12, 16}. Understanding such fundamental differences between disciplines can inform science policies across many levels from institutions to nations, and may foster better interdisciplinary collaborations \cite{10, 13}.

Although the idea that “hard” sciences produce more codified facts and consensus has been tested in some forms \cite{30, 11, 35, 40, 17}, the disciplinary designation and the operationalization of “hardness” were always based on disjoint disciplinary categories, because it was difficult to extend the notion of “hardness” in a continuous manner. Therefore, the results are always confounded with other disciplinary characteristics. The periodical embeddings, by contrast, offer a more natural way to quantitatively measure the scientific “hardness”, at a finer resolution—within individual disciplines, which in turn allows us to ask: within a discipline, is there a hot-spot of high impact papers? If such hot-spots exists, where is it on the spectrum? The hierarchy of the sciences hypothesis suggests that a hot-spot may be located close to the ‘hard’ end of the spectrum, because presumably it is easier to produce codified facts as the subject matter becomes
“harder”. An alternative hypothesis would be that research papers attract more citations if they provide critical translation of fundamental knowledge into application domains. This hypothesis implies that a hot-spot may emerge on the “soft” side of the spectrum.

To investigate this question, we consider the PageRank score of a paper calculated from the paper citation network as the proxies of impact (see SI Table S5 for corresponding results based on the number of citations [in-degree]). Specifically, we construct a citation network among all 22 million journal papers published between 1950 and 2000 (inclusive) in our dataset, and calculated the PageRank scores of 12 million papers in the largest connected component. Papers are left censored due to earlier ones having incomplete references in the data, and are right censored due to limited computational power. Changing the period to 1950 and 1990 does not change the results qualitative (results not shown here). Conference papers were excluded for the lack of discipline information, which account for less than 2% of all papers published in this period (SI Fig. S1). Here, utilizing the conceptual axis $v_{soft-hard}$ to measure scientific “hardness”, we show the distribution of impact along the “soft” to “hard” sciences dimension within each discipline. We consider a periodical’s projection value on the axis $v_{soft-hard}$ as its “hardness”.

We first illustrate the distribution of highly-cited papers in life sciences, which fall between physical sciences and social sciences according to the hierarchy of the sciences hypothesis [17]. Fig. 4b shows the density map of PageRank scores of papers published in biomedical journals (classified as “Biology”, “Biotechnology”, “Infectious Diseases”, “Health Professionals”, and “Medical Specialties”). The result concurs with the hierarchy of the sciences hypothesis that, in life sciences, the “harder” periodicals produced more high-impact papers than their “softer” counterparts. We also applied the Kernel Density Estimation (KDE) method to estimate the hardness distribution of high PageRank papers across this axis. The result supports our observation that papers with high PageRank scores have been biased towards relatively “harder” research in life sciences (Fig. 4b). To examine whether the observed pattern is simply due to the possibility that there were more “hard” papers than “soft” ones in earlier years, we constructed a null model where, for each citation pair ($P_x$, $P_y$) in the paper citation network, we randomly created a citation ($P_m$, $P_n$) with $P_m$ ($P_n$) published in the same year as $P_x$ ($P_y$), and recalculated the PageRank scores.

Fig. 4b indicates that, contrary to the lack of correlation in the null model, a clearly biased pattern can be observed in the empirical data. Further analysis reveals that the distribution of “hard” and “soft” papers is roughly balanced across the years (SI Fig. S11), thus there indeed exists a measurable difference between “soft” and “hard” research in terms of producing codified knowledge and achieving community consensus in life sciences.

We observed an even stronger bias towards “harder” research in disciplines at the soft-end of the spectrum, such as “Social Sciences” and “Humanities” (Fig. 4a and SI Table S4). However, such a discrepancy is less evident in disciplines at the middle ground of the spectrum, including “EE & CS”, “Engineering”, and “Earth Sciences” (Fig. 4c and SI Table S4), and is even partly reverses in “Math & Physics” (Fig. 4d). In “Math & Physics”, top 1% papers are skewed towards “soft” end of the spectrum, although the very
Figure 4: The scientific impact of soft and hard research in different disciplines. 

