Multi-state Research Topic Identification and Evolutionary Path Methodology: Postprint

Authors: Wang Kang, Gao Jiping, Pan Yuntao, Chen Yue

Date: 2023-04-01T00:00:00+00:00

Abstract

[Purpose/Significance] The evolution path of scientific topics holds significant importance for understanding the development process of science and predicting future trends. Addressing the limitation of existing research that treats topics on evolution paths equally, this paper proposes a novel method for multi-state scientific topic identification and evolution path analysis. [Method/Process] Using centrality and density, topics in each time interval are categorized into four types: core-mature, edge-mature, edge-immature, and core-immature, and cosine similarity is employed to associate topics across different time intervals, thereby revealing the dynamic cross-evolutionary relationships among different types of scientific topics. [Results/Conclusion] Taking literature in the field of 3D printing as a case study, the development process of 3D printing technology is measured from four dimensions: technology development stage, topic identification, topic type classification, and topic evolution path. The results demonstrate that the method is effective in scientific topic identification and evolution path visualization.

Full Text

Research on the Method of Multi-position Research Theme Recognition and Evolution Path

Wang Kang[1], Gao Jiping[2], Pan Yuntao[2], Chen Yue[1]

[1]Institute of Science of Science and S&T Management & WISE Lab, Dalian University of Technology, Dalian 116024
[2]Institute of Scientific and Technical Information of China, Beijing 100038

Abstract

[**Purpose/Significance**] The evolution path of scientific themes is of great significance for understanding the development process of science and predicting future trends. In view of the limitation that existing research treats themes on the evolution path equally, this paper proposes a new method for multi-position scientific theme identification and its evolution path. [**Method/Process**] Using centrality and density, themes in each time interval are divided into four types: core-mature, edge-mature, edge-immature, and core-immature. Cosine similarity is then used to associate themes across different time intervals to reveal the dynamic cross-evolution relationships between different types of scientific themes. [**Result/Conclusion**] Taking literature in the 3D printing field as an example, the development process of 3D printing technology is measured from four aspects: technology development stage, theme identification, theme type classification, and theme evolution path. The results demonstrate that this method achieves good effectiveness in scientific theme identification and evolution path visualization.

Keywords: topic recognition; topic evolution; strategic coordinates; topic similarity; 3D printing

1. Introduction

With the rapid development of science and technology, the growth rate of literature is accelerating daily. How to quickly and effectively discover research hotspots and frontiers from massive scientific achievements has become an important issue in library and information science, science of science, and related fields. Price argued that to better understand scientific fields in contemporary society, one must trace back along the trajectory of scientific historical development and grasp key turning points. Scientific literature not only carries the history of scientific and technological development but also guides humanity in continuing to understand and transform the world. Under the data-intensive research paradigm, mining the thematic evolution paths of scientific literature can help researchers quickly grasp the overview of field development and provide an important basis for predicting future directions.

Current research on thematic evolution path analysis primarily adopts two approaches: "time-topic clustering" and the more advanced "time-topic clustering-topic similarity." The "time-topic clustering" approach divides the target literature set into chronological intervals, then extracts and clusters keywords from each interval. For example, Dun Shuai et al. conducted a temporal analysis of keyword co-occurrence in Chinese enterprise sustainability research literature to reveal its evolutionary trends and thematic development. Du Lijun et al. analyzed the evolution of information retrieval research themes from an interdisciplinary perspective using informetrics and science of science methods, presenting the characteristics, general patterns, and outstanding contributions corresponding to China's S&T development stages through keyword clustering, burst detection, and strategic coordinate analysis. Y. Wu et al. selected all articles from 10 highest-impact psychiatry journals in Web of Science, divided them into three periods, and used the Sci2 information visualization software for co-word and clustering analysis to explore research priorities and development trends in psychiatry. O. B. Onyancha analyzed keywords from library and information science (LIS) research articles published every 10 years from 1971 to 2015 to identify the most prominent and common research themes and their evolution patterns. X. Y. Han divided LIS journal articles from 1996-2019 into five stages, used the LDA model to identify basic themes from 14,035 documents, and studied LIS development. C. Huang et al. constructed keyword co-occurrence networks for education research papers, analyzing network density changes across stages to determine core theme development trends.

