Research on Cross-media Science and Technology Information Data Retrieval

Yang Jiang, Zhe Xue*, Ang Li

(School of Computer Science (National Pilot School of Software Engineering), Beijing University of Posts and Telecommunications, Beijing Key Laboratory of Intelligent Telecommunication Software and Multimedia, Beijing, China 100876)

Abstract Since the era of big data, the Internet has been flooded with all kinds of information. Browsing information through the Internet has become an integral part of people's daily life. Unlike the news data and social data in the Internet, the cross-media technology information data has different characteristics. This data has become an important basis for researchers and scholars to track the current hot spots and explore the future direction of technology development. As the volume of science and technology information data becomes richer, the traditional science and technology information retrieval system, which only supports unimodal data retrieval and uses outdated data keyword matching model, can no longer meet the daily retrieval needs of science and technology scholars. Therefore, in view of the above research background, it is of profound practical significance to study the cross-media science and technology information data retrieval system based on deep semantic features, which is in line with the development trend of domestic and international technologies.

Key words technology information, cross media, semantic learning, retrieval and query

1 Introduction

Since the era of big data, more and more rich data has been flooding all aspects of life. The various types of data presented in the Internet can be used to meet the needs of different users, and the Internet has entered people's lives and become an inseparable part of their daily lives. Unlike news and social information on the Internet, cross-media technology information data has a different aspect. Cross-media technology information has a large amount of data, rich data information, according to the real-time information hotspots at the same time, and thus has a lot of similar semantic information and so on. However, due to the characteristics of multi-source and multi-modal information of cross-media technology information data, how to design a unified collection, filtering, storage and processing process for the multi-source cross-media technology information data and form related business applications or products is to meet the current market demand.

As the amount of science and technology information data becomes more and more abundant, the era of informationization is coming. The traditional science and technology information retrieval system for scientific scholars has gradually lagged behind the times because it only supports the data keyword matching model, and has long been unable to meet the daily retrieval needs of scientific scholars. How to allow researchers to retrieve more interesting scientific and technical information retrieval results from the ever-expanding data volume has put forward higher requirements for the retrieval system engine. At the same time, it is clear that the unimodal data retrieval model will gradually be abandoned by the times. Researchers' willingness to search is gradually changing from unimodal data retrieval to inter-modal data retrieval [3]. Therefore, how to deeply integrate machine learning and deep learning algorithms for the characteristics of cross-media science and technology information data, so as to research highly accurate cross-modal semantic learning algorithms and achieve mutual retrieval of cross-modal data based on the algorithm is in line with the domestic and international technology development trend.

2 Acquisition and Feature Extraction Analysis of Cross-media S&T Information Data

Due to the increasing abundance of technology-related data resources, and the limited processing capacity of the stand-alone service system. Distributed cluster technology [4][5] is one of the main implementation methods of current big data technology [6]. Reference [7] proposes a w
ay to analyze industrial data using ETL data processing tools. The main function of ETL is to preprocess the data that needs to be processed, that is, the merging of multi-source data, data analysis and noise reduction, and dimension transformation. To improve the module performance, Hadoop's MapReduce or Spark can be used for parallel processing. References describe how to convert scientific and technological data of different information sources and structures into structured data and store the m in a relational database, and conduct structured sampling of key information on the data system. However, at present, there is no mature crawling system for heterogeneous cross-media scientific and technological information data at home and abroad. How to uniformly collect, store and preprocess the multi-source and heterogeneous cross-media scientific and technological information data is an urgent problem to be solved.