- **Social Sciences** (0.7 million papers).
- **Life Sciences** (4.3 million papers).
- **EE & CS** (0.4 million papers).
- **Math & Physics** (1.0 million papers).

For each panel:
- **Top left**: the density map of papers’ PageRank scores. The horizontal axis stands for the scientific “hardness” of periodicals on the soft to hard sciences dimension. The gray line shows the average “hardness” using log bins on the y-axis, with 99% confidence intervals.
- **Bottom left**: the 1-d Kernel Density Estimation of the “hardness” distribution of top papers ranked by their PageRank scores.
- **Top right, Bottom right**: the patterns observed in the null model.

Top papers are skewed back. Our results indicate that both hypotheses may be in play. The theory of the hierarchy of the sciences may be applicable in most disciplines, in a way that citations are funneled into more methodological and mathematical contributions in the field. At the same time, in the very hard sciences, research that translates methodological studies (hard science) to social problems (soft science) may also have a great potential to make a large impact.
This finding may have important implications for understanding how we produce knowledge and how we evaluate research work, especially in interdisciplinary areas where the research products often spread widely across the spectrum of soft and hard sciences. As the scientific impact is increasingly operationalized and estimated with citation-based statistics, it will be critical to understand fundamental differences between disciplines in citation dynamics, which can be more readily studied with continuous embedding frameworks. For instance, our result suggests that measures such as PageRank would favor harder sciences over softer across most disciplines.

Discussion

Here we present a continuous embedding framework for scholarly periodicals to systematically investigate the structure of periodicals and disciplines. By applying our method to a large-scale bibliographic dataset, we obtain vector-space embeddings of scientific periodicals that reveal the complex disciplinary organizations of science which cannot be captured by an existing journal classification system. The framework allows us to make cross-disciplinary periodical recommendations using vector analogies, and to organize periodicals along conceptual scientific dimensions. Leveraging the periodical embeddings, we perform a novel measurement on the distribution of knowledge and long-term impact across the spectrum of soft-hard sciences in broad disciplines such as life sciences. Our results show that, concurring with the hierarchy of the sciences hypothesis, the ‘hard’ sciences seem to have produced more highly-cited or codified papers, although this pattern may not be universal across all disciplines. These findings may have a variety of implications. For instance, understanding such contrasting disciplinary characteristics may help funding agencies and governing bodies to take into account these differences in their policies and evaluation standards. More generally, the capacity to quantitatively operationalize relevant disciplinary dimensions will be a critical step towards developing more sophisticated measurement system for the Science of Science.

We also would like to point out limitations of our study. First, the quality of embeddings depends on the quality of the dataset, thus our embeddings may carry potential biases in the MAG data. For instance, the embeddings may be noisy for younger periodicals whose papers have not received enough citations, or it may be much less accurate for fields that are not well covered by the source bibliometric dataset. Second, the present study does not take into account the evolutionary characteristics of both periodicals and disciplines, falling short in providing a dynamic picture of the disciplinary patterns formed during different time periods. Future work can extend our framework to model the evolution of scientific periodicals and disciplines by incorporating temporal information in citations. Third, part of our analysis (e.g., the spectrum of science) still utilizes manually-curated, disjoint discipline categories of periodicals, which might cause bias in the findings. Despite these limitations, we argue that our framework can be leveraged to identify intuitive conceptual dimensions in disciplinary organizations and quantitatively measure academic periodicals and disciplines on these axes. Our results therefore open up new ways of making quantitative inquiries into the
organization of knowledge domains, to better understand how scientific enterprises work across diverse sets of disciplines and practices.

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Methods

Dataset

We used the Microsoft Academic Graph (MAG) data [47], which consists of 126 million papers published in 23,404 journals and 1,283 conference proceedings between 1800 and 2016 (see SI Dataset for more detail). From the full dataset, we extracted 53,410,055 papers that have information about their publication periodicals (journals or proceedings) and obtained 402,395,790 citation pairs between these papers, which were published in 24,020 periodicals.