The "time-topic clustering-topic similarity" approach builds upon the former by calculating similarity between themes in adjacent time intervals to establish cross-temporal theme associations that characterize evolution relationships. For instance, Niu Li et al. used community detection algorithms for thematic clustering based on keyword co-occurrence relationships, then outlined the dynamic changes in Chinese archival science research content through node overlap between communities across time periods. Wang Xiaoguang et al. constructed a research theme evolution analysis model based on community theme representation algorithms and community similarity matching algorithms. Tan Chunhui et al. used the LDA topic model for theme identification and cosine similarity for thematic path evolution analysis in the data mining field. Yan Duanwu conducted temporal theme association evolution analysis using LDA models to measure similarity between adjacent time window themes. Zhou Yaolin et al. used community detection algorithms for theme clustering and the CorTexT digital infrastructure platform to analyze the evolution of international LIS research themes. Zhao Yue et al. used the same method to study the core theme evolution trajectory of Chinese archival science over 40 years of reform and opening-up. Foreign scholars have similarly applied these approaches across various disciplines. A. Rule et al. proposed an automated text analysis strategy that clustered themes from the 1790-2014 State of the Union corpus and wove them into a river network to capture political discourse flows in American history. F. L. Matos et al. used the Louvain algorithm for theme clustering, then created cross-temporal networks and Sankey diagrams to map submarine canyon research, identifying knowledge groups, historical trends, and emerging topics. A. Marvuglia et al. dynamically assessed progress and challenges in urban sustainability using similar methods.

While these methods have important methodological significance in depicting thematic evolution paths, they neglect analysis of the relative importance of each theme, treating all themes equally—a limitation when formulating S&T policies. In reality, themes have positional distinctions based on their network positions and development states, including core vs. edge, mature vs. emerging types. Clarifying the dynamic interactive transformation relationships between different theme types is crucial for understanding field development processes and future trends. Yue Lixin et al. used the LDA model to divide Chinese healthcare information themes into core and edge themes for similarity evolution analysis, but this method only classified core-edge themes based on cluster size, lacking finer-grained distinction of each theme's position. Therefore, this paper introduces strategic coordinate analysis into thematic path research, using centrality and density to classify theme types across time periods, then employs cosine similarity to associate themes across adjacent periods. This proposes a new multi-position scientific theme identification and evolution path method to reveal dynamic evolution relationships between core, edge, mature, and emerging themes, forming a "time-topic clustering-topic position-topic similarity" analysis model.

2. Research Approach and Methods

Multi-position scientific theme evolution path analysis involves several aspects: predicting research theme development maturity, time interval division, research theme identification, and theme type classification.

2.1 Research Theme Development Maturity Prediction Rapid S&T development causes accelerated growth in scientific knowledge. As carriers of scientific knowledge, changes in scientific literature can directly reflect scientific development. Studying scientific information growth patterns reveals development characteristics, predicts growth trends, and identifies development stages. Kuhn proposed in *The Structure of Scientific Revolutions* that scientific development follows a pattern: gradual accumulation within paradigms during normal science → crisis caused by anomalies → scientific revolution triggered by new paradigms → new normal science accumulation—a dynamic historical process with revolutionary metabolism showing "stage-revolution" characteristics. To determine scientific theme development stages, this paper selects the logical growth model of literature, which has distinct stage characteristics and the greatest influence among scientific information growth models:

$$F(t) = \frac{k}{1 + ae^{-bt}} \quad (b > 0)$$

where $F(t)$ is the cumulative literature volume in year t, k is the cumulative volume as $t \to \infty$, and a and b are parameters determining the curve's position and shape, respectively.

Based on scientific literature growth patterns, the logical growth model curve can be divided into four stages: emergence, development, maturity, and decline (see Figure 1 [Figure 1: see original paper]).

Emergence (OA segment): A small number of scientists conduct original basic theoretical research on certain aspects. Due to the small base of scientists and the complexity of original theoretical research, scientific knowledge grows slowly, and literature volume maintains slow growth.

