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Review

A survey of research hotspots and frontier trends of recommendation systems from the perspective of knowledge graph

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ABSTRACT

With the advent of the era of big data, the recommendation system has become an effective solution to the problem of information overload. This paper takes the literature data related to the recommendation system theme from 2009 to 2018 and included in the core collection of Web of Science database as the research object, and utilizes bibliometric methods to analyze the theme of recommendation system. To this end, firstly, classify statistics and feature analysis of valid literature data. Secondly, use VOSviewer software to construct various different scientific knowledge graph to discover valuable knowledge. Thirdly, according to keyword co-concurrence graph conclude five main hotspots of current research about recommendation system and discover five main directions that have potential value in research field of recommendation system. Finally, deeply explore five main key issues and propose corresponding solutions.

1. Introduction

With the rapid development of information network technology, information technology products represented by e-commerce platforms and social software have been applied on a large scale. What follows is the massive data generation, and a lot of redundant information brings inconvenience to people's production and life. Such as the reflecting speed of user to information is much lower than the information transmission speed, and information selection beset leads to information utilization rate drop. This type of problem is called information overload. How to solve the problem of information overload has gradually attracted the attention of academic and industrial fields. Generally, there are two ways to solve information overload. One is search engine technology. Based on the keywords specified by the user, it passively filters out the information that the user interested in. However, the significant drawback is that as long as the keywords retrieved are the same, the search results obtained by the user are completely consistent and cannot highlight the user's individual needs. The other is the recommendation system. In the 1990s, the novel information filtering way named recommendation system came into being. It can better meet the needs of user information filtering requirements, and provide users with more intimate data services and invaluable business value. According to statistics, 35% of Amazon's revenue is brought by its own recommendation system (Lee and Hosanagar, 2014). Compared with the search engine, the recommendation system has a unique advantage of actively recommending the information of interest to the user based on the user's historical behavior and interest preferences. Thus, it has received strong attention from the academia and industry, especially the industry since the birth of the recommendation system.

In the era of big data, recommendation system has become an effective tool for information filtering. In a narrow sense, the recommendation system mainly emphasizes the characteristics of information filtering. That is, filtering out products that may be of interest to a user ((Konstan et al., 2000); Pazzani, 1999). In a broad sense, the recommendation system refers to guiding user to find interesting or useful items among a large number of potential candidates in a personalized way, or producing the items as output (Burke, 2002). From the implementation principle, the recommendation system can be divided into three categories: Content-based Recommendation System (Bhagavatula et al., 2018), Collaborative Filtering Recommendation System (Chen et al., 2018a) 0.3) and Hybrid Recommendation System (Burke, 2002). In recent years, literature review research related to recommendation systems has continued to climb, but most of them are limited to a certain sub-theme topic. For instance, R. Chen et al.'s

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review of Research on Collaborative Filtering Recommendation System (Chen et al., 2018a) emphasizes on the application research of collaborative filtering algorithm in recommendation system. H. Chen et al.'s review of research on interactive recommendation systems (Chen et al., 2016), Combining visualization technology with recommendation system, proposes a visual interactive framework. Z. Batmaz et al.'s review of recommendation system based on deep learning model (Batmaz et al., 2019) focuses on the application of various deep learning models in the recommendation system.

At present, scholars have carried out some research on the types, evaluations and algorithms of recommendation systems. However, there is still a lack of exploration of the research status and future trends in the field of recommendation systems from the perspective of scientific knowledge graph. For example, most of the research on recommendation systems discussed from a specific topic, has not combed the ins and outs of the recommendation system from a holistic and global perspective. In particular, it is short of in-depth systematic research on its hot spot exploration, cutting-edge trends, existing problems and coping mechanisms. Also, there is no use of knowledge graph tools for multi-angle visual research. Based on this, relying on the core collection database of Web of Science, this paper adopts the bibliometric method, and uses VOSviewer scientific knowledge mapping tool for visualizing the international literature on the topic of "recommender systems" in the period of 2009–2018 from multi-angle visualization analysis. Meanwhile, this article discusses the venation of the recommendation system research in detail, reveals the research hotspots and knowledge structure of international research system, and analyzes the problems existing in the future development of recommendation system and research countermeasures.

In summary, the goal of this paper is to combine the bibliometric content analysis method with knowledge mapping and clustering method and to use the combination of quantitative statistical analysis and visual profiling to explore the potential hidden knowledge of the literature in the recommendation system domain, so as to make up for the deficiency of existing research review limited to paper content induction and analysis in this field. Moreover, this work provides reference and inspiration for follow-up researchers in the field of recommended systems.

In this study, from the perspective of the scientific knowledge graph, the literature analysis method is used to summarize the literature in the field of recommendation systems for nearly ten years. Through the network diagram of visualization reveals its internal laws, the main research work is as follows:

(1) From the literature distribution and the proportion of articles in the past decade, the research hotspots and corresponding characteristics in the field of recommendation systems have been revealed.
(2) Visually analyze the distribution of literature sources, the comparison of research power, citation analysis and author distribution in the field of recommendation systems by constructing scientific knowledge graph to reveal the underlying laws behind the data.
(3) Through the statistical and visual analysis of keyword data in the recommendation system field, the current research hotspots and frontier dynamics are summarized.
(4) Combining relevant literature, potential research hotspots and cutting-edge trends, the problems are discussed in depth, and valuable solutions are proposed in the field of recommendation systems.

In short, we introduce literature quantitative analysis methods into the literature research of recommendation systems and construct scientific knowledge graphs for knowledge discovery to inspire and guide researchers interested in the field. The contributions of the review are as follows:

(i) For the first time, the literature quantitative analysis method and the visual clustering analysis method are introduced into the literature research in the field of recommendation systems and the hidden knowledge contained in the literature data related to the recommendation system theme is more effectively explored.
(ii) Using the knowledge mapping method provided by the VOSviewer tool to analyze the clustering map of high-frequency keywords, more objectively explore the research hotspots and frontier trends in the field of recommendation systems.
(iii) Analyze the five major open problems in the field of recommendation systems, propose potential feasibility plans, and verify the feasibility of some schemes through experiments to provide a basis for the reliability of the recommended methods.

2. Data sources and research methods

2.1. Data sources

Based on the authority, rigor and integrity of the data, this study selects the core collection of the Web of science literature database (SCI-EXPANDED, SSCI, CPCI-S, CPCI-SSH, CCR-EXPANDED, IC) as a specific source of sample data. The search method uses basic search, and the theme sets the phrase "recommender systems" as the subject (We use a series of search terms that are highly semantically related to "recommender systems", including "recommender", "recommendation", "recommender system", "recommendation system", etc., with the aim of finding the fullest possible articles related to the "recommender systems" topic. In addition, during the search process, Web of Science's topic search function can automatically identify all keyword variants related to "recommender systems", and the scope of search engine search covers document titles, document abstracts and document keywords.) for accurate retrieval of relevant literature. The range of searching year is from 2009 to 2018. Search date is March 13, 2019, the total number of obtained documents is 5540, including: the number of Academic papers is 2128; the number of Proceedings paper is 3369; the number of Review is 71, etc. The literature type ratio distribution is shown in Fig. 1, among them: conference papers accounting for 60.23% is the highest document type, which is just in line with the characteristics of large volume of papers published on top authoritative conferences in the field of

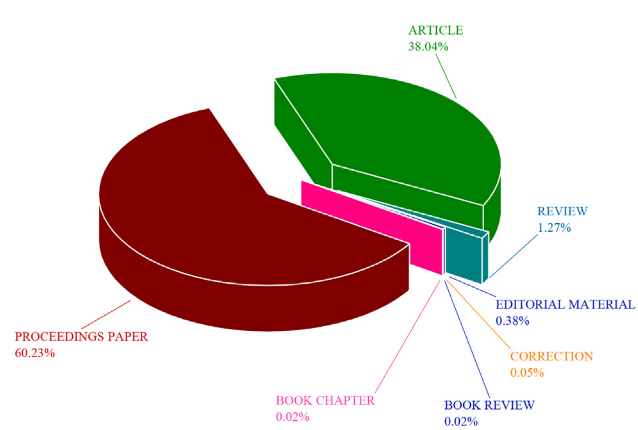

Fig. 1. Literature type ratio distribution.

recommendation system research; academic papers accounting for 38.04% is the second largest sample data source type; the literature of the review category is relatively small, accounting for 1.27%, and other types of literature samples can be ignored. However, in order to highlight the authority and reliability of the analysis, 5540 document records in the time span are used as the original sample data of the hotspot and frontier analysis of the international recommendation system. After the data is optimized by deduplication technology, the 5391 valid data samples obtained are taken as the data set for visual analysis in this paper.

2.2. Research methods

In this article, a bibliometric analysis software VOSviewer (Version 1.6.10) (Wong, 2018), to map scientific knowledge in various fields developed by Nees Jan van Eck and Ludo Waltman (van Eck and Waltman, 2009) of Leiden University in the Netherlands in 2009, was used to visualize 5,391 valid data samples (van Eck and Waltman, 2010). Combining with bibliometric methods (Gao, 2015; Van Eck and Waltman, 2017), quantitative analysis is carried out from multiple perspectives such as the age distribution of the literature, the types of literatures sources, the distribution of research power, important literature, research hotspots and research frontiers. Based on the data and data knowledge graph, the research hotspot and development status of international recommendation system field in the last ten years are comprehensively and objectively displayed.

3. Analysis of research results

Based on the VOSviewer scientific knowledge map analysis software, this work analyzes the research hotspots and development trends in the field of international recommendation systems from five dimensions: time distribution, literatures sources analysis, research power comparison, author analysis and citation analysis.

3.1. Time distribution

In general, the trend of changes in the number of articles reflects the research heat of related topics and the speed of knowledge growth. At the same time, it can also reflect the research direction and trend of the theme. Thus, to a large extent, the number of papers for a particular time span can reflect the research enthusiasm of the corresponding topic. By analyzing the number of literatures in the field of recommendation system at home and abroad in recent 10 years, this paper can roughly outline the correlation between the number of published literatures and time interval in this field. It is convenient for us to further understand and master the research status and mainstream technology in the world. Also, it provides valuable technical guidance and experience for the localization research of related topics. As shown in Fig. 2,

As can be seen from the Fig. 2, the growth trend of international research literature on recommendation systems from 2009 to 2018 is mainly divided into four stages:

The first stage is the stable period (2009–2012). During this period, the research on the recommendation system is relatively stable, and the amount of publications is rising slowly. The number of issued articles fluctuates between 259 and 325. Among them, 259 articles were issued in 2010; the numbers of articles published in 2012, is 325 and rank the highest at this stage. The proportion of the number of papers is maintained between 4.8% and 6.03%. Among them, the number of documents issued in 2010 and accounted for 4.8%, is the lowest value for this period.