Model

We consider the citation network between papers, where each node is a paper and a directed edge from A to B is formed if paper A cites paper B. We generate many citation trails \( \{ T_1, T_2, \ldots, T_N \} \) from the citation graph using random walks, where we first randomly choose a starting point (a paper) and randomly follow citations until we arrive at a dead-end (a paper without outgoing edges). Each trail \( T \) is a sequence of papers \((P^T_1, P^T_2, \ldots, P^T_{|T|}) \). We discard trails that are immediately terminated \((|T| = 1) \). We then create a corresponding periodical trail \( V_T = (V^T_1, V^T_2, \ldots, V^T_{|T|}) \) for each paper citation trail, where the \( i \)-th element \( V^T_i \) is the publication periodical of the \( i \)-th paper \( P^T_i \) in the paper citation trail. Using the periodical trails, we learn two vector representations of each periodical \( v(V) \) (“input”) and \( v'(V) \) (“output”) by employing the skip-gram with negative sampling (SGNS) method [34]. For a given periodical citation trail \( V_T \), the objective is to maximize the log probability

\[
O = \frac{1}{|V_T|} \sum_{t=1}^{|V_T|} \sum_{w \leq j \leq w, j \neq 0} \log p(V^T_{t+j} | V^T_t),
\]

where \( w \) is the context window size. This training objective can be efficiently approximated as

\[
E = \log \sigma(v'(V_O) \top v(V_I)) + \sum_{i=1}^k E_{V_i \sim \mathcal{U}(V)} \left[ \log \sigma(-v'(V_i) \top v(V_I)) \right],
\]

where \( V_I \) is the input periodical and \( V_O \) is the output (context) periodical in Eq. 1 and \( \sigma(x) = 1/(1 + \exp(-x)) \). For each periodical pair \((V_I, V_O)\), SGNS samples \( k \) negative pairs \((V_I, V_i)\) from the empirical distribution \( \mathcal{U}(V) \). Here we let \( k = 5 \) and \( \mathcal{U}(V) \) be the smoothed unigram distribution [34]. After training, the input vectors are used as the periodical embeddings [33]. All models are trained with \( N = 100,000,000 \). See SI Hyperparameter tuning for detail.

Data availability

The datasets analysed during the current study are available at: https://drive.google.com/open?id=1L60luUUCt8Ay1me1DP_Lr2Islt24TuZZW
Code availability

Code is available at: https://github.com/haoopeng/periodicals

Addendum

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Author Contributions

H.P., Q.K., C.B., D.M.R. and Y.A. conceived the idea and designed the study; H.P. performed the analyses; H.P. and Y.A. produced all visualizations; H.P., Q.K., C.B., D.M.R. and Y.A. discussed the results and contributed to the interpretation of the results; H.P. and Y.A. led the writing of the manuscript and all authors contributed to the final manuscript.

Competing Interests

The authors declare no competing interests.

Additional Information

Supplementary Information is available for this paper.

Materials & Correspondence

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Supporting Information (SI)

Dataset

The Microsoft Academic Graph data [https://www.microsoft.com/en-us/research/project/microsoft-academic-graph](https://www.microsoft.com/en-us/research/project/microsoft-academic-graph) we used in this study is the largest open access bibliometric dataset and has been used in previous study [2]. The snapshot (accessed on 02/05/2016) we used contains 126,909,021 papers published in scholarly periodicals covering most research fields. There are 528,245,433 citations between these papers.

![Figure S1: The cumulative number of journal and conference papers from 1800 to 2016. A total number of 53 million papers are used in this study.](image)

We focused on all papers that were published in either journals or conference proceedings, as the periodical information is needed to train the embedding model. Thus our study is based on a total number of 53,410,055 papers and 402,395,790 citations. They were published between 1800 and 2016 in 24,020 scholarly periodicals. Fig. S1 shows the number of papers over time.