Vectorization is an indispensable component for feature extraction of cross-media technological information data. It is necessary to combine machine learning and deep learning algorithm processing to perform a certain degree of semantic mapping of the semantics in text resources and image resources. With the development of deep learning, the formation of more abstract and higher-level attribute representations slowly replaced traditional machine learning algorithms. Therefore, text feature extraction and image feature extraction based on deep learning have gained more and more attention and development in recent years. Among them, the autoencoder can accurately express data compression based on distributed. Yoon Kim proposed the TextCNN method, which applies convolutional neural networks to text feature extraction, but it does not perform well in text feature extraction with time series. Therefore, the text feature extraction introduces the RNN network which has a good effect in sequence processing, and on this basis, the development direction of the neural network is more in line with people's cognition. The concepts of memory and selective forgetfulness proposed by LSTM and GRU are also greatly improved on the basis of RNN network. The BERT model adopts the Transformer network structure to train the language model. BERT can pass additional output layers without modifying the model for specific tasks, and only fine-tune the pre-trained model to meet various tasks. Long Short-Term Memory (LSTM) handles and predicts important events by introducing a method called LSTM. Bi-directional Long Short-Term Memory (BiLSTM) combines forward and backward LSTMs to build networks. The network structure of ELMo constructed by designing a two-layer bidirectional LSTM. BERT - Flow transforms the anisotropic sentence embedding distribution into a smooth and isotropic Gaussian distribution by improving the BERT model.

On the other hand, for the research on semantic representation of image resources, Simonyan et al. proposed the VGGNet model in 2014. Convolutional neural networks are constructed by stacking, and experiments are used to explore the relationship between the depth of layers of convolutional neural networks and their performance. ZFNet introduces visualization technology capabilities to gain insight into the functions of the intermediate layers. Dhankhar et al. used a combination of ResNet-50 and VGG16 convolutional neural network to recognize facial expressions, and achieved good results in the KD50 dataset. Li Shan and others proposed an optimization method based on dual-angle parallel pruning. By cutting the model, the number of parameters of the VGG-16 neural network is reduced, and the accuracy of feature expression is improved on the basis of maintaining the training time of the original model. Therefore, how to accurately extract image features and text features from scientific and technological information data is also a problem to be studied in this paper.

However, at present, the feature extraction algorithm model for text resources and image resources has many parameters and deep network layers. As a result, more server resources are consumed and the inference time is longer. How to optimize the model structure and apply these algorithms in practical scenarios is a problem that needs to be solved.

3 Deep Semantic Learning of Cross-Media Science and Technology Information

In the research on the semantic representation of cross-media scientific and technological information data objects, for the analysis and mining of semantic features, it is necessary to reasonably integrate traditional machine learning algorithms and deep learning technologies to achieve the effect that the semantics of different modal data can be mapped to each other.
Canonical correlation analysis (CCA) [39] proposes a subspace to maximize pairwise correlations between two sets of heterogeneous data. Joint feature selection and subspace learning (JFSSL) [40] proposes an iterative algorithm to jointly solve the two problems of association metric and coupled feature selection. Correspondence autoencoder (Corr-AE) [41] designs dual single-mode encoder networks to construct cross-media models. Joint representation learning (JRL) [42] is able to jointly explore association and semantic information in a unified optimization framework. Deep semantic matching (Deep-SM) [43] constructs a dual deep neural mapping network to build a homogeneous semantic space.

GANs [44][45] are jointly constructed by the generator and the discriminator to expect a distribution similar to the target. The generator aims to use the sample data to analyze the learning rules, and try to generate the distribution of samples that are fake and real through the neural network model [46]; the discriminator uses the neural network to determine whether the data is real data or fake data generated by the generator. Through continuous adversarial training, the generator model is affected, and finally the effect of the generator model is achieved. Therefore, it is a deep learning method that generates models through adversarial training. During adversarial training, the neural network learns to generate a distribution that is close to the target distribution. Through research on deep learning, researchers have deeply integrated the idea of adversarial learning with cross-media semantic learning. Wang et al. [47] proposed a cross-media semantic learning (ACMR) algorithm based on adversarial learning, by designing a feature mapper to confuse the modality classifier and form a modality-invariant representation. Then, a modal classifier is designed in the network model to minimize the distance of similar semantic vectors in different modalities. This modal classifier consists of label predictions and triplet constraints. Finally, through the interaction between the two processes of feature mapper and modal classifier, different modal data are mapped into a common subspace.

