
AI translation · View original & related papers at
chinaxiv.org/items/chinaxiv-201711.01969

Expert Retrieval and Expert Ranking Research Review Postprint

Authors: Ye Guanghui, Xia Lixin

Date: 2017-11-08T00:00:00+00:00

Abstract

[Purpose] To review existing expert retrieval and expert ranking methods, providing a theoretical foundation for subsequent research. [Literature Scope] Relevant literature was collected from databases such as Web of Science (WOS) and CNKI using search terms including “Expert Retrieval,” “Expert Ranking,” and “Ranking Fusion,” yielding 65 papers. [Method] Addressing the two-fold issue of insufficient coverage in expert retrieval and high computational complexity of expert features, this study systematically reviews and evaluates existing research progress from the perspectives of expert retrieval evaluation and ranking fusion. [Results] Integrating relational attributes represents the mainstream approach in current expert retrieval methods; research on retrieval result credibility primarily relies on user satisfaction and document credibility. Expert ranking employs friend recommendation models, PageRank, D-S theory, social network and complex network analysis to achieve ranking and ranking fusion, with fused results generally outperforming baseline rankings. [Limitations] There is limited comparative research among different ranking fusion methods. [Conclusion] Related research can provide references for constructing an expert consultation platform from an information fusion perspective, specifically in the aspects of expert information organization, expert selection, and expert opinion fusion.

Full Text

Preamble

ChinaXiv Collaborative Journal, Issue 2, 2017. A Review of Expert Retrieval and Expert Ranking Research. Ye Guanghui, Xia Lixin (School of Information Management, Central China Normal University, Wuhan 430079)

Abstract

[Objective] This paper reviews existing expert retrieval and expert ranking methods to provide a theoretical foundation for future research. **[Coverage]** Sixty-five relevant papers were collected from Web of Science (WOS), CNKI, and other databases using search terms including “Expert Retrieval,” “Expert Ranking,” and “Ranking Fusion.” **[Methods]** Addressing the dual challenges of insufficient expert coverage and high computational costs for expert feature extraction, we systematically review and evaluate current research progress from two perspectives: expert retrieval evaluation and ranking fusion. **[Results]** Fusion of relationship attributes has become the mainstream approach in expert retrieval methods, while research on retrieval result credibility primarily relies on user satisfaction and document credibility. Expert ranking and fusion are implemented through friend recommendation models, PageRank, D-S theory, social network analysis, and complex network analysis, with fusion results generally outperforming baseline rankings. **[Limitations]** Comparative studies across different ranking fusion methods remain scarce. **[Conclusions]** Related research can inform the construction of expert consultation platforms from an information fusion perspective, specifically in the areas of expert information organization, expert selection, and expert opinion fusion.

Keywords: Expert Retrieval, Ranking Fusion, Social Network, Relationship Attribute, Effect Evaluation

Classification Number: G350

Expert retrieval is the process of matching user knowledge needs with potential expert characteristics. Common stages include user knowledge need expression, expert feature identification, similarity computation between knowledge needs and expert features, and candidate expert result output. However, considering the time-sensitive nature of user knowledge needs (especially for emergency knowledge) and the high demands placed on retrieval results, this process currently fails to meet user requirements for speed and efficiency. The primary causes of this mismatch are insufficient coverage of expert types in retrieval systems and the substantial computational workload required for expert feature identification—problems that have become particularly pronounced in the social media era.

Insufficient expert type coverage manifests primarily in the emergence of “niche experts” as a new expert category in social network environments. These individuals may exhibit stark contrasts between their real-world and virtual identities, yet they directly participate in the emergence, evolution, and decline of online public events, wielding considerable influence over public opinion guidance and control. Traditional public affairs consultation has not recognized them as valuable supplements to conventional institutional and academic experts, resulting in incomplete expert type coverage. Therefore, the expert information organization phase must consider “niche experts” as integral components of the expert database to ensure comprehensive coverage of the retrieval expert set.