We trained a periodical embedding model using our framework, which covers 20,835 periodicals (see [Hyperparameter tuning](#)). However, MAG does not have the discipline information for these periodicals. We thus used the UCSD map of science data [8] to assign the discipline category to MAG journals. The UCSD map of science data contains discipline information for about 25K journals, which are classified into 13 academic disciplines. In total, 12,780 journals covered in the embedding model are matched between the two datasets (Table [SI](#)).
Table S1: The number of journals in 13 disciplines defined in the UCSD map of science. These 12,780 journals can be matched between the MAG data and the UCSD map of science data and are covered in the embedding model. 29 journals belonging to multiple disciplines are labeled as “Interdiscipline”. In the paper, we abbreviate “Chemical, Mechanical, & Civil Engineering” as “Engineering”, and “Electrical Engineering & Computer Science” as “EE & CS” to save space.
Hyperparameter tuning

We tuned two hyperparameters in the word2vec model: the context window size ($W$) and the number of dimensions for the embeddings ($D$). For each combination of $W$ (2, 5, and 10) and $D$ (50, 100, 200, and 300), we trained a model using the same 100 million periodical trails (Fig. S2). We set the minimum periodical frequency to 50, which means that the embedding model will exclude periodicals with less than 50 occurrences due to data sparsity. A good model would output similar embedding vectors for periodicals that are similar in terms of research topics. We thus compared the quality of different models based on the similarities between periodical embeddings.

![Figure S2: The length distribution of 100 million periodical trails. Length-one trails were discarded during the random walk process.](image)

Specifically, we randomly sampled 100,000 journal pairs for each of the three groups: (i) in the same discipline, (ii) in the same sub-discipline, and (iii) in any discipline. Note that we focused on 12,780 journals for which we have discipline categories and are covered in our embedding model (Table S1). Table S2 indicates that the model trained with $W = 10$ and $D = 100$, which covers 20,835 periodicals, gives the best result. Figs. S7C-D show that, based on the best model, journal pairs in the same discipline (and sub-discipline) are much more similar in the embedding space than those selected randomly from any discipline.
Table S2: **Hyperparameter tuning in the model training.** Each model is trained with the same 100 million periodical citation trails. The minimum frequency is set to 50 in all settings. \( W \) is the context window size, \( D \) is the number of embedding dimensions. \( \text{Mean} \text{(sub)}, \text{Mean} \text{(dis)}, \text{and } \text{Mean} \text{(rand)} \) are the mean cosine similarity of, journal pairs in the same sub-discipline, journal pairs in the same discipline, and journal pairs in any discipline, respectively. Note that we randomly selected 100,000 journal pairs for each group. \( \Delta \text{Mean(sub)} = \text{Mean(sub)} - \text{Mean(rand)}, \Delta \text{Mean(dis)} = \text{Mean(dis)} - \text{Mean(rand)} \).

| \( W \) | \( D \) | \( \Delta \text{Mean(sub)} \) | \( \Delta \text{Mean(dis)} \) | \( \text{Mean(rand)} \) |
|---|---|---|---|---|
| 2 | 50 | 0.302 | 0.105 | 0.233 |
| 2 | 100 | 0.349 | 0.118 | 0.253 |
| 2 | 200 | 0.314 | 0.103 | 0.250 |
| 2 | 300 | 0.299 | 0.096 | 0.243 |
| 5 | 50 | 0.432 | 0.179 | 0.073 |
| 5 | 100 | 0.457 | 0.183 | 0.086 |
| 5 | 200 | 0.419 | 0.165 | 0.084 |
| 5 | 300 | 0.399 | 0.157 | 0.082 |
| 10 | 50 | 0.420 | 0.172 | 0.069 |
| 10 | 100 | **0.469** | **0.192** | 0.069 |
| 10 | 200 | 0.428 | 0.172 | 0.067 |
| 10 | 300 | 0.406 | 0.161 | 0.066 |
Model validation

Our periodical embeddings provide a natural solution to recommending topically similar periodicals based on cosine similarity. We compared our model to two baseline methods. The first baseline recommends periodicals that are in the same discipline as the target periodical and rank candidates based on their scientific impact, measured using the PageRank algorithm. The PageRank scores are calculated on a directed and weighted periodical citation network in which edge weights represent the number of citations between a pair of periodicals. The second baseline also uses the cosine similarity metric for the recommendation task. Specifically, we constructed an adjacency matrix representing the citation counts between 24,020 periodicals, and assigned a 48,020-dimensional vector to each periodical by concatenating its in-degree vector and its out-degree vector (both are normalized to the unit length).