The second stage is the rapid growth period (2013–2015). In 2015, the number of issued articles reached 742, and the number

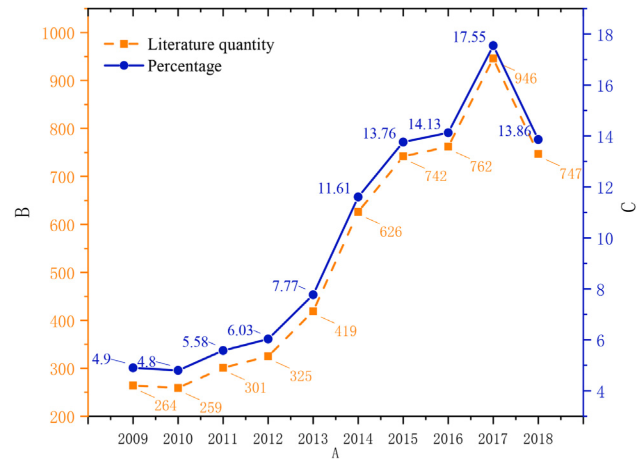

Fig. 2. Annual distribution and annual proportion of literature published (A stand for timeline, B stands for the number of papers and C stands for the percentage in total literature in Fig. 2).

of publications accounted for 13.76% in the total number of publications during the past decade. Compared with the number of 419 articles issued in 2013, the number of publications nearly doubled. The data shows that the research on international recommendation system at this stage has developed rapidly.

The third stage is the outbreak period (2016–2017). As can be seen from Fig. 2, the total number of papers issued in 2017 reached 946, and the proportion of documents issued reached a peak of 17.55% in the past decade. The data shows that the research of recommendation system in this stage has gained extensive attention and unprecedented development in the world. This trend of development coincides with the time node of the re-emergence of AI. On the other hand, 2017 is right at outbreak of research in the field of artificial intelligence from Fig. 2. In addition, due to the success of the artificial intelligence robot AlphaGo in the Go game in 2016, with deep learning as the core, research on artificial intelligence technology and application has once again received extensive attention and a large amount of research input from the academic community. As an important sub-area of artificial intelligence application research, the recommendation system is no exception.

The fourth stage is the fallback period (2018). After the explosive development in 2017, it is normal for the number of issued articles to fall back in 2018. However, it is not difficult to find out from the comparison of data in the past 10 years that the proportion of publications in 2018 also reached 13.86%, which lies between 2015 and 2016. The recommendation system is still in the international research boom from the chart of Fig. 2.

In addition, the number of articles is also related to the development trend of information technology and national policies. For example, the AI robot AlphaGo competed with Shishi Li, a nine-stage player in Go, and won the championship of "man-machine war" in March 2016. Subsequently, the global research fever of AI is the best evidence of technology (Wang et al., 2016).

In short, with the rapid development of artificial intelligence technology and strong support from national policies and unprecedented investment in research and development in the industry, the recommendation system will once again become the research hotspot in the industry and academia as one of the important branches in the field of artificial intelligence research.

3.2. Literature sources analysis

Literature sources have their own specific research areas and topics. In general, the amount of citations in a particular literature source can reflect the research heat of its corresponding field. Meanwhile, the number of corresponding literature topics can also reflect the attention paid to related topics. Consequently, the study of literature sources in specific fields not only helps to better understand the quality of literature sources and the distribution of literature in the field, but also has important reference value for the literature research on research topics. In this paper, the number of literature sources obtained by VOSviewer statistics is 2323. In order to better highlight the types of literature sources with high reference value and their associated relationships, using the number of articles $\geq$19 as the selective condition (In order to maintain the objectivity of threshold selection, we calculated the average, median, quantile, maximum, and minimum values of the published documents in the dataset by the statistical functions provided by Excel. Among them, the average value of the published articles is 3.953; the median is 2; the one-quarters quantile is 1; the two-quarters quantile is 2; the three-quarters quantile is 4; the maximum is 182 and the minimum value is 1. However, when these values are used as the threshold for visualization, the value is too small, causing too many overlaps of nodes to directly reflect important nodes. Conversely, the value is too large, resulting in too many nodes, and cannot fully respond to important nodes information. After repeated trials and trial comparisons, we finally chose a tenth of the maximum value and round up the value to 19 as the threshold), there are 21 literature sources meeting this condition. The comparison results of literature quantity, citation quantity and correlation strength of corresponding literature source are shown in Table 1 (Sorted by number of articles).

In Table 1, the meaning of total link strength is a standard type of node weight in VOSviewer software. When the user does not have a custom weight type, the system selects the total link strength by default, which is used to indicate the influence of a node. In general, the greater the total link strength value of a node, the greater its impact. The journal of expert systems with applications has 182 articles related to the theme "recommender systems". The citation volume is 3797 times, and ranks first in literature quantity and citation quantity. The journal of knowledge-based systems has a volume of 105 articles. The citation quantity is 2873, and ranks second. On the contrary, although the number of meetings related to the theme of "recommender systems" is large, the citation rate is obviously low. For instance, 12th acm conference on recommender systems (recsys) issued 73 articles, and cited 1 time. Conference proceedingseering of the eleventh acm conference on recommender systems issued 62 articles, and cited 117 times. The main reason of this kind phenomenon is the conference held at a relative new time. As a result, the chances of the articles included in the conference being known and adopted by readers are relatively small.

Table 1
Literature sources information statistical table.

Literature source name	Literature quantity	Citation quantity	Total link strength
Expert systems with applications	182	3797	637
Knowledge-based systems	105	2873	714
Information sciences	81	1664	462
12th acm conference on recommender systems (recsys)	73	2	74
Proceedings of the eleventh acm conference on recommender systems	62	117	56
IEEE access	57	172	277
Physica a-statistical mechanics and its applications	52	1335	174
USER modeling and user-adapted interaction	48	1295	187
IEEE transactions on knowledge and data engineering	46	877	138
MULTIMEDIA tools and applications	42	205	76
Neuro computing	42	271	131
PLOS one	38	295	124
ACM transactions on intelligent systems and technology	38	539	106
KNOWLEDGE and information systems	34	256	38
Decision support systems	32	880	198
information processing & management	27	390	141
Journal of universal computer science	26	177	44
Journal of intelligent information systems	23	116	55
CIKM '18- Proceedings of the 27th ACM International Conference on Information and Knowledge Management	23	1	15
Electronic commerce research and applications	21	301	87

The visualization network of Table 1 with literature as association weight is shown in Fig. 3. Among them, the size of the node represents the amount of publications in the literature source. The larger the node is, the more the number of articles in the corresponding literature source is. The edges between the literature sources represent their degree of association with each other. The shorter and thicker the sides are, the more the number of common citations of the articles published in the corresponding literature source is. Fig. 3 shows that 21 literature sources are clustered into three clusters: the ten red nodes centered on the journal of expert systems with applications represent a cluster; the nine green nodes centered on the journal of Neuro computing represent a cluster; the two blue nodes centered on the journal of physica a-statistical mechanics and its applications represent a cluster. In addition, the strength of the correlation between nodes is represented by the thickness of the lines. It can be seen that the correlation between journals expert systems with applications, information sciences, and knowledge-based systems is the closest.

In brief, according to the data in Table 1 and the network diagram of the literature source in Fig. 3, for the topic "recommender systems", the number of journals published is positively correlated with the number of citations. And the recommended system involves a wide range of applications. For example, it all has a wide range of applications in expert systems, decision support systems, neural computing, multimedia applications, and knowledge management. Journal of expert systems with applications, journal of information sciences and journal of knowledge-based systems are key journals with significant impact in the field of recommendation systems. In addition, ACM conference on recommender systems (recsys) is the top-level meeting of recommendation system, and is also an important source of conference papers in this field.

3.3. Research power comparison

To some extent, research power represents the input of a country or institution to human, material, and financial resources in a certain field. It is an important indicator for measuring the attention of a country or institution in this field. This article focuses on the topic of "recommender systems" from the perspectives of national distribution and institutional distribution.

3.3.1. National distribution

Analyzing the distribution of national attention in a particular research area will not only help the research team to quickly discover the geographical distribution of the topic, but also grasp the strength distribution of each country in the research field, and help to identify various research methods and research techniques, which lets researchers more objectively and quickly obtains cutting-edge academic trends in the required research fields or research directions. Analysis of the valid sample data shows that the sample data includes 93 countries. In order

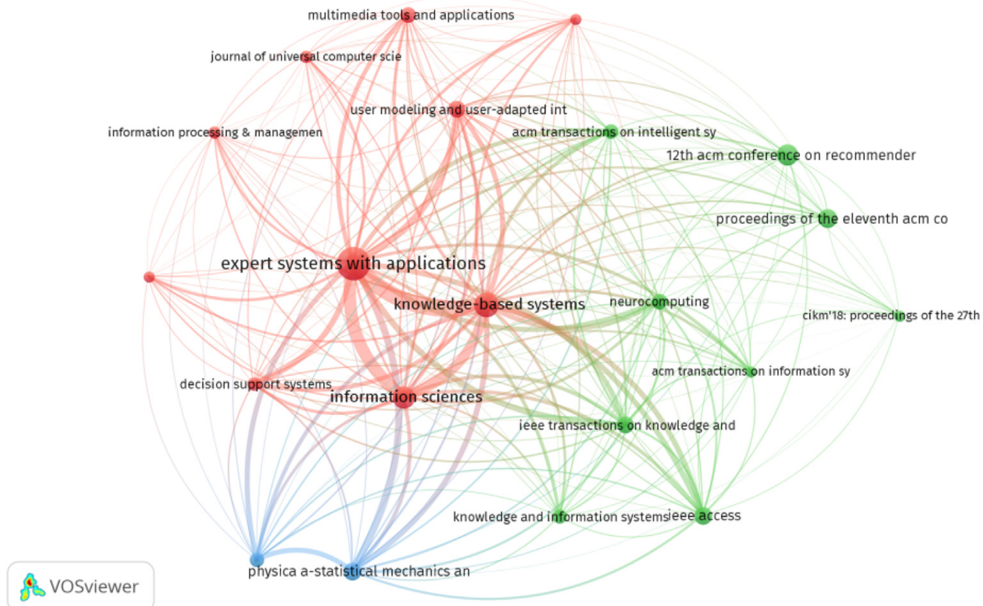

Fig. 3. Schematic diagram of the literature sources association network.

to facilitate the exploration of the scientific strength of the most important countries, with the number of publications ≥136 as the screening indicators (In order to maintain the objectivity of threshold selection, we calculated the average, median, quantile, maximum, and minimum values of the published documents in the dataset by the statistical functions provided by Excel. Among them, the average value of the published articles is 76; the median is 19; the one-quarters quantile is 5; the two-quarters quantile is 19; the three-quarters quantile is 68; the maximum is 1358 and the minimum value is 1. However, when these values are used as the threshold for visualization, the value is too small, causing too many overlaps of nodes to directly reflect important nodes. Conversely, the value is too large, resulting in too many nodes, and cannot fully respond to important nodes information. After repeated trials and trial comparisons, we finally chose a tenth of the maximum value and round up the value to 136 as the threshold.), there are 16 countries that meet this condition. As can be seen from Table 2 that the number of articles issued by China (peoples r china) is 1358, ranking first in the number of publications; the United States (usa) issues 831 articles, ranking second; Spain (spain) issues 443 articles, ranking third; the number of publications in India (india), Italy (italy), Germany (germany), and Australia (australia) is more than 250, and they are all high-producing countries in the field of recommendation systems. This also reflects the focus of relevant research in different countries from another level.

Table 2
National information statistical table.