The heavy computational workload for expert feature identification can be effectively addressed by conducting expert ranking prior to feature identification, thereby enabling pre-selection of candidates—feature identification is performed only on top-ranked experts. Since the metrics used for expert facet ranking are primarily explicit statistical indicators, this approach significantly reduces the computational burden compared to direct expert feature identification.

To illustrate, we previously provided the following example: Assuming the expert retrieval process obtains an expert set of capacity n , where the amount of type x resources associated with a particular expert e_i is q_i , the number of feature vectors that need to be extracted for expert organization is $\sum q_i$. After obtaining these feature vectors, at least $(2x-1)$ fusion operations are required to derive the expert's comprehensive feature vector. In contrast, ranking before feature fusion requires only selecting a subset of top-ranked experts (greater than or equal to r , where $r \leq n$) based on decision-maker requirements, reducing the number of feature vectors to be extracted to only r/n of the original amount.

Based on this two-pronged problem analysis, we surveyed literature from WOS, CNKI, and other databases using “expert retrieval,” “expert ranking,” and “ranking fusion” as search terms. We examined existing research methods, schemes, and tools from the perspectives of expert retrieval methods and credibility evaluation, as well as expert ranking fusion, providing targeted and timely critiques to offer comprehensive foundational references for future solution development.

2. Expert Retrieval and Expert Ranking Research Framework

Expert retrieval and expert ranking can be understood through two modes: ranking-first-then-retrieval and retrieval-first-then-ranking, as shown in Figure 1 [Figure 1: see original paper].

The difference between Figures 1(a) and 1(b) lies in whether expert ranking fusion is placed in the information organization phase or the information retrieval phase, which determines the ultimate objective. Figure 1(a) targets a single expert retrieval system, aiming to fuse expert ranking values across multiple facets during the organization phase to improve retrieval result accuracy and reduce information noise. Figure 1(b) addresses multiple expert retrieval or discovery systems, proposing methods to resolve conflicts and obtain comprehensive rankings given the inconsistencies across different systems. Regardless of the mode, the associated research themes remain consistent: expert retrieval credibility evaluation and expert ranking fusion. Subsequent content will evaluate existing research findings purely from a thematic perspective without service purpose delineation.

3. Expert Retrieval Methods and Credibility Evaluation

To better utilize expert resources, numerous researchers have actively constructed science and technology consulting systems, expert retrieval systems, ontology-based expert locator systems, the FacFinder expert search engine, and the SmallBlue expert search software. Retrieval systems have become crucial channels for locating and leveraging expert resources. Currently, China's three major academic databases (CNKI, Wanfang, and VIP) all provide scholar or expert retrieval portals, though their data volumes remain limited. As of September 1, 2016, Wanfang had collected only 12,120 experts, with expert information organization emphasizing external features while revealing limited content characteristics.

3.1 Expert Retrieval Methods

Existing expert retrieval research often integrates with general retrieval models, adapting and innovating according to user needs. In previous work, we identified that expert feature information comprises two components: expert attribute information and expert relationship information. Attribute information reveals intrinsic expert characteristics, while relationship information derives from expert annotations of audio, video, text, web pages, and other resources on public platforms such as social networks. Relationship information includes relationship type, tags, and relationship strength. Based on whether retrieval algorithms consider expert relationship attributes, existing expert retrieval methods can be categorized into relationship-attribute-fused methods and non-fused methods.

(1) Relationship-Attribute-Fused Expert Retrieval Methods

Since the Text Retrieval Conference (TREC) introduced the expert search task in 2005, researchers have conducted extensive explorations around the experimental datasets, producing influential results. Notable contributions include: Fang et al. recognized that discriminative models outperform the more widely used generative models in information retrieval and machine learning, designing a discriminative model-based expert retrieval method that fuses document credibility and document-expert relationship strength, demonstrating its effectiveness and robustness through TREC datasets. MacDonald et al. developed a document credibility-based expert search method where, given a query, the system first assesses document-query relevance, evaluates credibility across different documents for the same expert, and obtains final expert rankings supported by query expansion, proving superior performance using TREC 2005 and 2006 datasets. Zhai et al. from UIUC designed a language model-based expert finding method for TREC, while Zhu et al. proposed a novel language model integrating multiple document features, arguing that existing language models inadequately captured these features, and demonstrated improved Mean Average Precision (MAP) on W3C and CSIRO (TREC) datasets.