Our embedding model can efficiently identify similar periodicals for all 20,835 periodicals covered in the model. However, since the first baseline relies on the discipline information, we thus focused on the 12,780 journals that have discipline categories (Table S1). Each algorithm can rank, for a given target journal, the remaining 12,779 candidates in a certain order. The first baseline gives an arbitrary rank for journals whose disciplines are different from that of the target. Note that our embedding method is far more computationally efficient than the second baseline, since its number of vector dimensions is much less (100 vs. 48,040).

We evaluated the recommendation quality of three algorithms using expert knowledge collected through a Journal Recommendation Survey distributed over the authors’ institutions. The target population include faculties, doctoral students, and postdocs in different departments. To make the task feasible, we selected top 20 journals in each discipline based on their PageRank scores (calculated in the first baseline). Journals belonging to the “Interdiscipline” category were excluded in the survey. For each of the 260 target journals, we constructed a set of candidate journals and asked participants to rank them based on their topical similarities to the target. The candidate set is the union of the top 4 similar journals given by each algorithm. Due to the overlap between the three top lists, the size of the candidate set varies between 4 and 12.

Participants first selected a discipline as their fields to begin the survey (Fig. S3). They were then asked about their familiarity with the 20 target journals in the selected discipline. Participants were allowed to continue the task only if they were familiar with at least three target journals (Fig. S4). Participants who selected less than three targets were immediately directed to the end of the survey. After the screening phase, participants were asked to rank, for each selected target, the set of candidate journals based on their topical similarities to the target. Participants can place unfamiliar candidates in the “Unfamiliar Journals” group (Fig. S5).

We were able to distribute the survey to a few departments due to permission issues. Among 247 participants (out of 367) who finished the survey, 119 were qualified to complete the task of ranking journals, and each of them was rewarded a $10 Amazon gift card. Table S3 shows the statistics of qualified responses across different disciplines.

Experts can give quite different ranking of the same target journal. We use Kendall’s Rank Correlation
Figure S3: The survey interface where participants were first asked to choose a field from 13 disciplines to begin the task.

We used the coefficient $\tau$ to measure the level of agreement between two ranked lists of a target, based on the intersection of two lists. We focused on target journals $\mathcal{J}$ whose average pairwise expert agreement $\hat{\tau} \geq 0.2$ (we obtained similar results with different thresholds). In the evaluation step, in order to leverage more expert information, we appended to each ranked list the unfamiliar journals in a random order (the results are qualitatively the same without including unfamiliar journals). Then, each ranked list for a target in $\mathcal{J}$ was used as the ground truth to evaluate three algorithms. Specifically, for a ranked list $l^j_e$ of target journal $j$ from an expert $e$, we retrieved, from the full ranked list of an algorithm $a$, the order $l^j_a$ of journals in $l^j_e$, and we calculated $\tau(l^j_e, l^j_a)$.

Figs. S6a-d show the average correlation between each algorithm and domain experts. The two vector-space models perform much better than the first baseline. It also reveals that our periodical embeddings
Figure S4: Participants were asked about their familiarity with the 20 target journals in “Social Sciences”. The survey continues only if at least 3 target journals were selected.

are comparable to the citation-based vector model (the second baseline) in capturing similarities between journals. Although the two are not statistically different from each other in terms of quality, it should be noted that our embedding model is two orders of magnitude more efficient than the second baseline in terms of both time and space complexity.

We further evaluated our model in predicting the discipline category for each journal. We compared the periodical embedding model to the same citation-based vector model and another baseline method, called the voting method, which predicts the discipline of a target journal to be that of its most cited neighbor in the undirected journal-citation network based on edge weights. The edge weights are defined as the total number of citations between two journals (The undirected version performs better than the two directed versions). We used the $k$-nearest neighbors algorithm for the two vector-based models in the prediction task.