Development (AB segment): Breakthroughs in basic theory through the efforts of a few scientists form preliminary research paradigms, attracting large numbers of scientists. The development model shifts from "original science" to "normal science," with scientific knowledge increasing exponentially and literature volume showing exponential growth.

Maturity (BC segment): As research deepens and numerous problems are solved, research becomes increasingly difficult, slowing the growth of scientific knowledge. Conventional disciplines encounter bottlenecks.

Decline (CD segment): Conventional disciplines enter decline. Scientific problems are nearly all solved or encounter currently insurmountable obstacles, prompting scientists to exit the field. During this stage, a small number of scientists continue research, producing limited literature. When these scientists break through bottlenecks or discover new fundamental principles, scientific research re-enters the transition from "original science" to "normal science." Driven by scientific revolutions, the entire scientific development process repeats according to these rules.

This paper uses the logical growth model to predict the development stage of research objects, extending it to predict author and keyword growth to comprehensively judge field development stages and trends from both discipline scale (cumulative scientists) and content (cumulative keywords) perspectives.

2.2 Time Interval Division Thematic evolution research must consider literature temporal attributes, making appropriate time partitioning crucial. While software like CiteSpace and VOSviewer visualize theme evolution from temporal perspectives, they use individual words as evolution units and cannot show complex evolution relationships between themes. Common time interval division methods include the TimeLine method and fixed time window method. Due to the high complexity and uncertain effectiveness of the TimeLine method, this paper uses the fixed time window method for temporal partitioning based on literature volume and publication dates.

2.3 Research Theme Identification Theme identification is based on keyword co-occurrence matrices for each time zone. Common clustering algorithms include spectral clustering, hierarchical clustering, Fast Newman, and Louvain algorithms. This paper selects the Louvain algorithm for its fast operation speed, suitability for large network community detection, and heuristic approach that overcomes limitations of traditional Modularity algorithms. The algorithm maximizes the modularity Q value. The Louvain algorithm's core principle: First, treat all network nodes as independent communities, traverse each node's neighbors, and assign it to the neighbor's community based on Q value until no node changes communities; then treat communities as nodes, with edge weights being the sum of all original node edge weights within the two nodes, repeating until full convergence. The modularity Q value is calculated as:

$$Q = \frac{1}{2m} \sum_{i,j} \left[A_{ij} - \frac{k_i k_j}{2m} \right] \delta(c_i, c_j)$$

where m is the total number of edges, k_i is the sum of weights of edges pointing to node i, A_{ij} represents the weight between nodes i and j, and c_i and c_j represent the communities of nodes i and j. $\delta(c_i, c_j) = 1$ if $c_i = c_j$, otherwise 0.

2.4 Theme Type Classification Themes identified by the Louvain algorithm alone cannot fully reflect their development stages. This paper uses the strategic coordinate diagram proposed by J. Law et al. to classify theme development stages. Centrality (T_c) and density (T_d) metrics (see formulas (2) and (3)) measure the strength of connections between theme clusters and within theme clusters, respectively. Higher T_c values indicate tighter connections between theme clusters, suggesting the theme receives widespread attention, easily becomes a research hotspot, and plays a core role in the field. Higher T_d values indicate tighter internal connections within a theme cluster, suggesting relative maturity.

$$T_c = \frac{\sum_{i\in\phi_s, j\in(\phi-\phi_s),(i\neq j)} E_{ij}}{n(N-n)}$$

$$T_d = \frac{\sum_{i,j\in\phi_s,(i\neq j)} E_{ij}}{n(n-1)/2}$$

where E_{ij} is keyword co-occurrence frequency, n is the number of keywords in a theme cluster, N is the total number of keywords in the co-word matrix, and ϕ_s refers to a specific theme while ϕ refers to all themes.