Beyond TREC, other researchers have made significant contributions: Uddin et al. designed an expert search method combining ontology construction with

scientific community network approaches, using ontologies to describe node attributes and relationships in research community networks and ranking experts based on their contributions and impact scores. Zhou et al. identified that link analysis methods in research Q&A communities often overlook expert interests and reputation, proposing a topic probability model-based expert finding method and demonstrating its effectiveness through an extended PageRank algorithm. Wang et al. recognized problems in current expert organization and retrieval, proposing a novel expert retrieval technical scheme that integrates various expert features with social networks. Farhadi et al. observed that users sometimes require not a single expert but an expert team, designing the TeamFinder framework based on co-occurrence and clustering for social network expert discovery, and demonstrating its utility using DBLP author co-occurrence data. Sun et al. noted that graph-based retrieval models inadequately consider important contextual information, proposing a novel research community expert discovery method fusing expert quality and inter-expert relationships, with experiments confirming superior recommendation performance. Zhao et al. addressed natural language processing issues such as polysemy, synonymy, and proper nouns in expert identification, constructing an expert expertise vocabulary to improve retrieval accuracy and developing the WHU-ES prototype system for Wu University faculty.

(2) Non-Relationship-Attribute-Fused Expert Retrieval Methods

Compared to the diversity of relationship-attribute-fused methods, non-fused methods are fewer: Van Gysel et al. introduced an unsupervised discriminative model-based expert retrieval method using only expert text information, demonstrating superior ranking performance compared to vector space and probabilistic generative models. Yang et al., based on the consensus that experts' tacit knowledge is difficult to systematize, adopted an improved Fuzzy Abstraction Hierarchy framework for intelligent expert search, developing a prototype system. Stankovic et al., noting that linked data enables traceable user social behavior while existing expert retrieval uses single corpora, proposed using linked data metric analysis to select appropriate tracking types and expertise hypotheses for high-precision, high-recall expert identification. Fang and Wu et al. reviewed expert retrieval research objectives, content, and methods, focusing on expert description, query-expert relationship modeling, link analysis, query expansion, and expert evidence identification, forecasting future applications in research team discovery and enterprise knowledge management. Chen et al. recognized that existing expert finding methods each have advantages and disadvantages, proposing a fusion framework that effectively combines multiple models and demonstrating improved accuracy and robustness.

In summary, current expert retrieval research favors relationship-attribute-fused methods, driven by the rapid development of social network media and increasingly multi-sourced expert-related resources. While integrating expert features from comprehensive multi-channel information resources achieves information completeness, it also introduces significant information noise and

conflicts. Therefore, expert retrieval must strengthen expert information organization methods at the source and design credibility evaluation mechanisms for expert-related resources. Additionally, although multiple ExpertRank algorithms exist, they treat retrieval users merely as passive recipients of results without incorporating user participation variables, resulting in weak user autonomous retrieval functionality and no personalized expert retrieval. Consequently, expert retrieval research should not focus exclusively on improving general retrieval models; as user experience gains increasing attention, expert retrieval output should incorporate user ratings and associated resource credibility.

3.2 Expert Retrieval Credibility Evaluation

The credibility of retrieval results obtained from existing expert retrieval systems serves as a standard for relevance judgment and provides references for users to accept or reject information. Effective early-stage expert information organization ensures scientific and efficient later-stage expert selection. If expert organization guarantees the credibility of the information source (i.e., selected experts), then methods, models, algorithms, and systems applied to expert opinions or viewpoints in activities such as expert ranking, group decision-making, and peer review constitute credibility evaluation of the information source content. Current credibility evaluation research primarily targets information resources, particularly web-based resources, due to the proliferation of redundant, false, and ambiguous information online. As an important component of information resources, expert resources are evaluated through two main approaches: user satisfaction-based and document-based credibility assessment.