Country	Literature quantity	Citation quantity	Total link strength
Peoples r china	1358	11,617	5878
USA	831	8155	3142
Spain	443	6090	2659
India	363	876	932
Germany	284	2480	1009
Italy	279	2155	895
Australia	267	1984	1511
England	195	2511	1249
South Korea	181	2062	1033
France	176	586	379
Canada	160	1210	666
Iran	152	719	1031
Japan	149	384	350
Switzerland	143	3305	1968
Brazil	141	385	416
Greece	136	1263	700

In addition, it can be seen from the national information statistics table in Table 2 that Iran has 152 documents, which are between Japan (149) and Canada (160). Compared with Japan, although the number of documents is relatively close, the number of citations of Iranian articles (719 times) is close to twice that of Japan (384 times). To a certain extent, Iran's quality of papers in the field of recommendation systems is higher than that of Japan. In addition, Iran is significantly higher than Japan and Canada in terms of total link strength values. Therefore, compared with Japan and Canada, Iran has a higher academic influence in the field of recommendation systems.

For the national statistics of the number of Literature quantity ≥136 in Table 2, the VOSviewer visualization software is used to carry out the national coupling analysis with the weight of the literature. The results are shown in Fig. 4. The size of the node represents the number of articles published by the corresponding country. The edges between the nodes represent the strength of their association. The shorter and thicker the edges and the greater the degree of coupling between countries are, the more common references the papers have. Among them: the 11 red nodes represented by USA (usa) are grouped into one cluster; the green nodes represented by China (peoples r china), the United Kingdom (england) and Switzerland (switzerland) are grouped into one cluster; the blue nodes represented by Australia (australia) and Iran (iran) are grouped into one cluster. In addition, it should be noted that the same cluster of countries cooperation is relatively close. For example, China and the United Kingdom is in the green cluster. The sides between the nodes are short and thick, indicating that the research cooperation between the two countries in the field of "recommender systems" is quite close.

In short, from the data in Table 2 and the coupled visualization network diagram in Fig. 4, the recommendation system as an important branch of artificial intelligence has been rapidly developed in the past decade. In particular, China not only ranks first

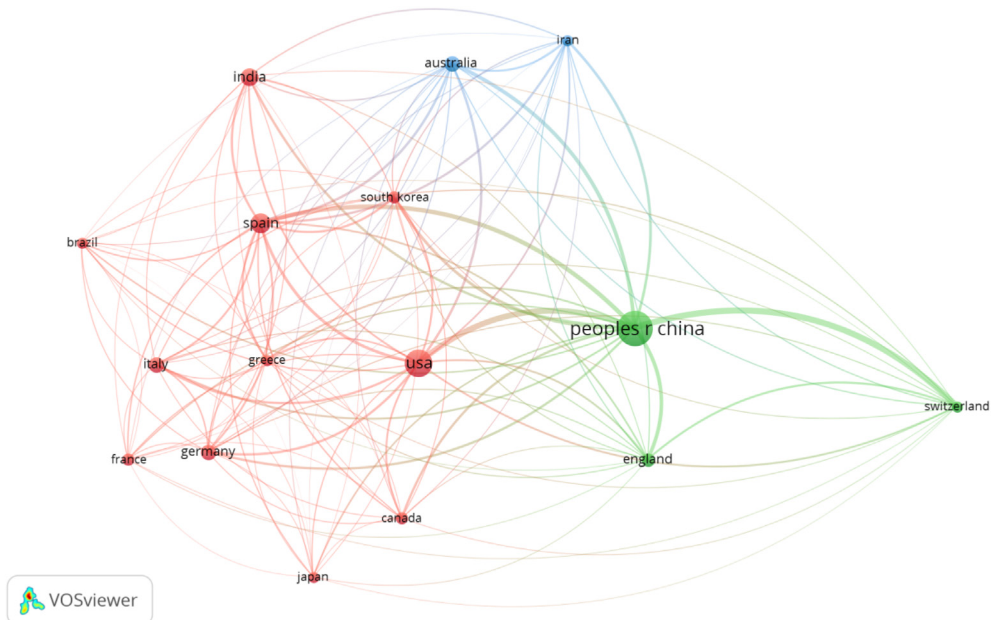

Fig. 4. Country coupling visual network diagram.

in the number of articles, but also has close cooperation with other countries, especially the United States. This also reflects that China's policy support and capital investment in the field of artificial intelligence have achieved remarkable results.

3.3.2. Institutional distribution

Based on the macro-state perspective analysis, the following is a comparison of research power from a more fine-grained-institutional perspective. Through the comprehensive comparison of research institutions, we will explore the cooperation between institutions and their research priorities so that researchers can track the institutional research trends and latest achievements related to their research topics. Here, the valid sample data analyzed by the VOSviewer visualization software, obtained 3007 research institutions. In order to better display the key institutions in the field of "recommender systems", 20 research institutions were selected according to the filtering conditions of ≥47 articles (Using the same method as Section 3.3.1, we also use the statistical method to calculate the relevant values for the problem of the threshold selection of the organization's publications involved in Section 3.3.2. Among them, the average is 7; the median is 4; the one-quarters quantile is 2; the two-quarters quantile is 4; the three-quarters quantile is 7, the maximum is 93, the minimum is 1. After repeated trials and experimental comparisons, we finally chose one-half of the maximum value and round up the value to 47 as the threshold.). The specific data is shown in Table 3 (sorted by the number of articles). As can be seen from the table: the University of Electronic Science and Technology of China (univ elect sci & technol china) issues 93 papers, ranking first; Tsinghua University (tsinghua univ) issues 82 papers, ranking second; the Chinese Academy of Sciences (Chinese academy sci) issues 73 papers, ranking third; the University of Fribourg (univ fribourg) publishes 72 papers, ranking fourth; the University of Minnesota (univ minnesota), the Australian University of Science and Technology (univ technol sydney), Zhejiang University (zhejiang univ) and other publications of more than 50 papers are also high-yield research institutions in this field.

Table 3
Organizational information statistical table.

Institution	Literature quantity	Citation quantity	Total link strength
Univ Elect Sci & Technol China	93	2668	1014
Tsinghua Univ	82	970	100
Chinese Acad Sci	73	718	118
Univ fribourg	72	2924	1002
Univ Technol Sydney	68	953	189
Zhejiang Univ	59	602	73
Univ Minnesota	55	955	58
Univ Autonoma Madrid	51	451	53
Univ Granada	49	796	217
Shanghai Jiao Tong Univ	48	271	40
Univ Jaen	47	918	596
Univ Sci & Technol China	47	2136	234

According to the statistical data in Table 3, the VOSviewer visualization software is used to carry out the mechanism coupling analysis with the weight of the literature. The result is shown in Fig. 5. Among them, the size of the node represents the number of articles issued by the organization. The thickness and length of the edges between the nodes reflect the strength of the correlation between the institutions. The thicker and shorter the edges are, the closer the cooperation between the organizations is.

According to the number of articles ≥47 the 12 research institutions selected are divided into two clusters by different color from Fig. 5. Among them: the three nodes of the University of Science and Technology (univ elect sci & technol china), the University of Science and Technology of China (univ sci & technol china), and the University of Fribourg (univ fribourg) form a cluster; Nine nodes represented by Tsinghua University (tsinghua univ) and Chinese Academy of Sciences (chinese acad sci), which are colored in red, form a cluster. In addition, it is found by the external form of the side between the Institutions in Fig. 5: in the field of recommended systems research, the University of Fribourg in Switzerland cooperates closely with the University of Electronic Science and Technology of China and the University of Science and Technology of China, especially the University of Electronic Science and Technology; Tsinghua University is a bridge and hub for cooperation between Chinese universities and foreign universities.

In one word, universities are the main research force in the field of "recommender systems" from the data in Table 3 and the

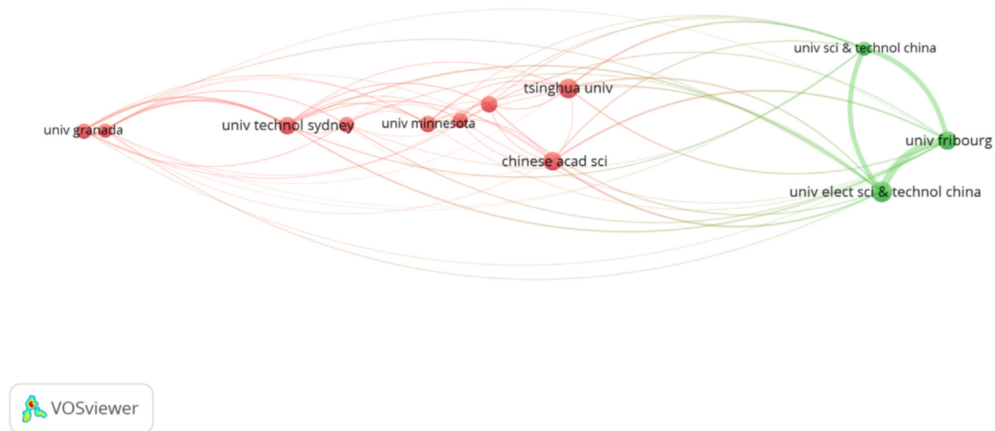

Fig. 5. Organization coupling visual network diagram.

mechanism-coupled visualization network diagram in Fig. 5. Chinese universities, especially the University of Electronic Science and Technology and Tsinghua University, have the highest contribution, especially the strength of overseas cooperation in the University of Electronic Science and Technology. Overseas cooperation in the university of information universities led by Tsinghua University is also a highlight. Of course, achieving such fruitful results is also inseparable from China's "double first-class" construction (the construction of world-class universities and first-class disciplines, referred to as "double first-class"). Meanwhile, from a more detailed dimension, China's investment in "double first-class" universities have already begun to bear fruit. In addition, it should be noted that the United States ranks second in this field. However, only 55 documents issued by the University of Minnesota are relatively prominent, and other universities and research institutions issue less than 47 articles. This phenomenon indicates that the cooperation between the institutions is loose and the amount of publications is not concentrated.

3.4. Author analysis

Scientific research usually reflects the latest academic achievements and cutting-edge dynamics in related fields in the form of academic papers, conference papers and technical patents. Exploring the author's distribution of relevant results help the research team to master the well-known experts and scholars in the field of concern from a deeper level, and timely track their latest research trends and research results to obtain a leap-forward improvement of academic thinking. To this end, valid sample data is analyzed by VOSviewer visualization software, and 11,365 authors are obtained. In order to better reflect the outstanding contributions of experts in the field of "recommender systems". Here, the number of posts $\geq$20 is used as a screening indicator (Using the same method as Section 3.3.1, we also use statistical methods to calculate the relevant values for the author's issue threshold selection problem in Section 3.4. Among them, the average is 5; the median is 2, the one-quarters quantile is 2; the two-quarter quantile is 3; the three-quarter quantile is 6; the maximum is 33; the minimum is 1. After repeated trials and experimental comparisons, we finally chose 60% of the maximum value and round up the value to 20 as the threshold.), and the total number of authors who meet this condition is 23. The specific statistical information is shown in Table 4 (sorted by the number of articles). As can be seen from the table: the author "Zhou, tao" publishes 33 articles, citing 2596 times and ranking first; the number of articles published by the author "zhang, yi-cheng" is 32, with 1587 citations and ranking second; the author "ricci, francesco" issues 31 papers, citing 443 times and ranking third; five authors having more than 25 articles are also prolific authors in the field such as "lu, jie" and "luo, xin".

Table 4
Author information statistical table.