Using T_c and T_d as horizontal and vertical axes with their means as the origin, a four-quadrant map of scientific theme development degrees is constructed (see Figure 2 [Figure 2: see original paper]). Each quadrant represents a theme type, with circles representing different themes. Solid lines between circles indicate close connections between target themes and others (core position), while dashed lines indicate loose connections (edge position). Nodes within a theme circle represent keywords, with solid lines indicating close internal connections (mature theme) and dashed lines indicating loose connections (immature theme). Therefore: - **Quadrant I (Core-Mature):** High centrality and density, representing widely-connected mature themes - **Quadrant II (Edge-Mature):** Low centrality but high density, representing relatively independent mature themes - **Quadrant III (Edge-Immature):** Low centrality and density, representing edge themes with loose internal structures that are either declining or emerging and require professional judgment - **Quadrant IV (Core-Immature):** High centrality but low density, representing widely-connected immature themes with great development potential

2.5 Theme Evolution Path While strategic coordinate diagrams excel at theme type classification, they remain static and cannot show connections between themes across time periods or study evolution and transformation trends between same or different theme types. Therefore, this paper proposes calculating similarity between themes in adjacent time zones' strategic coordinate diagrams to characterize evolution directions. Cosine similarity is used, mapping each theme's keywords into vectors and calculating the cosine of the angle between vectors of adjacent window themes to determine similarity. Larger values indicate higher similarity (see formula (4)). Combined with strategic coordinate characteristics, changes in quadrant positions across time periods reveal theme development type evolution trends (stable, emerging, mature, or declining themes).

$$\cos(\theta) = \frac{\sum A_i \times B_i}{\sqrt{\sum (A_i)^2} \times \sqrt{\sum (B_i)^2}}$$

where A and B are vectors corresponding to themes.

3. Thematic Evolution of 3D Printing Technology

This paper uses the 3D printing technology field as a case study. Data were sourced from the Web of Science Core Collection. Considering recall and precision, the search strategy was: TI=("Additive Manufact*" OR "Rapid Prototyp*" OR "3D Print*" OR "three dimensional print*" OR "Solid Free form Fabricat*"), language limited to English, document type limited to Article OR Review, spanning all years (search date: June 24, 2020), yielding 15,233 documents, of which 12,028 contained keywords. This dataset was used for multi-position research theme identification and evolution path analysis (see research framework in Figure 3 [Figure 3: see original paper]).

3.1 Development Stage of 3D Printing Technology The number of 3D printing papers, keywords, and authors all show rapid growth, especially after 2012 (see Figure 4 [Figure 4: see original paper]a). All three indicators fit well with the logical growth model curve, with goodness-of-fit R^2 values of 0.948, 0.957, and 0.960, respectively (see Figure 4b), effectively predicting 3D printing technology development stages. According to the four-stage division of the logical growth model curve, 3D printing technology is currently in the second development stage (AB segment), with only two years remaining until this stage ends. During this period, scientific literature on 3D printing will continue exponential growth, large numbers of researchers will enter the field, and research content will continuously expand. Therefore, China should seize this two-year opportunity period to strive for a commanding position in 3D printing.

3.2 Research Theme Identification in 3D Printing The fixed time window method was first used to partition 3D printing literature into time intervals. Considering the small literature volume during the early development stage, 1991-2009 was designated as the first interval, 2010-2014 as the second, 2015-2016 as the third, 2017-2018 as the fourth, and 2019-2020 as the fifth (see Table 1 for specific document counts).

3.2.1 Keyword Co-occurrence Matrix Construction

High-frequency keyword co-occurrence pairs (top 20 pairs, excluding search terms) were extracted for each time window (see Figure 5 [Figure 5: see original paper]). Over time, blank areas gradually decreased, indicating increasingly close connections among top keyword pairs. In 1991-2009 and 2010-2014, "scaffold" and "tissue engineering" showed far higher co-occurrence frequency than other pairs, indicating early research hotspots in using 3D printing for bone, cartilage, and vascular tissue engineering scaffolds. In 2015-2016, "scaffold" and "tissue engineering" remained highest, while "mechanical properties" and "microstructure" and "tissue engineering" and "bioprinting" began frequent co-occurrence, showing expanding research domains. In 2017-2018, "mechanical properties" and "microstructure" became the top pair, followed by "scaffold" and "tissue engineering," "laser 3D printing" and "microstructure," etc., indicating further expansion to printing processes (laser 3D printing) and materials (PLA, titanium alloy). In 2019-2020, "mechanical properties" and "microstructure" remained leading, followed by "fused deposition modeling" and "PLA," "wire arc additive manufacturing" and "microstructure," etc., showing process research (fused deposition modeling, wire arc, laser 3D printing) still dominates.