(1) User Satisfaction-Based Credibility Evaluation

User satisfaction-based credibility evaluation assesses expert retrieval effectiveness from the user perspective, either through external evaluation (e.g., experiments, questionnaires, interviews) to obtain users' subjective impressions of expert retrieval systems, or internal evaluation where users autonomously set parameters in retrieval algorithms to alter retrieval processes and results. Li et al. distinguished between back-end credibility evaluation (user-driven changes to internal information organization) and front-end credibility evaluation (changes to information retrieval), with back-end evaluation reducing retrieval noise through optimal expert feature vector length determination and front-end evaluation using user relevance feedback as a necessary reference for retrieval path selection. Kim et al. analyzed online health information search behaviors among college students and experts, demonstrating that good website design and navigation enhance retrieval experience. Wu et al. introduced an intermediary "mediated enterprise search" component using domain expert knowledge to analyze search result credibility before delivery, proving improved long-term ROI and accuracy for service developers. Liebrechts et al. built a university-wide expert search system and confirmed its efficiency and user satisfaction through query-based evaluation. Jefferson et al. proposed a method using information

retrieval techniques and domain expert knowledge to improve user satisfaction, demonstrating superior efficiency compared to traditional catalog systems.

(2) Document-Based Credibility Evaluation

Document-based credibility evaluation offers greater objectivity than user satisfaction-based approaches. Key research includes: MacDonald et al. demonstrated strong relationships between document ranking and expert ranking as critical factors for improving retrieval efficiency, analyzing failed experiments to illustrate document credibility's impact. Kim et al. noted that most automatic ranking systems use citation relationships to describe web document importance but fail to reflect user comment content, designing an expert team generation method based on specific web collections that calculates expert influence weights from user comment credibility and associated web sets. Noll et al. identified two factors for expert discovery in collaborative tagging systems: users posting high-quality relevant resources (dependent on tagging behavior) and users leading others in identifying relevant resources, designing the SPEAR (Spamming-Resistant Expertise Analysis and Ranking) graph model algorithm and demonstrating its effectiveness on Delicious data.

In summary, corresponding to the classification in Section 3.1, expert retrieval credibility evaluation comprises two categories: user satisfaction-based and document-based assessment. The former shifts focus from general retrieval model improvement to incorporating user ratings and enabling user participation in algorithm execution, enhancing autonomous retrieval functionality. The latter strengthens expert information organization methods and designs credibility evaluation mechanisms for expert-related resources at the source.

4. Expert Ranking Fusion

Expert ranking quantifies comprehensive expert influence, yet rankings obtained from different resources (e.g., academic networks, web resources, social networks) may be inconsistent or even conflicting. Therefore, fusing facet rankings based on different statistical indicators is necessary to obtain comprehensive rankings. Additionally, using simple statistical indicators to pre-rank topic-related experts enables pre-selection, significantly reducing expert feature fusion workload. Ranking metrics can derive from personal information (e.g., publication count, first publication date) or citation information (e.g., H-index, citation frequency), all requiring standardization for fusion. Most expert retrieval systems embed ranking within retrieval algorithms. Current research primarily focuses on expert ranking methods and ranking fusion techniques.