He et al. [48] proposed an unsupervised cross-media retrieval (UCAL) algorithm, which has a good effect on cross-media semantic learning with less data annotations. Andrew[49] et al. proposed the Deep Canonical Association Analysis Algorithm (DCCA) by effectively combining the deep learning-based association analysis method. By sorting out complex relationships in cross-media semantic learning data, the literature [50] used the optimized DCCA algorithm to realize cross-media semantic learning between text modalities and image modalities. Peng et al. [51] proposed a cross-media structure to simulate the joint distribution of different modal data through a generative network, and proposed a cross-media convolutional autoencoder with weight sharing constraints to form a generative model. Reference [52] used CNN for cross-media data semantic learning training for the first time. Reference [53] proposed a method that combines the convolutional network model with correlation to achieve effective extraction of image depth features, thereby improving the performance of cross-media retrieval. With the development of deep network models, the deep image features extracted by the pre-trained VGGNet [54] network are combined with advanced homogeneous semantic algorithms to improve the accuracy of cross-media semantic learning algorithms. Semantic Similarity based Adversarial Cross Media Retrieval (SSACR) [55] proposed to build a semantic similarity matrix in the feature mapping network to measure the semantic similarity, and build a cross-media semantic learning model through adversarial training. Semantics-adversarial and Media-adversarial Cross-media Retrieval method (SMCR) [56] is proposed to minimize the loss of intra-media discrimination loss, inter-media consistency loss, and intra-semantics discrimination loss.

Prototype-based Adaptive Network (PAN) [57] utilizes a unified prototype to represent each semantic category across modalities, provides discriminative information for different categories, and adaptively learns cross-modal representations with the unified prototype as an anchor.

However, the research on cross-media scientific and technological information data is not yet mature, so how to propose a semantic learning algorithm for cross-media scientific and technological information data has become a problem that needs to be solved.

### 4 Cross-media Sci-tech Information Data Retrieval Based on Deep Semantic Features

The recognized search engine [58, 59, 60] dates back to 1990. The search engine can retrieve the file name on the
FTP server and return to the user where the file exists. After 30 years of development, search engine technology has continued to innovate. How to provide users with better and more accurate search results is the goal of search engine technology development [61]. As an open source search engine [62], Lucene mainly includes three major modules: index establishment, search, and management [63]. The search engine creates dictionaries and indexes through syntactic analysis and language processing [64-66]. The retrieval set is processed by relevance sorting. Lucene relies on this scoring mechanism to provide comprehensive and complete query services.

Since search engines [67] often have a huge amount of data deployed, it is bound to be difficult to retrieve efficiently using single-machine processing, so a distributed retrieval scheme is about to emerge [68]. Elasticsearch and Solr [69] rely on mechanisms such as distributed indexing, load balancing, and failover and recovery to provide retrieval capabilities. The retrieval process is to sort the correlation between the user query statement and the data in the Elasticsearch and Solr databases, and return the set above the correlation score threshold to the user as the retrieval result, and finally update the retrieval model according to the user's feedback on the retrieval result. Reference [70] fully utilizes and mines the information in the user's historical behavior data, introduces the attention mechanism to the user's historical behavior for weighted calculation, builds a deep neural interest network, and completes the personalized retrieval function. Reference [71] combined deep learning with a text retrieval system, and finally implemented a distributed [72] architecture-based text retrieval system using the big data technology platform Hadoop and Spark streaming computing framework. Reference [73] abstracts the internal logical structure of scientific literature and combines semantic retrieval with the subject similarity of knowledge units, thereby enhancing the efficiency of users to collect and utilize information. Reference [74] proposed a method to construct a knowledge graph to extract the relationship between scientific and technological entities and entities, thereby constructing a retrieval system. However, the current retrieval systems cannot intelligently search for the interests of scholars and users. Therefore, if the interests of different scholars and users can be integrated, retrieval combined with search terms has become a problem that needs to be solved at present. To sum up, the current retrieval systems for cross-media scientific and technological information have problems in data collection, inaccurate semantic understanding, and inability to perform intelligent retrieval based on the interests of scholars and users.

5 Conclusion

The Internet is flooded with all kinds of information. In the era of big data, accessing information through the Internet has become an indispensable part of people's daily life. Cross-media science and technology information data has different features from other data on the Internet because of its scientific and technological attributes. It has gradually become an important source for research scholars to explore current science and technology hotspots and plan future research directions. With the increasing abundance of science and technology information data, the traditional keyword matching model and unimodal retrieval method have gradually lagged behind the times and can hardly meet the daily research needs of research scholars to retrieve information. Therefore, based on the above research background, this paper investigates the semantic learning of cross-media science and technology information data.