Author	Literature quantity	Citation quantity	Total link strength
"zhou, tao"	33	2596	831
"zhang, yi-cheng"	32	1587	782
"ricci, francesco"	31	443	23
"lu, jie"	29	626	178
"luo, xin"	28	490	69
"lops, pasquale"	26	109	126
"bellogin, alejandro"	25	136	33
"chen, li"	25	320	29
"bobadilla, jesus"	24	607	291
"de gemmis, marco"	24	108	126
"jannach, dietmar"	23	199	39
"zeng, an"	23	268	428
"semeraro, giovanni"	23	104	125
"zhang, guangquan"	22	494	166
"smyth, barry"	21	115	12
"cantador, ivan"	21	267	52
"felfernig, alexander"	21	75	6
"ortega, fernando"	21	598	286
"zhang, zi-ke"	21	869	533
"blanco-fernandez, yolanda"	20	161	31
"liu, jian-guo"	20	702	483
"lopez-nores, martin"	20	155	31
"musto, cataldo"	20	104	125

According to the statistical data of the authors in Table 4, the VOSviewer visualization software is used to carry out the author coupling analysis with the weight of the literature. The results are shown in Fig. 6. Among them, the size of node represents the number of articles issued by the author. The thickness and length of the edges between nodes reflect the coupling strength between the authors. The thicker and shorter the edges are, the closer the cooperation between the authors is.

The 23 authors selected form three clusters with the weight of the literature as the weight by different color in Fig. 6. Among them: the 14 red nodes with "lu, jie" as the central node form a cluster, and that are the largest academic cooperation network. The cooperation between the authors "ortega, fernando" and "bobadilla, jesus" is very strong. "lu, jie" and" zhang, guangquan" are following; the five green nodes with "zhou, tao" as the central node form a cluster. The authors "zhou, tao" and "zhang, yi-cheng" have the highest cooperation intensity; the blue clusters formed by the authors "lops, pasquale", "semeraro, giovanni", "musto, cataldo", "degemmis, marco" are relatively close to each other.

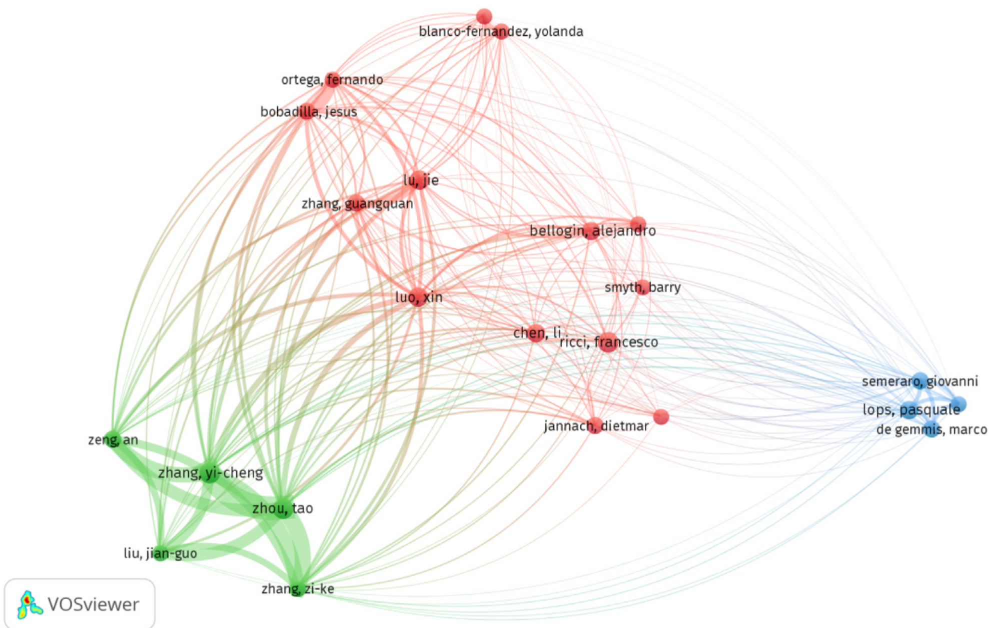

Fig. 6. Author coupling visual network diagram.

In summary, from the data in Table 4 and the author's coupled visualization network diagram in Fig. 6, it is known that Chinese scholars have contributed the most to the research on the topic "recommender systems", and have formed two typical academic cooperation teams respectively, which are presented by tao", especially the "lu, jie" team having a wide range of cooperation and a high degree of internationalization. Therefore, researchers in the field of recommended systems can use the "lu, jie" team as a key reference.

3.5. Citation analysis

Citation analysis is one of the main ways to mine the most valuable literature. This is because the highly cited literature not only has a relatively high reference value in the corresponding field, but also is the research basis in that field. Generally speaking, the more cited an article is, the greater the academic value of the article is. In order to dig out the most valuable literature data in the field of "recommender systems", the effective sample data is analyzed by the VOSviewer visualization software to achieve 85,511 citation data. In order to obtain more citation information with more academic value, the number of citations $\geq$147 times is used as the selective condition (Using the same method as Section 3.3.1, we also use statistical methods to calculate the relevant values for the threshold selection problem of the number of citations involved in Section 3.5. Among them, the average is 41; the median is 24; the one-quarters quantile is 17; the two-quarter quantile is 24; the three-quarter quantile is 39; the maximum is 1470; the minimum value is 3. After repeated trials and experimental comparisons, we finally chose a tenth of the maximum value, 147, as the threshold.), and finally 36 pieces of citation articles satisfying the requirements are obtained, as shown in Table 5 (sorted by citation). It is not difficult to find that:

Table 5
Literature information statistical data.

Cited literature information	Citation quantity	Total link strength
Adomavicius and Tuzhilin, 2005	1470	4537
Herlocker, et al., 2004	948	3357
Koren, et al., 2009	834	2731
Sarwar et al., 2001	662	2808
Linden, et al., 2003	559	2175
Burke, 2002	548	2037
Ricci et al., 2011a,b	482	1431
Resnick and Varian, 1997	401	1344
Bobadilla, Ortega, Hernando, & Gutiérrez, 2013	388	1225
Koren, 2008	354	1424
Goldberg et al., 1992	320	1323
Balabanovic and Shoham, 1997	305	1402
Deshpande and Karypis, 2004	299	1320
Breese et al., 2013	280	1252
Blei et al., 2012	275	815
Resnick et al., 1994	248	1024
Su and Khoshgoftaar, 2009	248	1045
Herlocker et al., 1999	244	1205
Hofmann, 2004	241	1303
Hu et al., 2008	229	850
Lops et al., 2011	226	825
Ricci et al., 2011a	207	820
Adomavicius and Tuzhilin, 2005	206	706
Adomavicius et al., 2011	202	660
Konstan et al., 2000	196	883
Goldberg et al., 2001	195	942
(Zhoua et al., 2010)	191	846
(Ricci et al., 2011b)	184	543
Pazzani, 1999	181	862
Rendle et al., 2010	166	468
Pazzani and Billsus, 2007	163	717
Breese et al., 2013	163	692
(Lü et al., 2012)	161	647
Shardanand and Maes, 1995	161	765
Ma et al., 2011	157	594
Ziegler et al., 2005	152	652

(1) Reference (Adomavicius and Tuzhilin, 2005).

The number of citations in the literature is 1470, ranking first in the citation. This article is a review of the next generation recommendation system. The recommendation system is divided into three categories: Content-based Recommendation system, Collaborative filtering recommendation system and Hybrid recommendation system. Also, reference (Adomavicius and Tuzhilin, 2005) describes the shortcomings of various recommendation systems and improvement measures.

(2) Reference (Herlocker et al., 2004)

The number of citations is 948, ranking second. This paper is an article to study the collaborative filtering recommendation system evaluation method. The paper reviews the key decisions for evaluating the collaborative filtering recommendation system, and divides the evaluation indicators into three equivalence classes through the empirical methods in the content recommendation field, each of which is equivalent. The metrics within the class are strongly correlated, and the indicators in the different equivalence classes are irrelevant.

(3) Reference (Koren et al., 2009)

The number of citations in the literature is 834, ranking third. This paper discusses the application of matrix decomposition techniques in recommendation systems. It is verified that additional information is superior to traditional neighbor technology in generating product recommendations, such as implicit feedback, time effect and confidence level matrix decomposition model.

(4) Reference (Sarwar et al., 2001; Linden et al., 2003) and (Burke, 2002)

The three articles are also high-reference articles, and the number of citations is more than 500 times. Among them:

Reference (Sarwar et al., 2001) mainly studies the Item-based Collaborative Filtering Recommendation Algorithm. In order to solve the low recommendation and large-scale data processing problems of traditional recommendation systems, this literature analyzes different Item-based Recommendation System Generation Algorithms, tries various techniques (such as item relevance and item vector cosine similarity) to calculate the similarity of the item, and uses different recommendation techniques (such as weighted summation and regression model) to obtain the recommended result. Then, the proposed algorithm is evaluated and compared with the K nearest neighbor method. Experiments show that the performance of the Item-based Algorithm is better than the User-based Algorithm performance and the robustness is better than the best User-based Recommendation Algorithm.

Reference (Linden et al., 2003) is an industry report introducing Amazon's material-object Collaborative filtering Recommendation system. This literature mainly analyzes Amazon's recommendation system from six aspects: recommendation algorithm, cluster model, material-object collaborative filtering, search-based method, system working method and performance evaluation.

Reference (Burke, 2002) is a review of research on hybrid recommendation systems. Based on the analysis of the advantages and disadvantages of existing hybrid recommendation systems, literature (Burke, 2002) proposes a novel hybrid of EntreeC, which is a restaurant recommendation system based on knowledge recommendation and collaborative filtering. The results prove that the semantic rating obtained based on the knowledge part can significantly enhance the collaborative effect of the system.

According to the citation data statistics of the cited number of times $\geq$147 in Table 5, the VOSviewer visualization software is used to carry out the literature reference coupling analysis with the reference quantity as the weight. The result is shown in Fig. 7. Among them, the size of the node represents the number of article's citation times. The larger the node is, the higher citation times of article are. The thickness and length of the edges between the nodes indicate the coupling strength between the citations. The thicker and shorter the edges are, the stronger the correlation between the citations is.

According to the number of citations of the literature $\geq$147 times, 36 citation articles selected, form four clusters with the weight of the citation of the documents from Fig. 7. Among them: the eleven red nodes with the central node reference (Koren et al., 2009) form a cluster; the ten green nodes centered on the document reference (Adomavicius and Tuzhilin, 2005) form a cluster; the five orange nodes with reference (Herlocker et al., 2004) as the central node form a cluster; the ten blue nodes centered on reference (Resnick and Varian, 1997) form a cluster. Reference (Resnick and Varian, 1997) is a conference paper, which first elaborates the recommended system technology design method from five dimensions. Then, the application of the recommendation system is analyzed and evaluated from the perspective of solving the problem. Finally, the development of future recommendation systems is prospected from the perspective of business models.

In one word, from the data in Table 5 and the referenced document visualization network diagram in Fig. 7, it can be seen that the highly cited literature mainly focuses on the Recommendation System Application, Improvement and Application of Collaborative Filtering Algorithms, Cold Start of Recommendation System in the research on the theme of "recommender systems".

To sum up, we introduced the quantitative analysis method and the visual clustering analysis method into the literature research of the field of recommendation systems. From the aspects of time distribution, periodical distribution, comparative analysis of research power, author analysis and citation analysis, we have made an in-depth analysis of the literature to better discover the hidden knowledge contained in the literature related to the theme of the recommendation system.