4.1 Expert Ranking Methods

Key research on expert ranking methods includes: Wu et al. described a geometric framework for data fusion representing retrieval results from different systems as points in multidimensional space, using Euclidean distance to measure similarity and demonstrating superior accuracy and efficiency. Uddin et

al. noted that while expert discovery is important in social network research, few studies address it from a semantic perspective, proposing an ontology-based method that calculates expert scores through contributions to topic-relevant documents and inter-expert relationships. Wang et al. emphasized the importance of enterprise microblogging management, designing an enterprise expert ranking method combining PageRank with expert-assigned tags. Jin et al. argued that finding experts may be easier than searching for direct answers in social networks, obtaining rankings by aggregating user centrality and question-user relevance. Moreira et al. noted the lack of effective algorithms fusing multiple explicit features in academic digital libraries, constructing a normalized expert fusion and ranking method from contextual resources, personal information, and graph structures formed by citation relationships, demonstrating its performance in computer science. Wu et al. proposed a flexible, topic-associated co-PageRank algorithm addressing the limited applicability of existing methods, using citation and social networks to calculate expert-topic preference degrees for ranking. Zhan argued that traditional expert search ignores expert-user relationships, proposing a socialized search approach incorporating user social networks that calculates rankings through user-topic relevance and network influence, demonstrating effectiveness in Friend Recommendation Models. Zhang considered both microblog content and user topology, extending PageRank with topic models to calculate users' social influence across topics, combining topical influence with content relevance for accurate expert positioning, and validating the method using Sina Weibo API data.

4.2 Ranking Fusion Methods

Beyond resource diversity enabling ranking fusion research, single-indicator rankings suffer from weak credibility, inconsistency, and conflicts. To address these issues, library and information science has developed internal methodologies. Some studies reduce data sparsity by extracting high-frequency authors to construct relationship matrices, using either subjective threshold-based methods (e.g., setting minimum frequency cutoffs) or objective methods based on data distribution patterns (e.g., Price's formula for power law distributions). However, both approaches remain imperfect: threshold setting lacks training data support and cannot resolve end-data consistency issues, while objective extraction imposes strict distribution requirements.

Consequently, expert ranking fusion research actively adapts methods from other disciplines (e.g., remote sensing, face recognition, expert systems). Santos et al. surveyed expert search modules in web search engines, arguing that documents used for expert retrieval should be assigned credibility, fusing existing expert ranking indicators and generating seven different expert rankings from TREC data to demonstrate improved enterprise intranet retrieval performance. MacDonald et al. interpreted expert ranking through voting models, using 11 data fusion techniques and TREC enterprise datasets to prove stable retrieval performance and improved candidate expert ranking. Mourão et

al. addressed challenges from multi-source heterogeneous medical information, proposing a medical information retrieval system supporting multidimensional data fusion and vocabulary recommendation, with experiments showing superior performance compared to systems like ImageCLEFMedical 2013. Yang et al. noted that increasing elements in belief functions theory frameworks escalates computational costs in evidence combination, proposing methods to reduce costs from both element count and mass value assignment perspectives, validating performance through experiments. Nuray et al. proposed a novel ranking method merging relevant documents from different retrieval systems through multi-source data fusion algorithms, selecting Top-N documents as pseudo-relevant feedback to evaluate and rank retrieval systems, with TREC dataset analysis showing high consistency with manual assessments. Franceschini et al. addressed ordering inconsistencies from different agent preferences in multi-criteria decision-making, proposing the Ordered Paired-Comparisons Algorithm (OPCA) that transforms multi-agent rankings into paired comparisons, fuses them based on priority principles, and generates unified agent importance rankings, validating effectiveness through examples. Zhao et al. proposed GRoMO (Graph-based Ranking of Multi-type Interrelated Objects), a novel ranking framework for personalized tag recommendation in social platforms, analyzing tagging resources and user histories to recommend Top-N tags, with Delicious data confirming superior performance and scalability to resource recommendation.

4.3 Evaluation of Ranking Fusion Research

Expert ranking fusion encompasses both ranking methods and fusion techniques. As Sections 4.1 and 4.2 reveal, current expert ranking methods exhibit four characteristics: (1) Most combine expert attribute and relationship features using multiple indicators; (2) Ranking value calculation methods vary widely, including weighted averaging, friend recommendation models, voting models, PageRank, D-S theory, and social/complex network analysis; (3) Ranking targets include enterprise, academic, and social network experts, with social network experts receiving extensive attention due to ease of constructing social-semantic networks; (4) Fusion-based methods outperform single-indicator approaches in resolving ranking conflicts, though cross-method comparative studies remain underexplored due to dataset variations.