Acknowledgment

This work is supported by National Key R&D Program of China (2018YFB1402600), the National Natural Science Foundation of China (61772083, 61877006, 61802028, 62002027).

References

[1] Kou Feifei, Du Junping, He Yijiang, Ye Lingfei. Social network search based on semantic analysis and learning. CAAI Transactions on Intelligence Technology[J], 2016, 1(4): 293-302.

[2] Yang Yuehua, Du Junping, and Ping Yuan. Ontology-based intelligent information retrieval system[J]. Journal of Software, 2015, 26(7): 1675-1687.

[3] Liang Meiyu, Du Junping, Liu Wu, Xue Zhe, Geng Yue, and Yang Congxian. Fine-grained Cross-media Representation Learning with Deep Quantization Attention Network[C]/Proceedings of the 27th ACM International Conference on Multimedia, 2019: 1313-1321.

[4] Xue Zhe, Du Junping, Du Dawei, Lyu Siwei. Deep low-rank subspace ensemble for multi-view clustering[J]. Information Sciences, 2019, 482:
[5] Sun Bo, Du Junping, Gao Tian. Study on the improvement of K-nearest-neighbor algorithm[J]. 2009 International Conference on Artificial Intelligence and Computational Intelligence, 2009, 4: 390-393.

[6] Gu Jiawei. Design and implementation of business service system for log big data analysis [D]. South China University of Technology, 2018.

[7] Cai Minggao. Design and implementation of distributed ETL system for industrial big data [D]. University of Chinese Academy of Sciences (Shenyang Institute of Computing Technology, Chinese Academy of Sciences), 2017.

[8] Soft Computing; Investigators from Fu Jen Catholic University Report New Data on Soft Computing (Parallel and Distributed Architecture of Genetic Algorithm On Apache Hadoop and Spark). 2020, 377.

[9] Wen Anzhan. Research on key technologies of scholar user portrait based on multi-source heterogeneous big data [D]. South China University of Technology, 2018.

[10] TimeRank : A dynamic approach to rate scholars using citations[J] . Massimmo Franceschet,Giovanni Colavizza . Journal of Informetrics . 2017 (4)

[11] Wu Bo, Liang Xun, Zhang Shusen, Xu Rui. Frontier Progress and Applications of Graph Neural Networks[J]. Journal of Computer Science, 2022, v. 45;No.469(01):98-114.

[12] Guo Yuhui, Liang Xun. Local View Distorted Banknote Recognition Based on Heterogeneous Feature Aggregation[J].Journal of Computer, 2022; v. 45;No.469(01):98-114.

[13] Zhang Tianyi. Design and Implementation of Science and Technology News Analysis System Based on Topic Model [D]. Beijing University of Posts and Telecommunications, 2019.

[14] Ji Shouling, Du Tiantyu, Deng Shuiguang, Cheng Peng, Shi Jie, Yang Min, Li Bo. A Review of Research on Robustness of Deep Learning Models[J].Journal of Computer, 2022; v. 45;No.469(01):190-206.

[15] Bu Zhan, Wang Yueyao, Ma Lina, Jiang Jiuchuan, Cao Jie. Attribute Graph Clustering Method Based on Dynamic Cluster Formation Game[J]. Journal of Computer Science, 2021; v. 44;No.465(09):1824-1840.

[16] Liu Jianwei, Wang Yuanfang, Luo Xionglin. Research Progress of Deep Memory Networks[J].Journal of Computer, 2021; v. 44;No.464(08):1549-1589.

[17] Zhang Kun, Lu Guangyi, Wu Le, Liu Qi, Chen Enhong. Validity Verification and Analysis of Image Information for Sentence Understanding and Representation[J].Journal of Computer, 2021; v. 44;No.459(03):476-490.