The research has found that: (1) Judging from the time distribution and change trend of published literature, with the development of artificial intelligence, thematic research related to recommendation systems will once again become a hot spot in academic research, especially with the rapid landing of the research results of the recommendation system in the industry, it will inject a strong internal driving force for the application research of the recommendation system. Because personalized recommendation can truly reflect the differentiation and diversification of needs; (2) From the perspective of the distribution of published journals, the recommendation system will no longer be limited to meet people's personalized needs, but more will serve the fields of assisted decision-making and knowledge management, that is, assisted decision-making will become an indispensable part of the recommendation system. This can also be corroborated from the source of journals that have published literature. For example, the research results related to the recommendation system topics included in the journal of expert systems with applications, information sciences and knowledge-based systems can show that; (3) From the comparative analysis of the research strength of published literature, with the extension of artificial intelligence to cognitive intelligence, cooperation between countries, especially cross-regional or transnational cooperation between universities will become the new normal, this move will facilitate the rapid spread of new knowledge and technologies. As an important part of artificial intelligence, the recommendation system will also usher in more international cooperation and obtain the injection of new technologies and new methods to promote the rapid development of its theoretical research and landing applications; (4) From the analysis of the authors of the published literature, in the topic research related to the recommendation system, the degree of international cooperation of Chinese scholars has been continuously improved, and fruitful results have been achieved in the relevant research in the field of recommendation systems; (5) From the citation analysis of published literature,

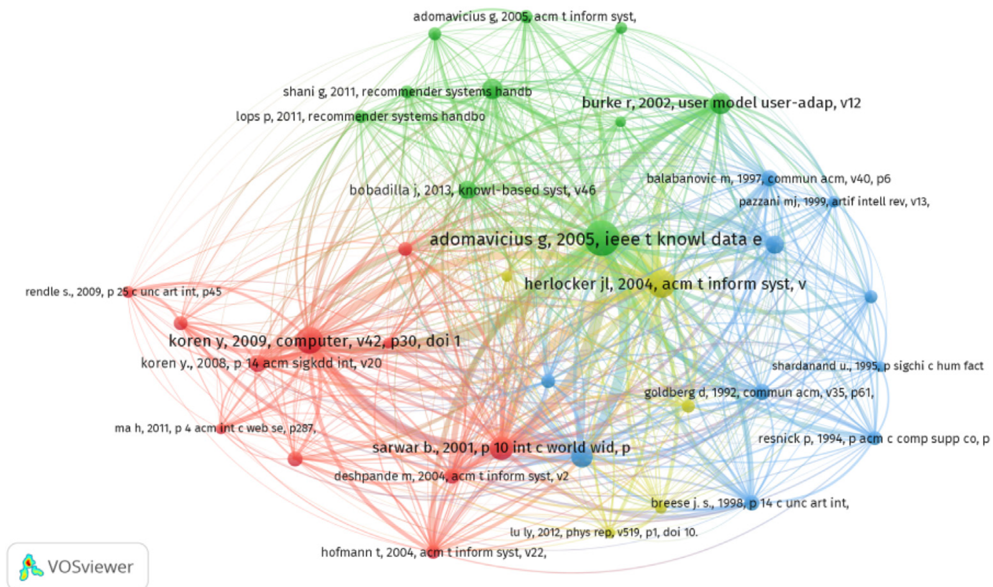

Fig. 7. Literature visualization network diagram.

the recommendation system with collaborative filtering technology as the core has been continuously successful in the industry. The classic collaborative filtering algorithm is an important support for the development of recommendation system technology, however problems derived from it such as cold start and fusion improvement of collaborative filtering algorithms are still the key issues to be solved urgently in the field of recommendation systems. The integration of interdisciplinary and multidisciplinary technologies and collaborative filtering methods will better improve the overall performance of the recommendation system.

In short, the paper adopts a combination of literature measurement content analysis method, knowledge mapping and clustering method, and builds a relevant scientific knowledge map to discover the hidden knowledge of literature in the field of recommendation systems to inspire and guide the interested researchers, especially those who have just been engaged in research in this field, it will help them fully grasp the field dynamics and lay a solid theoretical foundation for their in-depth research. It is worth mentioning that as an important application scenario of artificial intelligence, the recommendation system is once again highly valued by industry and academia. The integration of theoretical research and industrial practice in academia and industry will also become a new driving force for the development of recommendation system applications.

4. Research hotspot analysis

The key words are not only the high concentration and generalization of the article title and abstract, but also the core and essence of the article content. Generally, the higher the numbers of occurrences for a keyword in a specified time period are, the higher the research heat of the topic corresponding to the keyword is. Therefore, the academic community usually uses the frequency of keywords appearing in the article to identify hot issues in an academic subject research. In order to dig out the most representative keywords in the field of "recommender systems", the VOSviewer visualization software is used to analyze the effective sample data for all keywords and obtain 9872 keywords. The screening conditions are based on the number of keyword co-occurrences ≥38 times (Using the same method as Section 3.3.1, we also use the statistical method to calculate the relevant value for the threshold selection problem of the number of co-occurrences of the keywords involved in Section 4. The average value is 19 and the median is 7. The one-quarters quantile is 4; The two-quarter quantile is 7; The three-quarter quantile is 13; the maximum is 2738, and the minimum is 2. After repeated trials and experimental comparisons, we finally chose twice the average value 38 as the threshold.). Finally, 75 high-frequency keywords that meet the requirements are selected, as shown in Table 6 (Sorted by the number of keyword co-occurrences). From the data in the table 6, it is easy to find: the keyword "recommender systems" appears 2738 times, ranking first; the keyword "collaborative filtering" appears 1150 times, ranking second; the keyword "recommender system" has a total of 716 times, ranking third; the keywords "accuracy", "algorithm", "algorithms", "classification", "clustering", "networks", "personalization", "data mining", "e-commerce", "information", "matrix factorization", "model", " recommendation"," similarity"," social networks"," systems"," trust" and " web", have a co-occurrence frequency of more than 100 times.

Comparing the co-occurrence frequency of the above high frequency keywords with the corresponding co-occurrence intensity, the two indicators are positively correlated and basically consistent. Therefore, it can be determined that these keywords can reflect the research hotspot of the current recommendation system to a certain extent. Meanwhile, it can be seen from the above hotspot keywords that the application research of the recommendation system in the field of e-commerce is hot in recent years. The application of the recommendation system based on collaborative filtering is particularly prominent, which is also consistent with the actual situation. In the past ten years, e-commerce has achieved unprecedented development in the world, and has resulted in a surge in data volume and a crisis of information overload. The recommendation systems have effectively solved this business problem. For example, the ancestor of recommendation system, an e-commerce giant of Amazon, generates 35% of its annual revenue from personalized recommendation. 2/3 of the movies that Netflix users watch come from the recommendation system. 38% of the clicks on Google News are generated by its own news recommendation algorithm (Lee and Hosanagar,

Table 6
Keyword statistical table.

Key words	Co-occurrence	Total link strength	Key words	Co-occurrence	Total link strength
Recommender systems	2738	3865	Information retrieval	61	105
Collaborative filtering	1150	2274	Content-based filtering	59	135
Recommender system	716	1076	Semantic web	59	124
Systems	623	1256	User modeling	58	111
Matrix factorization	328	684	Tourism	57	134
Model	250	686	Sparsity	56	160
Information	227	581	E-learning	54	144
Personalization	220	463	Personalized recommendation	54	154
Algorithms	214	562	Complex networks	53	123[a]
Trust	200	526	retrieval	52	118
Social networks	182	412	social media	52	98
Recommendation	175	289	prediction	52	125
Networks	156	382	cold start	51	131
Web	139	367	cold-start problem	51	121
E-commerce	131	304	sentiment analysis	49	106
Algorithm	127	309	deep learning	48	75
Clustering	110	271	selection	47	135
Data mining	109	248	behavior	47	121
Machine learning	106	195	information filtering	46	132
Classification	106	256	implicit feedback	46	94
Accuracy	104	359	impact	45	136
Similarity	102	277	optimization	45	110
Framework	95	274	context-awareness	45	95
Diversity	91	261	experimentation	43	176
State-of-the-art	91	276	decision-making	43	106
Social network	88	218	similarity measure	42	140
Context	88	194	ranking	42	114
Ontology	80	195	internet	42	110
System	78	148	management	41	124
Models	72	176	e-commerce	41	118
Recommendation system	72	102	social recommendation	41	84
Performance	70	212	data sparsity	39	111
Privacy	70	164	preferences	39	97
Search	66	175	dynamics	38	128
Evaluation	65	143	link prediction	38	112
Recommendation systems	64	92	context-aware	38	109
Design	63	173	ontologies	38	102
Big data	62	124			

[a] This row is table content, not header information.So the corresponding font boldness needs to be removed.

2014). In addition, the recommended algorithm has increased the viewing time of hundreds of thousands of hours per day for YouTube and an annual increase in video clicks of 50% since 2008.

From the high-frequency keyword data statistical information in Table 6, the VOSviewer visualization software is used to perform keyword coupling analysis with the co-occurrence times as the weight. The results are shown in Fig. 8. Among them, the size of the node represents how often the keyword appears. The thickness and length of the edges between the nodes reflect the coupling strength between the keywords. The thicker and shorter the edges are, the closer the linkage between the keywords is.

According to the number of co-occurrences of keywords $\geq$38 times, 75 keywords selected form seven clusters with the number of co-occurrences as weights by different color from Fig. 8. Among them: the 11 words centered on the keyword "recommender systems" form a cluster (purple node in Fig. 8); the 12 words centered on the keyword "collaborative filtering" form a cluster (the blue node in Fig. 8); The 4 words centered on the keyword "social recommendation" form a cluster (orange node in Fig. 8); the 15 words centered on the keyword "information" form a cluster (green node in Fig. 8); the 6 words centered on the keyword " algorithms" form a cluster (the azure node in Fig. 8). the 12 words centered on the keyword " Personaliztion" form a cluster (the bluish yellow node in Fig. 8). The 15 words centered on the keyword " social networks" form a cluster (the red node in Fig. 8). These seven clusters represent highly aggregated research hotspots related to the topic "recommender systems". It mainly includes: Recommendation Technology and Recommendation System, Collaborative Filtering and Matrix Decomposition, Information Technology and Recommendation System, Personalized Recommendation Model and Framework, Recommendation Algorithm and Performance Evaluation.

4.1. Recommendation technology and recommendation system

The cluster represented by the keyword "recommender systems" (Helberger et al., 2018) reflects the hot words related to the recommendation technology and the recommendation system research, including: "content-based filtering" (Zhao et al., 2017), "context", "e-commerce", "e-learning", "information retrieval", "ontology", "personalization", "recommendation", "recommendation system", "recommender systems", "retrieval", "search", "semantic web", "user modeling" etc. These hot words cover the implementation principles, implementation techniques, application scenarios and practical uses of the recommendation system. With the continuous development of artificial intelligence technology and data mining technology, the recommendation system as a subset of its application has been continuously improved in technology. User portrait, semantic web, ontology and other technologies provide a strong guarantee for the precise and personalized development of the recommendation system.