We identified two key issues in expert retrieval: insufficient expert coverage and heavy feature computation workload, systematically reviewing and evaluating research on retrieval methods, credibility evaluation, and ranking fusion. Expert retrieval evaluation focuses on retrieval methods and credibility assessment. Current retrieval methods typically adapt general retrieval models, with relationship-attribute-fused approaches dominating. Correspondingly, credibility evaluation comprises user satisfaction-based and document-based assessments, emphasizing user ratings and resource quality respectively. Expert ranking fusion includes ranking methods and fusion techniques, combining at-

tribute and relationship features through weighted averaging, friend recommendation, voting models, PageRank, D-S theory, and network analysis. Empirical results show fused rankings generally outperform single-indicator baselines, though cross-method comparisons remain limited.

Corresponding solutions can be described as: fusing academic, web, and social network resources for traditional expert feature identification; designing multi-source information fusion methods like weighted averaging to address noise and conflicts; incorporating “niche experts” into expert databases for network public opinion management; combining retrieval methods with ranking fusion algorithms to improve information organization accuracy and completeness while reducing computational workload through effective pre-selection; and implementing personalized evaluation algorithms based on document or user satisfaction for secondary feedback to improve retrieval credibility.

Future Trends

Based on current research and ongoing work, we identify the following trends: As expert-related resources diversify and mobile social Q&A platforms proliferate, the definition of experts will expand further. “Niche experts” will become increasingly active online, with growing intersections between traditional institutional experts, technical experts, and niche experts.

Resource diversity will drive multi-source information fusion, requiring algorithms and models to address two key problems: information noise and information conflict. Improvements and innovations targeting these issues will constitute the main future trend, advancing personalized, semantic, and precise expert retrieval services.

References

- [1] Li G, Ye G H, Zhang Y. Feature Recognition of Niche Expert——Empirical Analysis Based on MetaFilter Dataset[J]. *New Technology of Library and Information Service*, 2015(6): 71-77.
- [2] Ye G H, Li G, Wu C. Research on Construction Mode of Emergency Experts Team for Virtual Reference[J]. *Journal of the China Society for Scientific and Technical Information*, 2015, 34(7): 734-742.
- [3] Wang Y F, Wang X F, Yang X X. Research on Construction Schema and Program Design of Social Network-based Expert Database in Scientific and Technical Consulting[J]. *Journal of the China Society for Scientific and Technical Information*, 2012, 31(2): 116-125.
- [4] Wang Y F, Wang X F, Yan D W. Prototype System Design and Implement of the Database About Science and Technical Consulting Experts Based on Social Network[J]. *Journal of the China Society for Scientific and Technical Information*, 2012, 31(3): 250-258.