[18] Eisa TAE, Salim N, Alzahrani S. Figure plagiarism detection based on textual features representation[C]/Student Project Conference (ICT-ISPC), 2017 6th ICT International. IEEE, 2017: 1-4.

[19] Zhao Z, Wu Y. Attention-Based Convolutional Neural Networks for Sentence Classification[C]//INTERSPEECH. 2016: 705-709.

[20] Li Wenling, Jia Yingmin, Du Junping. Variance-constrained state estimation for nonlinearly coupled complex networks. IEEE Transactions on Cybernetics[J], 2017, 48(2): 818-824.

[21] Li Wenling, Jia Yingmin, Du Junping. Recursive state estimation for complex networks with random coupling strength[J]. Neurocomputing, 2017, 219: 1-8.

[22] Zaremba, Wojciech, Ilya Sutskever, and Oriol Vinyals. Recurrent neural network regularization. arXiv preprint arXiv:1409.2329, 2014.

[23] Zhao Hongke, Liu Qi, Zhu Hengshu, Ge Yong, Chen Enhong, Zhu Yan, Du Junping. A sequential approach to market state modeling and analysis in online p2p lending[J]. IEEE Transactions on Systems, Man, and Cybernetics: Systems, 2017, 48(1): 21-33.

[24] Dey R, Salent F M. Gate-variants of gated recurrent unit (GRU) neural networks[C]/2017 IEEE 60th international midwest symposium on circuits and systems (MWSCAS). IEEE, 2017: 1597-1600.

[25] Chung J, Gulcehre C, Cho KH, et al. Empirical evaluation of gated recurrent neural networks on sequence modeling[J]. arXiv preprint arXiv:1412.3555, 2017.

[26] DEVLIN J, CHANG MW, LEE K, et al. Bert: Pre-training of deep bidirectional transformers for language understanding [JOL]. 2018, arXiv: 1810.04805, ( 2018-10-11 ) [2019-06-01] . https://arxiv.org/abs/1810.04805.

[27] VASWANI A, SHAZEER N, PARMAR N, et al. Attention is all you need[C]//Advances in Neural Information Processing Systems. 2017:5998-6008.

[28] S. Hochreiter and J. Schmidhuber , "Long Short-Term Memory," in Neural Computation, vol. 9, no. 8, pp. 1735-1780, 15 Nov. 1997, doi : 10.1162/neco.1997.9.8.1735.

[29] Lin C , Weihua LI , Chen JJ , et al. Bi-directional Long Short-term Memory Neural Networks for Chinese Word Segmentation[J]. Journal of Chinese Information Processing, 2018.

[30] Sarzynska-Wawer J, Wawer A, Pawlak A, et al. Detecting formal thought disorder by deep contextualized word representations[J]. Psychiatry Research, 2021, 304: 114135.

[31] Li B, Zhou H, He J, et al. On the sentence embeddings from pre-trained language models[J]. arXiv preprint arXiv:2011.05864, 2020.

[32] Simonyan K, Zisserman A. Very deep convolutional networks for large-scale image recognition[J]. arXiv preprint arXiv:1409.1556, 2014.

[33] Zeiler MD, Fergus R. Visualizing and understanding convolutional networks[C]//European conference on computer vision. Springer, Cham, 2014: 818-833.

[34] DHANKHAR P. ResNet-50 and VGG-16 for recognizing Facial Emotions[J]. International Journal of Innovations in Engineering and Technology (IJIET), 2019, 13(4): 126-130.

[35] Li Shan, Xu Xinzheg. VGG16 optimization method based on dual-angle parallel pruning [J/O]. Computer Science: 1-12 [2021-04-16 ].
[36] Yang Xiaochun, Li Xiaojing, Zheng Han, Wang Bin, Zhang Xiaohong. A semantic-based image-text cross-modal retrieval method [P]. Liaoning Province: CN113902764A, 2022-01-07.

[37] Lu Bo, Duan Xiaodong, Yuan Ye. Self-supervised Deep Semantic Preservation Hash for Cross-modal Retrieval[J]. Journal of Tsinghua University (Natural Science Edition):1-8[2022-03-05].DOI:10.16511/j.cnki.qdhxb.202126.040.