3.2.2 3D Printing Theme Extraction

Keywords with frequency $ $5 were selected to construct co-occurrence matrices. Python's community package was used for Louvain clustering and network metrics calculation (see Table 1). Network nodes, edges, and average degree gradually increased, while density and average clustering coefficient decreased, indicating loose overall connections with substantial association potential remaining. Time-window-based keyword clustering clearly shows 3D printing research theme evolution: 3D printing processes and computer-aided design persist throughout; plastics, metals, and biomaterials are primary material sources; biological applications expanded from tissue engineering scaffolds to broader biological fields; wire arc additive manufacturing and 3D printing waste recycling for sustainability have emerged as new themes.

3.3 Theme Type Classification and Evolution Path While clustering effectively identifies themes in each interval, it treats all themes equally without distinguishing their status or revealing relationships between adjacent themes. Therefore, this paper uses density and centrality metrics to classify theme types and cosine similarity (threshold $ $0.1) to measure specific evolution relationships (see Figure 6 [Figure 6: see original paper]). Quadrant positions indicate theme status, with evolution connections showing similarity values (higher values indicate greater content inheritance).

In 1991-2009, tissue engineering scaffolds were core-mature themes. Compared to other tissue engineering construction technologies, 3D printing is particularly suitable for complex scaffold structures, offering unique advantages in manufacturing composite implants with porous and complex microstructures. This theme differentiated in the next interval, continuing along its own path while evolving toward metal 3D printing.

In 2010-2014, few themes existed with no core-mature themes. Tissue engineering scaffolds shifted from Quadrant I to II (core to edge) but evolved into bioprinting in the next period, showing expanded research scope. Metal 3D printing emerged in Quadrant III and continued along its path in the next interval. 3D printing processes and computer-aided design remained in Quadrant IV as developing themes, later differentiating into separate themes.

In 2015-2016, metal 3D printing moved from Quadrant III to I (emerging to core-mature). Bioprinting evolved from edge-mature (Quadrant II) tissue engineering scaffolds to core-mature (Quadrant I). 3D printing processes and computer-aided design remained developing themes in Quadrant IV. New themes emerged: 3D printing materials (focused on PLA, a degradable material) and microfluidics (enabled by improving 3D printing precision for flexible microfluidic chip manufacturing).

In 2017-2018, metal 3D printing and bioprinting remained core-mature (Quadrant I), with plastic 3D printing added. 3D printing materials evolved from emerging (Quadrant III) to developing (Quadrant IV), expanding to polymers, biomaterials, composites, ceramics, etc. Computer-aided design remained stable in Quadrant IV. Electrochemistry evolved from microfluidics, increasing maturity but remaining edge. 3D concrete printing emerged in Quadrant III, with applications in construction showing initial scale (e.g., Dubai's 3D-printed R&D laboratory). Binder jetting 3D printing also emerged, with companies like GE Aviation and HP demonstrating strong capabilities. This technology combines material jetting and sintering to produce full-density metal parts 60-100 times faster than laser-based methods, with lower costs due to recyclable materials.

In 2019-2020, theme classification became more detailed. 3D printing processes became independent themes. Fused deposition modeling and PLA evolved from plastic 3D printing, remaining core-mature (Quadrant I). Stereolithography and selective laser sintering evolved from 3D printing materials, remaining core-immature (Quadrant IV) with development potential. Metal, laser, and wire arc 3D printing evolved from previous themes, occupying Quadrant I as core-mature themes with centrality and density far exceeding others, indicating current hotspots. Bioprinting shifted from Quadrant I to II (core-mature to edge-mature), suggesting declining research. 3D printing models (medical) evolved from computer-aided design, providing conditions for precision medicine by printing patient organ models for surgical simulation and physician training. Computer-aided design remained in Quadrant IV as a declining theme. 3D printing sustainability emerged in Quadrant III. While 3D printing is material-efficient, improper handling of materials and waste poses safety risks (e.g., toxicity to fish embryos found by UC Riverside researchers). Identifying toxic materials and achieving sustainable waste treatment warrant further attention.