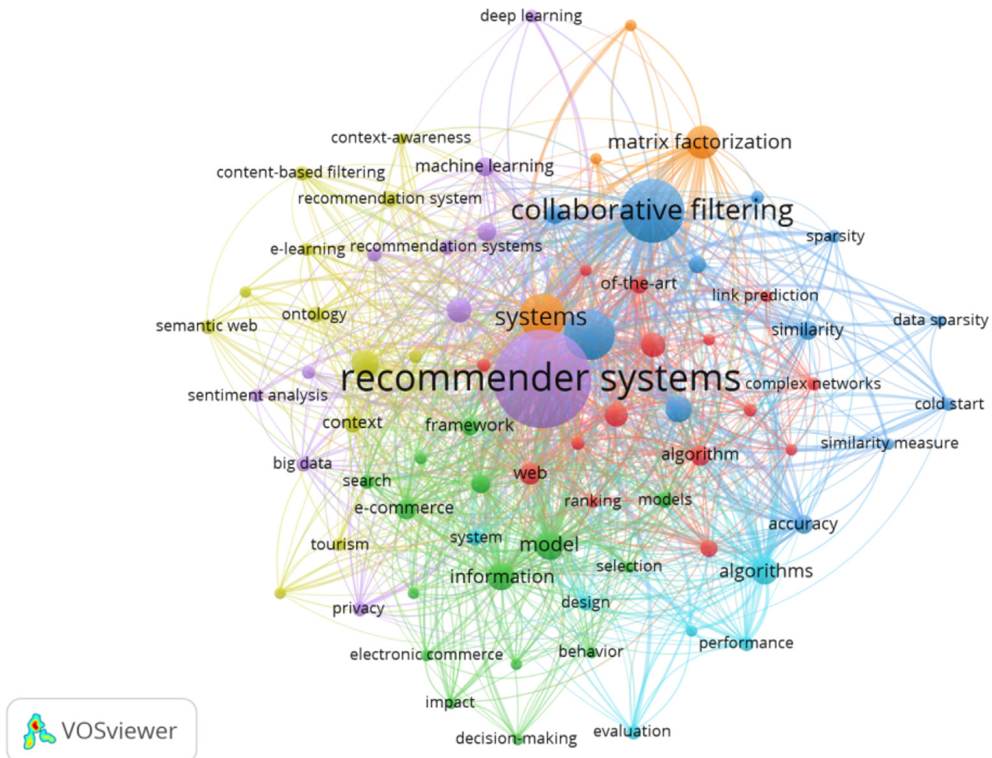

Fig. 8. Keyword coupling network diagram.

4.2. Collaborative filtering and matrix decomposition

The cluster represented by the keyword "collaborative filtering" (Almahairi et al., 2015) reflects the relatively mature implementation methods and existing problems in the recommendation system, including: "cold start", "collaborative filtering", "matrix factorization" (Yi et al., 2019), "recommender system", "similarity", "social network", "sparsity", "systems", "trust" etc. These terms cover techniques used by recommendation systems based on collaborative filtering (such as similarity calculations, matrix factorization, etc.) and difficulties (such as data sparsity and cold start) (Fernández-Tobías et al., 2019). Cold start and data sparsity are the main reasons for the low accuracy of collaborative filtering algorithms (Son, 2016). The accuracy of the collaborative filtering recommendation system can be effectively improved by using additional information such as social networks. In addition, the user's credibility of the system itself can also improve the accuracy of personalized recommendations.

4.3. Information technology and recommendation system

The cluster represented by the keyword "social networks" reflects the hot words related to the research of information technology and recommendation system, including: "big data", "classification", "clustering", "data mining", "machine learning", "models", "networks", "recommendation systems", "privacy", "social media"," social networks" etc. . These terms cover the technologies and methods that information technology (such as big data, data mining, machine learning, etc.) provides for high performance recommendation systems. Additional information such as social media and social networks provides data guarantees for the bias of the recommendation system. In addition, with the continuous development of information technology, the privacy protection of users' sensitive personal data in the recommendation system is also an important security topic.

4.4. Personalized recommendation model and framework

The cluster represented by the keyword "information" reflects the hot words of the personalized recommendation model and framework research, including: "accuracy", "algorithm", "cold-start problem", "complex networks", "diversity", "framework", information","model","state-of-the-art" (Boratto and Carta, 2010), "personalized recommendation" (Zheng et al., 2014), "prediction", "tourism", "web" etc. These hot vocabularies cover the performance requirements, model building and system applications of recommended systems in the field of personalized recommendations. For example, for the recommendation system in the tourism field, the diversity needs of users are a very important evaluation indicator. Combining complex networks and related algorithms to overcome the cold start problem, achieving high-precision personalized recommendations to meet the bias needs of tourists and improving the quality of tourism services are also an application market where the recommendation system has great potential.

4.5. Recommendation algorithm and performance evaluation

The cluster represented by the keyword "algorithms" reflects the hot words related to the recommendation algorithm and performance evaluation (Del Olmo and Gaudioso, 2008), including: "algorithms", "design", "evaluation", "performance". These hotspot keywords cover the algorithms and performance evaluations associated with the recommendation system. Generally, a good recommendation algorithm is a powerful guarantee to improve system performance. The overall evaluation of the recommendation system not only includes the efficiency of the algorithm calculation used by it, but more importantly, the recommendation system can filter out novelty and individuality relevant information satisfying user needs.

5. Research frontier analysis

Accurate acquisition of frontier information will help research teams to keep abreast of the latest frontier trends of relevant research topics and predict the direction of development of the discipline and future research hotspots. Usually, the degree of heat and cold of keywords related to the research topic can well reflect the current heat and future trend of the topic itself. Guided by the high-frequency keywords in Table 6 and the keyword co-occurrence network diagram in Fig. 8, combining with the "recommender systems" theme evaluation indicators (Ge and Persia, 2018; Del Olmo and Gaudioso, 2008), the key words that have potential research value are as follows: "semantic web", "cold start", "privacy", "diversity", "user modeling", "ontology", "personalization", "sparsity". These keywords with potential research value objectively reveal the overall development direction of the recommendation system.

The keywords "semantic web" (Geroimenko, 2005) and "ontology" (Pouriyeh et al., 2018) represent the development trend of recommendation system data source representation technology, which are used to solve the problem of multi-source heterogeneous data representation. The Knowledge Graph technology proposed by Google is a continuation of semantic network and ontology technology. It can solve heterogeneous data representation problems well, and is one of the core technologies supporting the next generation recommendation system.

The keywords "cold start" (Son, 2016) and "sparsity" (Torfi et al., 2019) are the main problems faced by the collaborative filtering recommendation system. At the same time, they are also the driving force for the development of Collaborative filtering Recommendation systems. Data sparsity is the main cause of cold start. In addition, the recommendation system based on collaborative filtering algorithm is relatively mature and has been widely used in many fields. Therefore, the use of advanced artificial intelligence technology to extract data features and to alleviate the problem of cold start and data sparseness is also a hot issue to be solved.

The keywords "personalization" (Meng et al., 2017) and "diversity" (Helberger et al., 2018) reflect the development trend of the recommendation system. With the development of information processing technology and internet technology, people's demands for personalized services are becoming more and more intense. In the era of information explosion, personalized recommendation system is an effective way to solve this appeal. Therefore, it is particularly important to use the personalized recommendation system to quickly filter out the content of interest from the massive information.

The keyword "privacy" (Yin et al., 2019) reflects the privacy protection in the recommendation system. Personalized recommendations with biasedness require the user's own sensitive data as a support. Moreover, all third-party recommendation systems also collect user's personal preference information and recommendation results. In general, the recommendation is a product of a compromise between recommended system accuracy and privacy protection levels. Therefore, it is necessary to explore a high-precision recommendation system with a privacy protection mechanism.

The keyword "user modeling" (Liu, 2018), which expresses and stores the potential intentions and interests of users, and summarizes them according to the user's basic information, access information, behavioral preferences, implicit interests and computable user model. It represents the development trend of the recommended system user modeling method, and is the cornerstone of the recommended system value. The quality of the model directly affects the recommendation effect, especially for the personalized recommendation system. User modeling becomes more and more important.

6. Existing problems and countermeasures analysis

The evaluation index of recommendation system is the measurement criterion of its research method and technology application. The shortcomings of technology itself are the driving force for the continuous development of technology. These two factors interact and promote each other, which jointly promote the continuous development of recommendation system application and related information technology. Generally, there are many open problems (such as Amazing problem, Value-aware recommendations and so on) in recommender systems. According to Coupling network clustering map based on keywords in Fig. 8, the following mainly focuses on the research and prospects of key issues such as cold start in collaborative filtering algorithm, privacy protection of recommendation system, research on universal recommendation system, accuracy of recommendation system, and interpretability of recommendation system.

6.1. Recommended system cold start problem

The Collaborative Filtering (CF) recommendation system based on CF algorithm is a mature method in the implementation of recommendation system, and has been widely used in many fields. However, the CF algorithm itself requires a large amount of historical data to analyze the characteristics of the user/item so as to predict the user's potential preferences. Also, the recommendation system caused by the new user's historical data vacancies cannot correctly guess the new user's preference, which leads to the recommendation failure, is called cold start problem. The cold start problem mainly includes three types: cold start of items (how to recommend new items to interested users), cold start of users (how to recommend items to new users) and cold start of systems (how to realize personalized recommendation in a new system with only items and no users). In order to alleviate the cold start problem caused by the missing user/item data, literature (Xu and Yuan, 2017) proposes a Trust and Behavior based Singular Value Decomposition (TBSVD) algorithm. TBSVD is a matrix decomposition algorithm that extracts social trust and social behavior in Weibo and integrates it into the feature matrix as additional information, which can better determine user preferences. Experiments prove that the TBSVD algorithm combining with the data set extracted by Tencent Weibo social network is better than the traditional recommendation system, which alleviates the cold start problem to a certain extent. Literature (Zhang et al., 2017a,b) proposes a Kernel-based Attribute-aware Matrix Factorization (KAMF) model, which is used to customize rating project forecasts. The model combines project attribute information with a project user rating matrix to mitigate cold-start problems caused by data sparsity. Experiments conducted on the Movielents dataset and the Yelp social networking site shows that KAMF improves the recommended performance under cold start conditions.

Although the above methods alleviate the cold start problem to some extent compared with the traditional CF recommendation system. However, the cold-start problem of recommendation system has not been solved from the root cause. This is due to the fact that the data sparseness makes feature extraction and similarity calculation more difficult. Moreover, these cold-start improvement methods lacking of versatility are tested on specific data sets to improve the performance of verification. To this end, more relevant data can be extracted from multiple data sources related to new users (new items) to compensate for the lack of historical data of users (items). Using the Knowledge Graph (Bellini et al., 2017) performs a unified semantic representation of multi-source heterogeneous data (Sun et al., 2017). On this basis, a case-based reasoning system (Zahra et al., 2017) based on knowledge base (Viktoratos et al., 2018) is constructed by combining artificial neural network, which fundamentally solves the problem of data sparsity. And then the cold-start problem of CF recommendation system is thoroughly solved.

In order to verify the feasibility of our proposed knowledge graph and neural network fusion solution in solving the cold start problem, movielens-1M, a benchmark data set widely used in movie recommendation, was used as the data source to compare the benchmark reference method with our proposed solution. Among them, (1) User-specific Feature-based Similarity Model (UFSM) uses the attribute information of the project to establish a regression model for level prediction (Elbadrawy and Karypis, 2015). (2) Singular Value Decomposition (SVD) is a singular value matrix decomposition method for scoring prediction (Koren, 2008). (3) Attribute Fusion Method (Neighborhood, Category, Popularity and Geographical, NCPD) This method combines neighborhood, category, popularity and site geographic distance attributes, and uses the matrix factorization method of cropping to predict the score (Hu et al., 2014). For a fair comparison, we directly use all the original benchmark results in their respective studies and compare these benchmark results with our proposed approach (the implementation of the knowledge fusion training method ((Wang et al., 2019)) by using the root mean square error (RMSE). The result of performance is shown in Table 7.