Fig. S6e shows that our model can be used to more accurately predict the disciplinary categories for
Q8: In this survey, you’ll be ranking journals by their topical similarities. According to your expert opinion, if someone publishes papers in the journal Psychological Bulletin, how likely are they to also publish papers in the following journals? Please rank the journals by arranging them from the top (most likely) to the bottom (least likely). You can put the journals you are unfamiliar with in the “Unfamiliar Journals” bucket in any order. If you are unfamiliar with any journal, please do not attempt to evaluate it purely based on its name.

| Items | Ranked Journals | Unfamiliar Journals |
|-------|-----------------|---------------------|
|       | 1. Journal of Personality and Social Psychology | 1. Econometrica      |
|       | 2. American Psychologist                     | 2. American Political Science Review |
|       | 3. Journal of Consulting and Clinical Psychology | 3. The American Economic Review |

Figure S5: Screenshot of the rank task interface for the target journal Psychological Bulletin. The candidate journals on the left side are randomly stacked on top of each other. Participants can place unfamiliar candidates in the “Unfamiliar Journals” bucket in any order.

journals, indicating that our periodical embeddings can capture more nuanced relationships between journals than the vector model based on pure citations.
| Discipline                  | Num. of Participants | Num. of Selected Targets |
|----------------------------|----------------------|--------------------------|
| Social Sciences            | 50                   | 318                      |
| EE & CS                    | 39                   | 224                      |
| Engineering                | 20                   | 129                      |
| Math & Physics             | 3                    | 21                       |
| Earth Sciences             | 2                    | 10                       |
| Health Professionals       | 2                    | 9                        |
| Biology                    | 1                    | 11                       |
| Brain Research             | 1                    | 5                        |
| Biotechnology              | 1                    | 4                        |

Table S3: The number of qualified participants and the total number of target journals selected by them across different disciplines.

Figure S6: Model validation results. a-d, The average Kendall’s Rank Correlation coefficient between experts and algorithms. Target journals with an average expert agreement above 0.2 are used in the evaluation. The three labels — pr_disc, citation, and j2v — represent baseline #1, #2, and the periodical embeddings. e, The $F_1$ score of the classification task in predicting the discipline category for 12,751 journals (excluding 29 interdisciplinary journals). The results are based on a 5-fold cross validation. The three labels — vote, citation, and j2v — represent the majority voting method, the citation-based vector model, and our periodical embedding model. The green curve is a horizontal line unrelated to the x-axis.
Recommending similar periodicals

The periodical embeddings can also serve as a useful recommendation system. Compared to the existing journal classification system, our model can identify similar periodicals beyond disciplinary boundaries. As an example, Fig. S7A lists the 10 most similar periodicals to PNAS, a multi-disciplinary yet biomedical-dominated journal, based on the cosine similarities between periodical embeddings. Other multi-disciplinary journals, such as Nature, Science, Nature Communications, and some biological journals are among the top list. We can also detect interesting periodicals across disciplines using vector analogy. Fig. S7B shows that the two most similar periodicals to \( v(\text{Biochemical Journal}) - v(\text{Cell}) + v(\text{Physical Review Letters}) \) are Physical Review B and Journal of Physical Chemistry.

| A | Top 10 venue similar to PNAS | B | Biochem. J. − Cell + PRL |
|---|---|---|---|
| Journal | Similarity | Journal | Similarity |
| Nature | 0.87 | Phys. Rev. B | 0.64 |
| Science | 0.82 | J. Phys. Chem. | 0.59 |
| BioEssays | 0.80 | Trans. Faraday Soc. | 0.58 |
| Cell Rep. | 0.80 | J. Electrochem. Soc. | 0.57 |
| EMBO J. | 0.79 | Acta Chem. Scand. | 0.57 |
| Nat. Commun. | 0.78 | Phys. Rev. A | 0.56 |
| Curr. Biol. | 0.77 | Helv. Chim. Acta | 0.55 |
| Annu. Rev. Biochem. | 0.77 | Anal. Chem. | 0.54 |
| PLoS Biol. | 0.77 | Phys. Rev. | 0.54 |
| BMC Biol. | 0.75 | Analyst | 0.53 |

Figure S7: Periodical recommendations. (A) The 10 most similar periodicals to PNAS based on the cosine similarities between periodical embeddings. (B) The 10 most similar periodicals to the vector analogy: \( v(\text{Biochemical Journal}) - v(\text{Cell}) + v(\text{Physical Review Letters}) \). (C) The histogram of cosine similarities of 100,000 randomly selected journal pairs that are in the same discipline (within-disc.) or in any discipline (random). (D) As in (C), but for journal pairs in the same sub-discipline (within-sub.).
Spectrum of journals in sub-disciplines

The periodical embeddings allow us to identify conceptual dimensions in all sciences. We can further organize sub-disciplines along these axes. Here we show three examples. Figs. S8–S10 present the spectrum of sub-disciplines in “EE & CS”, “Social Sciences”, and “Brain Research”, respectively, along the “soft” to “hard” sciences axis.