[38] Feng Xia, Hu Zhiyi, Li Caicai. A Review of Research Progress in Cross-modal Retrieval[J]. Computer Science, 2021, 48(08):13-23.

[39] DR Hardoon, S. Szedmak, J. Shawe-Taylor. Canonical correlation analysis: An overview with application to learning methods, Neural computation 16 (12) (2004) 2639–2664.

[40] K. Wang, R. He, L. Wang, W. Wang, T. Tan, Joint feature selection and subspace learning for cross-modal retrieval, IEEE transactions on pattern analysis and machine intelligence 38 (10) (2015) 2010–2023.

[41] F. Feng, X. Wang, R. Li, Cross-modal retrieval with correspondence autoencoder, in: Proceedings of the 22nd ACM international conference on Multimedia, 2014, pp. 7–16.

[42] X. Zhai, Y. Peng, J. Xiao. Learning cross-media joint representation with sparse and semisupervised regularization, IEEE Transactions on Circuits and Systems for Video Technology 24 (6) (2013) 965–978.

[43] Y. Wei, Y. Zhao, C. Lu, S. Wei, L. Liu, Z. Z, S. Yan, Cross-modal retrieval with cnn visual features: A new baseline, IEEE transactions on cybernetics 47 (2) (2016) 449–460.

[44] Kurach K, Łuść M, Zhai X, et al. A large-scale study on regularization and normalization in GANs[C]/International Conference on Machine Learning. PMLR, 2019: 3581-3590.

[45] Fang Yuke, Deng Weihong, Du Junping, Hu Jiani. Identity-aware CycleGAN for face photo-sketch synthesis and recognition[J]. Pattern Recognition, 2020, 102: 107249.

[46] Xu Liang, Du Junping, Li Qingping. Image fusion based on nonsubsampled contourlet transform and saliency-motivated pulse coupled neural networks[J]. Mathematical Problems in Engineering, 2013.

[47] Wang K, He R, Wang L, et al. Joint feature selection and subspace learning for cross-modal retrieval[J]. IEEE transactions on pattern analysis and machine intelligence, 2016, 38(10): 2010-2023.

[48] He L, Xu X, Lu H, et al. Unsupervised cross-modal retrieval through adversarial learning[C]/2017 IEEE International Conference on Multimedia and Expo (ICME). IEEE, 2017: 1153-1158.

[49] Andrew G, Arora R, Bilmes J, et al. Deep canonical correlation analysis[C]/Proceedings of the ACM International Conference on Machine Learning, 2019: 1247-1255.

[50] Wang Shu. Cross-media semantic retrieval based on deep canonical correlation analysis [J]. Journal of University of Science and Technology of China, 2018, 48(4): 322-330.

[51] Peng Y, Qi J. CM-GANs: Cross-modal generative adversarial networks for common representation learning[J]. ACM Transactions on Multimedia Computing, Communications, and Applications (TOMM), 2019, 15(1): 1-24.

[52] Wei Y C, Zhao H Y, Liu L Q, et al. Cross-modal retrieval with CNN visual feature: a new baseline[J]. IEEE Transactions on Cybernetics, 2017,47(2):449-460.

[53] Zou Hui, Cross-Media Retrieval Based on Deep Learning and Consistent Representation Space Learning [J]. Journal of Huazhao University, 2018, 39(1): 127-132.

[54] Jin Hanjun, Research on the Application of Convolutional Neural Networks in Cross-Media Retrieval [J]. Electronic Measurement Technology, 2018,41(7):54-57.

[55] C. Liu, J. Du, N. Zhou, A cross media search method for social networks based on adversarial learning and semantic similarity, SCIENCE CHINA Information Sciences (2021).

[56] Li Ang, Du Junping, Kou Feifei, Xue Zhe, Xu Xin, Xu Mingying, Jiang Yang. Scientific and Technological Information Oriented Semantics-adversarial and Media-adversarial Cross-media Retrieval[J]. arXiv preprint arXiv:2203.08615, 2022.

[57] Z. Zeng, S. Wang, N. Xu, W. Mao, Pan: Prototype-based adaptive network for robust cross-modal retrieval, in: Proceedings of the 44th International ACM SIGIR Conference on Research and Development in Information Retrieval, 2021, pp. 1125–1134.