In general, the method with a smaller RMSE value is more accurate. That is, the prediction accuracy of the corresponding model is higher. It can be seen from Table 7 that the RMSE of the strategy combining the knowledge graph and the neural network is relatively low, which fundamentally alleviates the cold start problem. In summary, to some extent, the experimental comparison data proves the effectiveness of our proposed scheme. Next, we will use the combination of knowledge graph and different neural networks on different types of data to demonstrate the feasibility of the scheme, and try to evaluate the effectiveness of the scheme by using multiple evaluation indicators.

6.2. Recommended system privacy protection issues

The privacy protection of data is a hot issue of concern to industry and academia. The recommendation system provides convenience for the user, and there is a potential leak in the collected household privacy data. In the case of not infringing on personal privacy information and efficiently solving the problem of information overload caused by massive data is a pain point that plagues the recommendation system. To this end, J. Kim et al. propose a privacy protection method based on matrix factorization (Kim et al., 2016a, 2016b; Jinsu et al., 2018). This method, which uses the homomorphic encryption technology (Xu et al., 2018; Min et al., 2019) to implement the privacy protection of the recommendation system, performs matrix decomposition on the encrypted user rating data and returns the encrypted output so that the recommendation system does not collect any content in the rating data and the recommendation result. Moreover, the method uses an encryption vector to avoid computational performance degradation caused by fully homomorphic encryption. However, the entire test is performed in a simulated environment. And the actual application performance is yet to be verified. In order to overcome the privacy leakage caused by the user's sensitive data and the credibility of the third-party recommendation service when the collaborative filtering algorithm calculates the similarity, S. Badsha et al. propose a privacy protection protocol for user-oriented web service recommendations (Badsha et al., 2018). This protocol enables the untrusted third-party recommendation system to provide the recommendation service normally without disclosing the personal privacy information. And the Quality of Service precision loss can be neglected. However, the efficiency of finding similar user collections needs to be further improved. In order to solve identity theft and relationship privacy leakage in traditional recommendation system, S. W. Zhang et al. propose K-degree anonymous friend recommendation model (Zhang et al., 2018), which abstracts social networks into hypergraphs and designs an edge segmentation algorithm to hide user's identity privacy and social relationship privacy so as to realize privacy protection recommended by friends in social networks (Chen et al., 2018a; Guo et al., 2014; Zhang et al., 2018). However, the extra edge calculation overhead of the hypergraph is too large. The overall computing performance of the system needs to be improved.

Table 7
Performance comparison table between proposed scheme and benchmark model (Among the methods: Content-based, Collaborative filtering and Attribute-aware are benchmark model; Knowledge graph-based method is our solution.)

Method	Model	RMSE
Content-based	UFSM	2.2653
Collaborative filtering	SVD	1.7998
Attribute-aware	NCPD	1.5623
Knowledge graph-based	**KG + MKR**	**0.3020**

Although the above privacy protection strategy has a certain deterrent effect on the disclosure of personal information in the recommendation system in different fields, it is not desirable to replace the privacy protection function at the cost of the overall performance of the system. In addition, with the rapid spread of smart terminals and the advent of the 5G era, data privacy protection for smart terminals as the main front of various APP applications for social, gaming and shopping is becoming more and more severe. Considering the bottleneck of computing performance caused by the limitation of hardware resources of intelligent terminals and the decrease of recommendation accuracy caused by the protection of user sensitive data, this is also an urgent problem to design a lightweight protocol (Becchetti et al., 2014) which can simultaneously satisfy data privacy protection and high performance recommendation results.

It should be noted that the high-efficiency of the privacy protection of the recommended system is a prerequisite for the implementation of lightweight protocols. This is because only when the local computational cost of the user is greater than the sum of the computational cost of the recommendation model training and the prediction of the recommendation result, the user with limited storage and computing resources has the possibility to outsource the recommendation task to a third-party recommendation server with huge hardware and software resources to complete the recommendation. To further reduce the computational and communication overhead of using the fully homomorphic encryption technology to achieve the privacy protection of the recommendation system, scholars are devoted to researching efficient privacy protection outsourcing computing strategies based on fully homomorphic encryption and have produced a series of research results (Cao et al., 2016; Liu et al., 2018; Canetti et al., 2017). In addition, in the actual application process, an improved efficient homomorphic encryption scheme can also be used to reduce the space–time complexity of the encryption algorithm. For example, the fast homomorphic linear transformation software library HElib built by scholar Halevi et al. (Halevi and Shoup, 2018), which uses ciphertext compression technology to optimize the traditional homomorphic encryption algorithm, compared with the traditional homomorphic encryption algorithm, its computing performance has been improved by 30 to 75 times, and the space complexity used by it has also been reduced by 33–50%. However, although the computing performance of the homomorphic encryption algorithm has been greatly improved, its computational complexity is still too high for resource-constrained mobile users (Zhou et al., 2017), as for the privacy protection of the recommendation system based on public key homomorphic encryption, it is still difficult to meet the actual needs of mobile users with limited local storage and computing resources. Therefore, the realization of lightweight algorithms still needs further exploration.

6.3. Universal recommendation system research problem

In the era of data explosion, the traditional information filtering algorithm can only present the sorting result of the same item or user to the user, and cannot provide biased service for different user preferences. In order to solve the information overload and bring people a crisis of choice, the recommendation system comes into being, and the recommendation systems for different application topics emerges one after another (Batmaz et al., 2019; He and Chu, 2010; Ramaswamy et al., 2009; Zhang et al., 2017b), which alleviates the troubles caused by information overload. However, the performance of recommendation system mainly depends on the characteristics of the data set that is faced. The recommendation systems built on different types of data sets cannot be mutually common resulting in poor compatibility of the recommendation system and cannot effectively solve the integration problem of the data source (Chen et al., 2018a; Dara et al., 2019; Desrosiers and Karypis, 2011; Dessì et al., 2019; Karimi et al., 2018; Vinh et al., 2014; Szczerbicki, 2010; Tzamousis and Papadopouli, 2019). In order to improve the versatility of the recommendation system (namely, enhancing the universal of recommender system, such as multi-function algorithm or multi-function model that can satisfy different processing requirements for different data sets), the concept of "configuration software" can be adopted (Mauro et al., 2018; Mohammed et al., 2018; Vlaeminck et al., 2009). The recommended system of different technical implementation methods is used as a component to construct a recommendation system function building pool. Then, the knowledge graph is used to perform unified semantic representation of data sources of various structures to form a consistent data format. In this way, when the recommendation system needs to be built, the appropriate functional components can be selected according to the business requirements, the recommendation system is constructed in the form of configuration, and finally the general hybrid recommendation system of "knowledge graph + configuration software" is realized.

In addition, as a representation of global information, knowledge graph itself contains rich semantic information. Knowledge graph can not only improve the accuracy of recommendation and the diversity of recommendation results, but also increase the interpretability of recommendation results. The knowledge graph recommendation system is mainly composed of three parts: user knowledge graph, project knowledge graph and recommendation method (can be divided into three types: sequential training method, such as Deep Knowledge-aware Network, DKN; joint training method, such as Ripple Network; alternating training method, such as Multi-Task Learning for KG enhanced Recommendation, MKR). On this basis, we constructed the logical framework of the knowledge graph recommendation system as shown in Fig. 9.

In the framework, the user knowledge graph is first constructed according to the user information source and the project knowledge graph is constructed according to the project data source. Then, the relevant features are extracted from the user knowledge graph and the project knowledge graph as input of the recommendation method, and the recommendation result is generated and pushed to the target user. Finally, the recommendation results are evaluated in conjunction with user feedback, and the recommended items are further optimized to meet user preferences.

In addition, the knowledge graph recommendation system feature extraction method has three forms: one is the feature-based recommendation method (mainly extracting some user and item attributes from the knowledge graph as features, put it into the traditional model); the second is path-based Recommended method (this method treats the knowledge graph as a heterogeneous information network and then constructs *meta*-path or *meta*-graph based features between items. Simply put, *meta*-path is a specific path connecting two entities. For example, the "student->tutor->student" *meta*-path can connect two students, so it can be seen as a way to explore potential relationships between students. The advantages of this method are fully and intuitively utilized. The network structure of knowledge graph has the disadvantage of requiring manual design of *meta*-path or *meta*-graph. The third is knowledge graph feature learning (this method obtains a low-dimensional vector for each entity and relationship learning in the knowledge graph, while maintaining the original structural or semantic information. There are two types: distance-based translation models and semantic-based matching models.).

6.4. Recommended system recommendation accuracy problem

Deep learning (Deng and Yu, 2013) has been widely favored in various fields of computer science (such as natural language processing, image and video processing, data mining, etc.). As a subarea of data mining applications, the recommendation system is no exception. According to different needs, deep learning technology can be applied to different recommendation systems. Its main purpose is to reduce the dimensions of large-scale data sets, effectively extract the hidden features of data sets (Sedhain et al., 2015), and achieve high-precision recommendations. In content-based filtering, deep learning techniques are used to extract features from a multi-source heterogeneous data set to generate a representation of a content-based user (item). In the collaborative filtering recommendation system, deep learning technology is used as a model method to extract potential factors in the user-item matrix (Dai et al., 2016; Deng et al., 2017; Devooght and Bersini, 2017). In the hybrid recommendation system, deep learning techniques are used to extract features from additional information and integrate them into the recommendation process (Yin et al., 2019).

However, there are still some shortcomings in the recommendation system based on deep learning, such as:1) In the product recommendation system, the recommendation system based on deep learning technology can obtain satisfactory high-precision recommendation on the public data set, but in the application oriented to the private data set, the system's recommendation accuracy and data privacy level conflict. The higher the privacy level is, the lower the recommendation accuracy is. 2) In terms of feature extraction, deep learning techniques have been very successful. However, in the memory-based collaborative filtering algorithm, the deep learning technology cannot effectively identify the nearest neighbor of the active user. And the recommendation accuracy cannot be further improved. In order to make up for the problem of low recommendation accuracy caused by deep learning technology, we can combine deep learning technology with reinforcement learning technology (Muresan et al., 2019), synthesize the advantages of two machine learning technologies, and use deep reinforcement learning technology (Li et al., 2018; Xiong et al., 2017) to further improve the accuracy of recommendation system.