Figure S8: The spectrum of journals in sub-disciplines of “EE & CS”, along the soft to hard sciences dimension. Each journal is represented by a vertical line inside the box. The color represents the discipline category in the UCSD map of science. We focused on the top 20 sub-disciplines based on the number of journals, and ordered each category by the mean projection value (the black vertical line). Research topics such as Library Science, Information Retrieval, User Interface Design, Machine Learning, and Data Mining are “softer” than topics such as Signal Processing, Robotics, Wireless Communication, and Controls Systems.
Figure S9: Same as Fig. S8, but for the spectrum of journals in “Social Sciences”. Sub-disciplines such as Law, Psychology, Communication, Education, Management are, on average, “softer” than Economics and Finance.
Figure S10: Same as Fig. S8, but for the spectrum of journals in “Brain Research”. Sub-disciplines such as Neurology, Medical Imaging, and Magnetic Resonance Imagery are “harder” than Psychiatry, Speech, Hearing, Headache, and Consciousness.
Impact of “soft” and “hard” research

We have analyzed the difference between “hard” periodicals and “soft” periodicals in terms of producing high impact papers in each discipline. However, several factors can affect papers’ scientific impact, such as the age of publication—older papers have the apparent advantage over younger ones in accumulating citations.

Figure S11: The yearly density map of the scientific “hardness” of all papers published in journals in a, “Social Sciences”; b, life sciences (classified as “Biology”, “Biotechnology”, “Infectious Diseases”, “Health Professionals”, and “Medical Specialties”); c, “EE & CS”; and d, “Math & Physics”. The line curve in each subplot shows papers’ mean “hardness” value on a yearly basis, with 99% confidence intervals.

We thus further verify that the observed pattern is not because of the imbalanced distribution of “soft” and “hard” papers over the years. Fig. S11 shows the density map of the scientific “hardness” of papers on a yearly basis, which is based on the same number of papers used in Fig. 4 in the main text. It shows that the number of papers published in “hard” journals is roughly the same as that in “soft” journals across different years, confirming our findings in the paper.

Besides the disciplines discussed in the main text (Fig. 4), we also show the result for each of the 13 disciplines. To save space, we only present the KDE of the hardness distribution for top papers. Table S4
| Discipline               | # Journals | # Papers | Top 1% ∆Mean | Top 1% ∆Median | Top 0.1% ∆Mean | Top 0.1% ∆Median |
|-------------------------|------------|----------|--------------|----------------|----------------|------------------|
| Social Sciences         | 2,194      | 712,313  | 0.08***      | 0.10***        | 0.12***        | 0.17***          |
| Humanities              | 559        | 80,039   | 0.03***      | 0.04***        | 0.04*          | 0.13**           |
| Health Professionals    | 1,040      | 720,726  | 0.02***      | 0.00           | 0.00           | -0.05            |
| Brain Research          | 578        | 699,799  | 0.02***      | 0.07***        | 0.00           | 0.07***          |
| Medical Specialties     | 1,224      | 1,822,771| 0.03***      | 0.01***        | 0.05***        | 0.03***          |
| Biology                 | 847        | 712,462  | 0.02***      | 0.01***        | 0.03***        | 0.05***          |
| Earth Sciences          | 381        | 248,582  | 0.03***      | 0.00           | 0.04***        | -0.02            |
| Chemistry               | 484        | 1,027,050| 0.03***      | 0.08***        | 0.04***        | 0.07***          |
| Engineering             | 765        | 627,962  | 0.01**       | 0.00           | 0.01*          | 0.02**           |
| Infectious Diseases     | 486        | 752,074  | 0.02***      | 0.00***        | 0.05***        | 0.01***          |
| EE & CS                 | 575        | 394,427  | -0.01**      | -0.03          | 0.00           | 0.01             |
| Biotechnology           | 178        | 324,126  | 0.05***      | 0.03***        | 0.06***        | 0.03***          |
| Math & Physics          | 601        | 967,554  | -0.04***     | -0.08***       | -0.01*         | -0.04***         |

Table S4: The hardness distribution of top papers in each discipline. Papers are ranked based on their PageRank scores. ∆Mean (∆Median) is the difference between the mean (median) hardness of top papers in the empirical citation network and that based on the null model. Significance levels: ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$. shows the comparison between the empirical observation and the null model in terms of the mean and the median hardness of top papers.