[58] Wang Chunqing, Liu Li, Tan Yanyan, Zhang Huaxiang. Image retrieval method based on fuzzy color features and fuzzy similarity[J]. Computer Science, 2021,48(08):191-199.

[59] Ji Yan, Dai Hua, Jiang Yingying, Yang Geng, Yi Xun. Parallel Multi-KeyWord Top-k Ciphertext Retrieval Technology for Hybrid Cloud[J]. Computer Science, 2021, 48(05): 320-327.

[60] He Xia, Tang Yiping, Wang Liran, Chen Peng, Yuan Gongping. Multi-task Hierarchical Image Retrieval Technology Based on Faster R-CNNH [J]. Computer Science, 2019, 46(03): 303-313.

[61] Duan Chendi. Design and Implementation of Vertical Search Engine Based on ElasticSearch for MOOC [D]. Beijing Jiaotong University, 2019.

[62] Sha Yangyang, Wu Chen. Research on Web-based Lucene Full Text Search Algorithm [J]. Computer and Digital Engineering, 2019,47(05):1208-1211+1239.

[63] Ding Chu. Research on basic sorting algorithm based on Lucene and its application of improved algorithm [D]. University of Electronic Science and Technology of China, 2016.

[64] Zhe Peng. Research on the performance of inverted index based on Lucene [J]. Wireless Internet Technology, 2018 (08): 149.

[65] Liu Jing. In-depth study of index files based on Lucene [J]. Software
[66] Hu W, Gao J, Li B, et al. Anomaly detection using local kernel density estimation and context-based regression[J]. IEEE Transactions on Knowledge and Data Engineering, 2018, 32(2): 218-233.

[67] Liu Fan. Research and implementation of a retrieval system for scientific and technological resources based on ElasticSearch [J]. Modern Computer, 2021, 27(26): 93-100.

[68] Zheng Rongzeng, Lin Shiping. Research on Chinese Inverted Indexing Technology Based on Lucene [J]. Computer Technology and Development, 2010, 20(03): 80-83. [23] Dou Xiaofeng, Chen Sheng, Wang Yihang, Mai Liantao, You Jianhong. Application of Distributed Index to Improve Mass Data Query Performance[J]. Computer System Application, 2019, 23(06): 259-261.

[69] Tao Lin. Design and implementation of distributed e-commerce platform based on ElasticSearch and aggregated payment [D]. Central China Normal University, 2020.

[70] Zhou G, Zhu X, Song C, et al. Deep interest network for click-through rate prediction[C]//Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining. ACM, 2018: 1059-1068.

[71] Tang Zhoulin. Design and implementation of a text retrieval system based on deep learning [D]. Beijing University of Posts and Telecommunications, 2019.

[72] Li Wenling, Jia Yingmin, Du Junping. Distributed consensus extended Kalman filter: a variance-constrained approach[J]. IET Control Theory & Applications, 2017, 11(3): 382-389.

[73] Li Zhenjing. Resource Semantic Space and Retrieval Research of Scientific and Technological Literature[D]. Xidian University, 2019.

[74] Ren Yaqi. Construction and application of Chinese medical knowledge graph based on CNKI [D]. Dalian University of Technology, 2019.

Yang Jiang was born in 1995, is a Master candidate in Computer Science of Beijing University of Posts and Telecommunications. His research interests include natural language processing, cross-modal retrieval and deep learning.

Zhe Xue (corresponding author) received the Ph.D. degree in computer science from University of Chinese Academy of Sciences, Beijing, China in 2017. He is currently an associate professor with the school of computer science, Beijing University of Posts and Telecommunications, Beijing, China. His research interests include machine learning, data mining and multimedia data analysis.

Ang Li received the BS degree from the Nanchang Hangkong University, China, in 2015 and the MS degree from the Beijing University of Posts and Telecommunications, China, in 2019, all related to computer science. He is currently working toward the Ph.D. degree in Computer Science and Technology at the Beijing University of Posts and Telecommunications, China. His major research interests include information retrieval and data mining.