It is worth noting that deep reinforcement learning can more effectively mine the future information implied by user interaction in specific scenarios, and apply it to the recommendation algo-

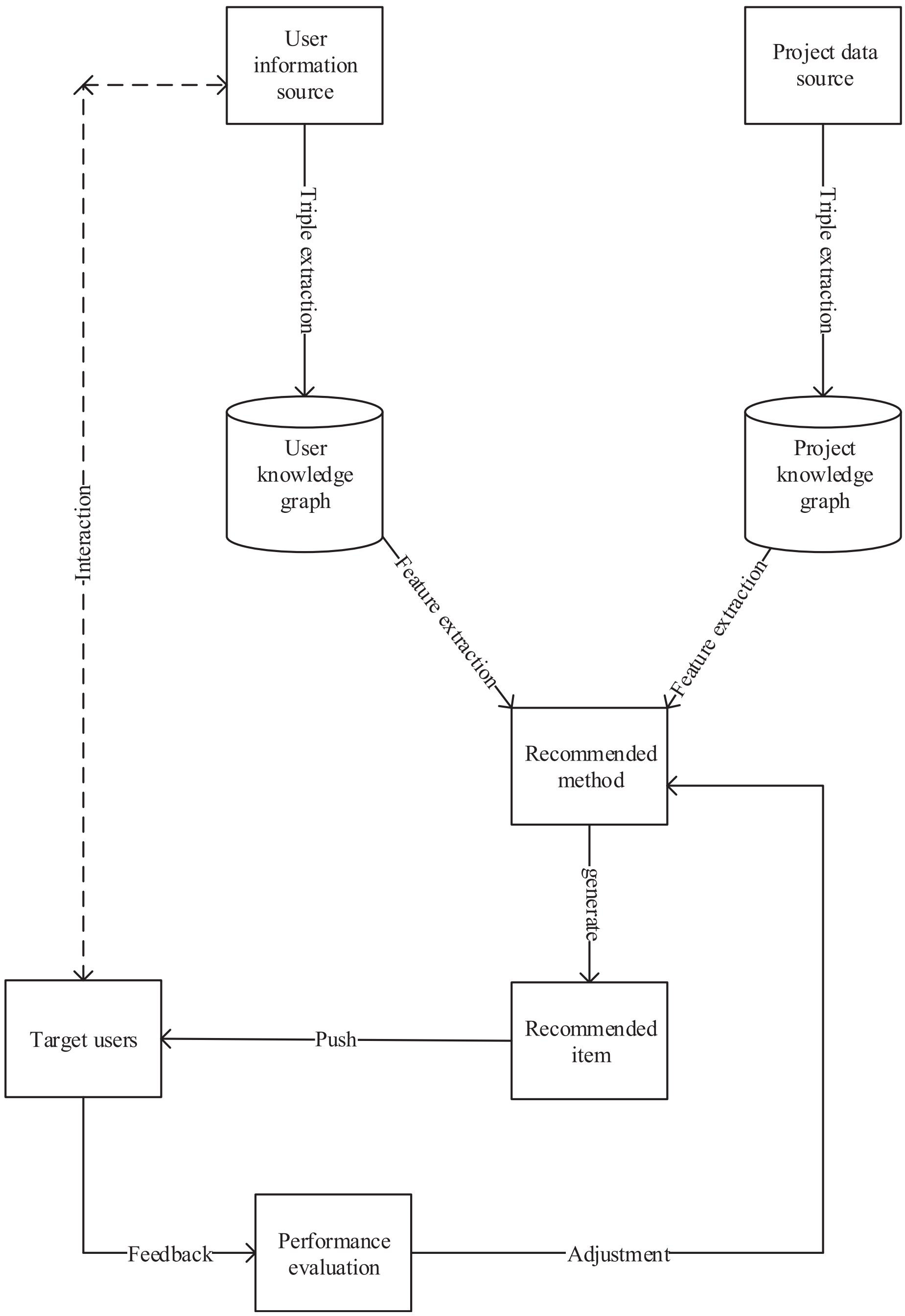

Fig. 9. Knowledge map recommendation system logic framework diagram.

rithm of the recommendation system as an auxiliary feature of user dynamic interaction. To a certain extent, it can effectively alleviate the problem of low recommendation accuracy caused by insufficient user behavior information. For example, scholar Zheng et al. proposed a deep reinforcement recommendation framework for the challenging recommendation problem of news recommendation scenarios, and effectively proved that deep reinforcement learning technology can use the obtained future information contained in user interactions to improve the accuracy of the recommendation system (Zheng et al., 2018). This is because the dynamics of the news itself and the dynamic changes of user preferences in online news recommendation scenarios are not easy to capture, while the deep reinforcement learning recommendation framework using the Deep Q-Network (DQN) algorithm (Mnih et al., 2015) can explicitly capture the future rewards received by users, and use the acquired future information generated by the interaction between the user and the system as an auxiliary feature of user feedback to improve the accuracy of recommendations. At the same time, the effective self-exploration strategy provided by the framework itself is also conducive to improving the matching rate of user interest. Experiments show that, compared with the benchmark reference method, this method can significantly improve the system's recommendation accuracy and the diversity of results (Zheng et al., 2018). However, there are still some technical difficulties in the experimental design of deep reinforcement learning that need researchers to solve urgently. For example, how to design a more effective reward function to avoid the agent obtaining local optimization results and more effectively predict the future knowledge in the process of human–computer interaction, which still needs further research.

6.5. Recommended system interpretability problem

The recommendation system has become an indispensable information filtering tool to people's daily study, work and life. Such as reading news with news recommendation system, watching movies with movie recommendation system, listening music with music recommendation system, and shopping with an item recommendation system provided by the e-commerce platform, these different kinds of recommendation systems save users time costs while facilitating user choice. However, the user can only passively accept the recommendation results of the system, and is not clear about the cause of the result and the reason for accepting the result. Studying the interpretability of the recommendation system (Zhang et al., 2015, 2014) is precisely to make up for the shortcomings of the traditional recommendation system. In the formation of the recommendation results not only the biased results, but also the reasons for the recommendations are given. In this way, it will not only enhance the persuasion of the recommendation results, but also enhance the satisfaction of users.

At present, scholars have proposed a large number of interpretable recommendation methods (Chen et al., 2018b, 2018c; Zhang and Chen, 2020), especially the model's interpretable recommendation algorithm (Zheng et al., 2017; Pei et al., 2017), and have applied it to the real recommendation system. For example, C. Xu et al. propose an interpretable framework LRPPM (Learn to Rank user Preferences based on Phrase-level sentiment analysis across Multiple categories)-CF that combines LRPPM technology with CF method to improve the recommended performance. The model introduces the tensor matrix decomposition algorithm into the LRPPM technology, and combines it with the CF method to rank the user preferences by analyzing the multi-domain emotional phrases to improve the accuracy of the recommendation. Experiments show that the LRPPM-CF interpretable model improves the recommendation accuracy of the system to some extent. However, the framework contains a single algorithm that does not meet the application needs of more scenarios (Xu et al., 2018). H. Park et al. propose an interpretable and accurate recommendation system based on social networks and rating data, UniWalk, which combines two kinds of data into a unified graph to learn the potential characteristics of users and items, and then learn from them. The feature recommends the appropriate item to the user and gives a reason for the recommendation. A large number of experiments have shown that UniWalk gives the best interpretation and precision. However, the rating data generated by the rating data and the social network is too large and the computing resources are too large and the method does not support the distributed system (Park et al., 2017). P. Kouki et al. propose a probability-based programmable hybrid recommendation system, HyPER, which uses a mixed statistical model to analyze user preferences and gives a reasonable recommendation. However, the system does not support personalized recommendations and reflect user-specific preferences (Kouki et al., 2017). In order to avoid the problem of insufficient persuasiveness of single interpretation method and difficulty for users to trust recommendation results to the maximum extent, we can combine the advantages of recommendation model and interpretability of recommendation results, and use knowledge graph (Wang et al., 2017) as the feature extraction technology of multi-source heterogeneous data sets (Milosevic et al., 2019; Wang et al., 2018) so as to form a hybrid interpretable recommendation system based on knowledge mapping, which enables users to understand the value of recommendation from two perspectives, such as recommendation mechanism and recommendation results, and then enhances user satisfaction and maximizes the value of recommendation system.

In short, in order to improve the accuracy of recommendation, mitigate cold start, enhance privacy protection, enhance system universality and interpretability, it is necessary to use privacy protection as a premise, and try to use multi-source heterogeneous data and hybrid algorithms in the process of system design. Consider performance indicators such as recommended accuracy, universality, and cold start to achieve an interpretable recommendation system.

7. Conclusions

This paper has sorted out the literature on the theme "recommender systems" in the Web of Science core collection database in the past ten years, and has obtained 5,391 valid articles in total literature.

Firstly, for the valid data, the relationship between the Quantity of articles and Time and the Proportion of articles and Time are analyzed. It is found that the development of recommendation system in recent ten years can be divided into four stages: the stable period (2009–2012), the rapid growth period (2013–2015), the outbreak period (2016–2017) and the fallback period (2018). Moreover, the development of recommendation system application is closely related to the development trend of artificial intelligence technology.

Secondly, using the knowledge map visualization software VOSviewer to analyze the effective data from the five perspectives of time distribution, literature source distribution, research power comparison, author distribution and citation analysis, the results show that: the articles related to the recommendation system topic have higher publications in the three journals such as expert systems with applications, information sciences and knowledge-based systems, and their influence is strong in the field of recommendation system application research; from the perspective of research power, whether it is the number of articles issued or the importance attached by academic institutions, China's research investment in this field has been at the forefront of the world; from the perspective of the distribution of authors, China's high-yield authors have a greater influence in this field, especially the "lu, jie" team, which not only has a large domestic influence, but also has a high degree of international cooperation; from the analysis of citation analysis, it is found that the high-cited literature in the field of recommendation system mainly focuses on the research applications such as recommendation system application, collaborative filtering algorithm improvement and application, recommendation system performance evaluation, and recommendation model design.

Thirdly, combined with keyword co-occurrence frequency statistics and keyword co-occurrence coupling network, the keyword clustering rules are explored. The research finds: it has formed five research hotspots: Recommendation technology and Recommendation system, Collaborative filtering and Matrix decomposition, Information technology and Recommendation system, Personalized recommendation model and Framework, Recommendation algorithm and Performance evaluation; five potential research directions, such as user feature representation technology, cold start and data sparsity, personalized recommendation, privacy protection, and user modeling, are formed.

Finally, combined with research hotspots and potential research directions, the five key issues of cold start, privacy protection, universality, recommendation accuracy and interpretability of the recommendation system are analyzed, and corresponding solutions are proposed.

Compared with other research reviews on recommendation systems, this paper introduces document quantitative analysis and cluster visualization analysis into the literature research in the field of recommendation systems for the first time, and explores the hidden knowledge contained in the relevant literature data of the recommendation system, such as the distribution characteristics of journal sources and analysis of national research strength; Next, using the visualization method provided by VOSviewer tool to analyze the clustering map of high-frequency keywords, more objectively explore the research hotspots and frontier trends in the field of recommendation systems. Finally, the five major open problems in the field of recommendation systems are analyzed, and potential feasibility schemes are proposed. The feasibility of some schemes is verified through experiments.

Future research will focus on model validation, algorithm implementation and performance evaluation of solutions proposed in "Section 6 Existing problems and countermeasures analysis". Thereby, it provides new ideas and new methods for solving the open problems involved in the recommendation system to improve the recommendation quality of the recommendation system. At the same time, in order to maximize the overall performance of the recommendation system, we will also explore new research directions of the recommendation system, such as: (1) Introducing the psychological personality evaluation system into the recommendation system, so as to describe the user preference from the perspective of personality traits; (2) Introducing research methods in the field of complex networks into the recommendation system, enhance the ability to integrate heterogeneous data based on knowledge graphs; (3) Considering the fusion technology of heterogeneous networks and graph neural algorithms, explore the use of subgraphs to depict projects Features and mine new similarity assessment methods.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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