- [5] Lu W, Han S G. Design and Implementation of Organization Expert Search System[J]. Journal of the China Society for Scientific and Technical Information, 2008, 27(5): 657-663.
- [6] Liu P, Ye Y. An Ontology-based Experts Locator System within Academia[J]. Journal of the China Society for Scientific and Technical Information, 2010, 29(5): 813-819.
- [7] Fang Y, Si L, Mathur A. FacFinder: Search for Expertise in Academic Institutions[R]. West Lafayette: Purdue University, 2007.
- [8] Ehrlich K, Lin C Y, Griffiths-Fisher V. Searching for Experts in the Enterprise: Combining Text and Social Network Analysis[C]//Proceedings of the 2007 International ACM Conference on Supporting Group Work. New York: ACM, 2007: 117-126.
- [9] Lin C Y, Ehrlich K, Griffiths-Fisher V, et al. SmallBlue: People Mining for Expertise Search[J]. IEEE MultiMedia, 2008, 15(1): 78-84.
- [10] Li G, Ye G H. Research on Information Fusion for Multiple-Sensor Expert Features[J]. New Technology of Library and Information Service, 2014(4): 27-33.
- [11] Peng H B, Wang J. Topology of the Knowledge Communication Network in Virtual Communities Based on CSDN[J]. New Technology of Library and Information Service, 2009(4): 44-49.
- [12] Fang Y, Si L, Mathur A P. Discriminative Probabilistic Models for Expert Search in Heterogeneous Information Sources[J]. Information Retrieval Journal, 2011, 14(2): 138-155.
- [13] Fang Y, Si L, Mathur A P. Discriminative Models of Integrating Document Evidence and Document-Candidate Associations for Expert Search[C]//Proceeding of the 33rd International ACM SIGIR Conference on Research and Development in Information Retrieval. New York: ACM, 2010: 683-690.
- [14] MacDonald C, Ounis I. Using Relevance Feedback in Expert Search[C]//Proceedings of the European Conference on Information Retrieval. Berlin: Springer, 2007: 431-443.
- [15] Fang H, Zhou L, Zhai C X. Language Models for Expert Finding—UIUC TREC 2006 Enterprise Track Experiments[C]//Proceedings of 15th Text Retrieval Conference(TREC 2006), Gaithersburg, Maryland, USA. 2006.
- [16] Zhu J, Huang X, Song D, et al. Integrating Multiple Document Features in Language Models for Expert Finding[J]. Knowledge and Information Systems, 2010, 23(1): 29-54.
- [17] Uddin M N, Duong T H, Oh K, et al. Expert Search and Rank with Social Network: An Ontology-Based Approach[J]. International Journal of Software Engineering and Knowledge Engineering, 2013, 23(1): 31-50.

- [18] Uddin M N, Duong T H, Oh K, et al. An Ontology Based Model for Experts Search and Ranking[A]// Lecture Notes in Computer Science[M]. New York: ACM, 2011, 6592(6): 250-258.
- [19] Zhou G, Zhao J, He T, et al. An Empirical Study of Topic-Sensitive Probabilistic Model for Expert Finding in Question Answer Communities[J]. Knowledge-Based Systems, 2014, 66(9): 136-145.
- [20] Wang X F, Wang Y F. Research on Expert Retrieval Technical in Expert Database[J]. Information Studies: Theory & Application, 2011, 34(2): 96-99.
- [21] Farhadi F, Hoseini E, Hashemi S, et al. TeamFinder: A Co-clustering Based Framework for Finding an Effective Team of Experts in Social Networks[C]. In: Vreeken J, Ling C, Zaki M J, et al. Proceedings of the 2012 IEEE 12th International Conference on Data Mining Workshops. Washington: IEEE Computer Society, 2012: 107-114.
- [22] Guan Z, Miao G, McLoughlin R, et al. Co-Occurrence-Based Diffusion for Expert Search on the Web[J]. IEEE Transactions on Knowledge and Data Engineering, 2013, 25(5): 1001-1014.
- [23] Sun J, Xu W, Ma J, et al. Leverage RAF to find Domain Experts on Research Social Network Services: A Big Data Analytics Methodology with MapReduce Framework[J]. International Journal of Production Economics, 2015, 165: 1-9.
- [24] Zhao H B, Lu W. The Study of Expert Research Field Automatic Recognition[J]. New Technology of Library and Information Service, 2010(2): 63-67.
- [25] Van Gysel C, De Rijke M, Worring M. Unsupervised, Efficient and Semantic Expertise Retrieval[C]//Proceedings of the 25th International Conference on World Wide Web. New York: ACM, 2016: 1069-1079.
- [26] Yang K, Huh S. Intelligent Search for Experts Using Fuzzy Abstraction Hierarchy in Knowledge Management Systems[J]. Journal of Database Management, 2007, 18(3): 47-68.
- [27] Stankovic M, Jovanovic J, Laublet P. Linked Data Metrics for Flexible Expert Search on the Open Web[C]//Proceedings of the Extended Semantic Web Conference. 2011, 6643: 13-27.
- [28] Fang K. A Review on Expert Retrieval[J]. Science & Technology Association Forum, 2013(2): 102-104.
- [29] Wu H, Wang M J, Feng J M, et al. Research Advance of Expert Finding[J]. Application Research of Computers, 2010, 27(10): 3633-3638.
- [30] Chen X D, Ding H. On Fusion Framework for Expert Finding Models[J]. Computer Applications and Software, 2014, 31(12): 74-79.
- [31] Moreira C, Wichert A. Finding Academic Experts on a MultiSensor Approach Using Shannon's Entropy[J]. Expert Systems with Applications, 2013,

40(14): 5740-5754.