Conclusion

Thematic evolution analysis is an important method for studying disciplinary development that has attracted widespread attention. However, current research treats different themes equally, failing to effectively distinguish their importance. The multi-position scientific theme identification and evolution path method proposed in this paper addresses this limitation, facilitating detailed demonstration of the emergence, development, and decline trends of core, edge, mature, and immature themes, as well as dynamic interactions between different theme types. This is significant for grasping disciplinary development processes and future directions, particularly for identifying and developing disruptive technologies.

References

[1] Tony H, Stewart T, Kristinn T, et al. The Fourth Paradigm: Data-Intensive Scientific Discovery [M]. Translated by Pan Jiaofeng, Zhang Xiaolin, An Peijun, et al. Beijing: Science Press, 2012.
[2] Dun Shuai, Chen Qiang. Chinese Enterprise Sustainability Research: Situation Evolution and Thematic Evolution [J]. Scientific Management Research, 2020, 38(1): 94-100.
[3] Du Lijun. Analysis of Information Retrieval Research Theme Evolution from an Interdisciplinary Perspective—Taking Informetrics and Computer Science as Examples [J]. Information Technology and Informatization, 2020(1): 178-183.
[4] Wang Luyao, Qu Guannan, Li Nan, et al. Contributions, Evolution, and Prospects of Chinese S&T Management Research—Bibliometric and Knowledge Graph Analysis of 40 Years of *Science of Science and S&T Management* [J]. Science of Science and S&T Management, 2020, 41(5): 3-21.
[5] Wu Y, Jin X, Xue YZ, et al. Evaluation of Research Topic Evolution in Psychiatry Using Co-word Analysis [J]. Medicine, 2017, 96(25): 7349.
[6] Onyancha OB. Forty-five Years of LIS Research Evolution, 1971-2015: An Informetrics Study of Author-supplied Keywords [J]. Publishing Research Quarterly, 2018, 34(3): 456-470.
[7] Han XY. Evolution of Research Topics in LIS Between 1996 and 2019: An Analysis Based on Latent Dirichlet Allocation Topic Model [J]. Educational Review, 2020, 72(3): 281-297.
[8] Huang C, Yang C, Wang ST, et al. Evolution of Topics in Education Research: A Systematic Review Using Bibliometric Analysis [J]. Journal of the Association for Information Science and Technology, 2006, 57(3): 359-377.
[9] Niu Li, Du Lihua. Research on Domestic Archival Science Subject Network Construction and Evolution Analysis [J]. Archives Science Study, 2020(2): 12-18.
[10] Wang Xiaoguang, Cheng Qikai. Visualization Analysis of Disciplinary Theme Evolution Based on NEViwer [J]. Journal of the China Society for Sci-