We report similar results in Table S5 when using citation counts, other than the PageRank, as a measure of papers’ impact. Note that the number of papers used in the analysis for each discipline increased since some papers may not have PageRank scores but they all can have citations.
| Discipline               | # Journals | # Papers     | Top 1% |          |          | Top 0.1% |          |
|-------------------------|------------|--------------|--------|----------|----------|----------|----------|
|                         |            |              | ∆Mean | ∆Median | ∆Mean   | ∆Median  |
| Social Sciences         | 2,331      | 1,672,054    | 0.07   | 0.08     | 0.11     | 0.11     |
| Humanities              | 615        | 729,686      | 0.03   | 0.00     | 0.07     | 0.13     |
| Health Professionals    | 1,115      | 1,367,231    | 0.06   | 0.05     | 0.04     | 0.01     |
| Brain Research          | 619        | 1,041,126    | 0.05   | 0.07     | 0.05     | 0.07     |
| Medical Specialties     | 1,294      | 2,809,364    | 0.07   | 0.06     | 0.10     | 0.11     |
| Biology                 | 896        | 1,126,507    | 0.07   | 0.09     | 0.09     | 0.11     |
| Earth Sciences          | 410        | 443,220      | 0.03   | -0.00    | 0.03     | -0.00    |
| Chemistry               | 523        | 1,743,523    | 0.11   | 0.17     | 0.13     | 0.22     |
| Engineering             | 840        | 1,169,780    | 0.06   | 0.05     | 0.08     | 0.09     |
| Infectious Diseases     | 517        | 999,078      | 0.07   | 0.06     | 0.08     | 0.05     |
| EE & CS                 | 620        | 722,626      | 0.03   | 0.03     | 0.02     | 0.03     |
| Biotechnology           | 186        | 418,588      | 0.04   | 0.00     | 0.04     | 0.03     |
| Math & Physics          | 639        | 1,889,157    | -0.09  | -0.13    | -0.07    | -0.12    |

Table S5: The hardness distribution of top papers in each discipline. Papers are ranked based on their number of citations. ∆Mean (∆Median) is the difference between the mean (median) hardness of top papers in the empirical citation network and that based on the null model. Significance levels: ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$. 


Annotated map of journals in each discipline

The 2-d projection of 12,780 periodical embeddings provides an overview of the organizational structure of major disciplines. Here we further investigate the complex interdisciplinary nature of scholarly periodicals. Figs. S12–S24 highlight all journals in each discipline with all other journals blurred in the background. Some exemplar journals and micro-clusters that are located near disciplinary boundaries or are far away from their main discipline clusters are annotated in each map, further revealing the interdisciplinary nature of scholarly periodicals that cannot be properly captured by an existing journal classification system.

**Social Sciences**

![Diagram of Social Sciences journals]

Figure S12: The realm of “Social Sciences” journals in the embedding space.
Figure S13: The region of “Humanities” journals in the embedding space.
Figure S14: The colony of “Health Professionals” journals in the embedding space.
Figure S15: The realm of “Brain Research” journals in the embedding space.
Figure S16: The region of “Medical Specialties” journals in the embedding space.
Figure S17: The colony of “Biology” journals in the embedding space.
Figure S18: The realm of “Earth Sciences” journals in the embedding space.
Figure S19: The region of “Chemistry” journals in the embedding space.
Figure S20: The colony of “Chemical, Mechanical, & Civil Engineering” journals.
Figure S21: The realm of “Infectious Diseases” journal in the embedding space.
Figure S22: The region of “Electrical Engineering & Computer Science” journals.
Figure S23: The colony of “Biotechnology” journals in the embedding space.
Figure S24: The territory of “Math & Physics” journals in the embedding space.