[32] Wang Y, Zhang L J, Ning K, et al. Experts Ranking on the Enterprise Microblogging Based on the PageRank Algorithm[C]//Proceedings of the 2012 IEEE Asia-Pacific Services Computing Conference. Washington: IEEE Computer Society, 2012: 345-349.

[33] Jin L, Yoon J Y, Kim Y H, et al. Based on Analyzing Closeness and Authority for Ranking Expert in Social Network[C]//Proceedings of the 7th International Conference on Advanced Intelligent Computing Theories and Applications: with Aspects of Artificial Intelligence. Berlin: Springer, 2011: 277-283.

[34] Moreira C, Calado P, Martins B. Learning to Rank for Expert Search in Digital Libraries of Academic Publications[C]//Proceedings of the Portuguese Conference on Artificial Intelligence. Berlin: Springer, 2011: 431-445.

[35] Wu H, Li H, Zhang X, et al. Topic-Sensitive Link-Ranking Approach for Academic Expert Recruiting[C]//Proceedings of the 2008 International Multi-Symposiums on Computer and Computational Sciences. Washington: IEEE Computer Society, 2008: 150-157.

[36] Zhan Z J. Socialized Expert Finding Based on the Relationship Between Experts and the Users[D]. Shanghai: Shanghai Jiaotong University, 2012.

[37] Zhang B. The Research on Expert Location in Microblogging Based on LDA[D]. Shanghai: East China Normal University, 2013.

[38] Santos R L T, MacDonald C, Ounis I. Mimicking Web Search Engines for Expert Search[J]. Information Processing & Management, 2011, 47(4): 467-481.

[39] MacDonald C, Ounis I. Voting Techniques for Expert Search[J]. Knowledge & Information Systems, 2008, 16(3): 259-280.

[40] Mourão A, Martins F, Magalhães J. Multimodal Medical Information Retrieval with Unsupervised Rank Fusion[J]. Computerized Medical Imaging & Graphics, 2014, 39: 35-45.

[41] Yang Y, Han D, Han C, et al. A Novel Approximation of Basic Probability Assignment Based on Rank-Level Fusion[J]. Chinese Journal of Aeronautics, 2013, 26(4): 993-999.

[42] Nuray R, Can F. Automatic Ranking of Information Retrieval Systems Using Data Fusion[J]. Information Processing & Management, 2006, 42(3): 595-614.

[43] Franceschini F, Maisano D, Mastrogiacomo L. A Paired-Comparison Approach for Fusing Preference Orderings from Rank-Ordered Agents[J]. Information Fusion, 2015, 26: 87-99.

[44] Franceschini F, Maisano D, Mastrogiacomo L. A Novel Algorithm for Fusing Preference Orderings by Rank-ordered Agents[J]. Fuzzy Sets & Systems, 2015, 266: 84-100.

[45] Zhao W, Guan Z, Liu Z. Ranking on Heterogeneous Manifolds for Tag Recommendation in Social Tagging Services[J]. *Neurocomputing*, 2015, 148: 521-534.

Author Contributions: Ye Guanghui: conceptualization, proposition formulation, data collection, manuscript writing, and proofreading; Xia Lixin: final manuscript revision.

Conflict of Interest Statement: All authors declare no conflict of interest.

Received Date: 2016-09-12 **Revised Date:** 2016-12-13

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

Source: ChinaXiv — Machine translation. Verify with original.