entific and Technical Information, 2013, 32(9): 900-911.
[11] Tan Chunhui, Xiong Mengyuan. Comparative Analysis of Hot Topic Evolution in Domestic and International Data Mining Research Based on LDA Model [J]. Information Science, 2021, 39(4): 174-185.
[12] Yan Duanwu, Su Qiong, Zhang Xinyue. Frontier Detection in Scientific Fields Based on Temporal Topic Association Evolution [J]. Journal of Intelligence, 2019, 38(7): 144-150.
[13] Zhou Yaolin, Chai Hao, Zhao Yue. Analysis of Big Data Research Status and Trends in International LIS Field [J]. Library Journal, 2019, 38(12): 16-27, 44.
[14] Tancoigne ER, Barbier M, Cointet JP, et al. The Place of Agricultural Sciences in the Literature on Ecosystem Services [J]. Ecosystem Services, 2014, 10(SI): 35-48.
[15] Zhao Yue, Qiao Jian. A Panoramic Perspective on Chinese Archival Science Research in 40 Years of Reform and Opening-up—Based on Theme Mining and Evolution Analysis [J]. Archives Science Study, 2019(3): 44-54.
[16] Rule A, Cointet JP, Bearman PS, et al. Lexical Shifts, Substantive Changes, and Continuity in State of the Union Discourse, 1790-2014 [J]. Proceedings of the National Academy of Sciences of the United States of America, 2015, 112(35): 10837-10844.
[17] Matos FL, Ross SW, Huvenne VAI, et al. Canyon Pride and Prejudice: Exploring the Submarine Canyon Research Landscape, a History of Geographic and Thematic Bias [J]. Progress in Oceanography, 2018, 169(12): 6-19.
[18] Marvuglia A, Havinga L, Heidrich O, et al. Advances and Challenges in Assessing Urban Sustainability: An Advanced Bibliometric Review [J]. Renewable & Sustainable Energy Reviews, 2020, 124(3): 1-12.
[19] Yue Lixin, Zhou Xiaoying, Chen Yini. Visualization Method for Identifying Core Research Themes and Their Evolution Paths in Journal Articles—Taking Chinese Healthcare Information Field as an Example [J]. Library and Information Service, 2020, 64(5): 89-99.
[20] Wang Wei. Informetrics and Its Medical Applications [M]. Beijing: People's Medical Publishing House, 2014.
[21] Wang Haishan. On the Regularity of Scientific Development from Popper and Kuhn's Views of Science [J]. Studies in Science of Science, 1984(1): 34-40.
[22] He Rongli. Reflections on Scientific Literature Growth Models [J]. Journal of Intelligence, 1994(6): 40-41, 64.
[23] Chen C. CiteSpace II: Detecting and Visualizing Emerging Trends and Transient Patterns in Scientific Literature [J]. Scientometrics, 2020, 125(3): 2561-2595.
[24] Van Eck NJ, Waltman L. Software Survey: VOSviewer, a Computer Program for Bibliometric Mapping [J]. Scientometrics, 2010, 84(2): 523-538.
[25] Wu Bin, Wang Bai, Yang Shengqi. An Event-Based Framework for Social Network Evolution Analysis [J]. Journal of Software, 2011, 22(7): 1488-1502.
[26] Qian Tieyun, Li Qing, Xu Chengyu. Community Core Circle Technology for Segmenting S&T Theme Development [J]. Computer Science and Exploration, 2010, 4(2): 170-179.

[27] Ulrike VL. A Tutorial on Spectral Clustering [J]. Statistics and Computing, 2007, 17(4): 1-32.
[28] Han JW, Kamber M. Data Mining: Concepts and Techniques [M]. New York: Academic Press, 2001.
[29] Newman MEJ. Fast Algorithm for Detecting Community Structure in Networks [J]. Physical Review E, 2004, 69(6): 1-15.
[30] Blondel VD, Guillaume JL, Lambiotte R, et al. Fast Unfolding of Communities in Large Networks [J]. Journal of Statistical Mechanics: Theory and Experiment, 2008, 9(10): 1-12.
[31] Law J, Bauin S, Courtial JP, et al. Policy and the Mapping of Scientific Change: A Co-word Analysis of Research into Environmental Acidification [J]. Scientometrics, 1988, 14(3/4): 251-264.
[32] Lee B, Jeong YI. Mapping Korea's National R&D Domain of Robot Technology by Using Co-word Analysis [J]. Scientometrics, 2008, 77(1): 3-19.
[33] Tian Ye, Zeng Qinghui, Hu Xianghua, et al. Research Progress of 3D Printing Technology and Its Application in Tissue Engineering [J]. China Medical Device Information, 2015, 21(8): 7-12.

Author Contributions: Wang Kang: conceptualization, data processing, writing, revision; Gao Jiping: data processing and analysis; Pan Yuntao: methodology and results analysis; Chen Yue: conceptualization, revision.

Note: Figure translations are in progress. See original paper for figures.