Cross-media Scientific Research Achievements Query based on Ranking Learning

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Abstract With the advent of the information age, the scale of data on the Internet is getting larger and larger, and it is full of text, images, videos, and other information. Different from social media data and news data, scientific research achievements information has the characteristics of many proper nouns and strong ambiguity. The traditional single-mode query method based on keywords can no longer meet the needs of scientific researchers and managers of the Ministry of Science and Technology. Scientific research project information and scientific research scholar information contain a large amount of valuable scientific research achievement information. Evaluating the output capability of scientific research projects and scientific research teams can effectively assist managers in decision-making. In view of the above background, this paper expounds on the research status from four aspects: characteristic learning of scientific research results, cross-media research results query, ranking learning of scientific research results, and cross-media scientific research achievement query system.

Key words science and technology big data; cross-media retrieval; cross-media semantic association learning; deep language model; semantic similarity

The data scale of scientific research results has grown faster and faster with the progress of the times, and now it has a huge scale. Major universities and research institutions are producing scientific research results all the time. These scientific research results may come from a professor, a student, or a team, and may be published individually or as part of a scientific research project. Scientific research results have a variety of media science and technology resource information, including images, texts, etc.. How to efficiently collect, process, and store these multi-source and heterogeneous cross-media scientific research results data is an important issue[1].

With the advent of the information age, the traditional query system for various scientific research results only for keywords has gradually lagged behind the times. For researchers, CNKI's text results query has been relatively complete, but the matching model based only on keywords has long been unable to meet their daily retrieval needs. In text retrieval, synonyms and polysemy become problems that cannot be ignored, and simple keyword matching cannot solve these problems. Deep language models such as BERT provide a good foundation for solving problems such as polysemy. How to use deep language models to retrain scientific research results to better meet query needs has profound practical and research significance[2][3]. At the same time, the single-modal data retrieval mode will be gradually eliminated, and the cross-modal retrieval is the trend of domestic and foreign technology development. Researchers may want to find papers and patents they are interested in through a circuit diagram and a neural network model diagram.

For the project managers of universities, fund committees, and the Ministry of Science and Technology, the National Natural Science Foundation of China and other systems only support keywords and accurate query of scientific research projects. It can only be queried and counted one by one according to the name of the person, which is very inconvenient. The query technology that integrates scientific research results, scientific research teams, scientific research projects and other information is generated to meet the above application scenarios. Supervisors urgently need technical tools to obtain valuable information from a large number of scientific research scholars and research teams.

1 Characteristic learning of scientific research results

Cross-media scientific research results have scientific and technological resources in different fields and different modalities. Literature[4-8] proposes different methods to convert cross-media data into unified features. The main method is to pass data from different modalities according to different modal characteristics. Cross-
cooperative learning maps to a unified feature subspace. The cross-media data in this paper mainly include text and images. In order to establish a unified feature subspace, it is necessary to convert the text and images in the cross-media scientific research results into effective and unified feature vectors respectively.

Computers are not good at directly processing text symbol sets. Converting text into feature vectors is an indispensable part of NLP tasks. The simplest processing methods are one-hot and TF-IDF. One-hot[9] uses an N-dimensional vector to indicate whether it is one of N words, and the vector has one and only one bit set to 1. TF-IDF[10] is a statistical method, its role is to count the importance of a word in a document or file. The importance of a word is proportional to its frequency in its individual documents, and decreases as its overall frequency in the corpus increases. Although these two methods also have novel application methods[11], the shortcomings are also very obvious. They do not consider the appearance order of each symbol in the text collection, and cannot reflect the position information of the symbols, and rely heavily on the corpus. The direct application of One-hot and TF-IDF to the extraction of text feature vectors of scientific research results is insufficient. The number of scientific and technological entities and proper nouns in scientific research results is huge. The use of one-hot encoding and TF-IDF encoding will make the vectors too long. It is verbose and neither of them has the above information, and there is no better way to deal with synonyms.

In 2013, Google open sourced the Word2vec word vector calculation tool. Word2vec[12-14] can be effectively trained on large datasets and million-word-level dictionaries. Words can get word-embedding through Word2vec, and various distances between vectors can measure the similarity of vectors. Word2vec has two basic implementation methods, CBOW and Skip-gram. CBOW[15,16] (Continuous Bag-of-Words Model) predicts the current word based on the context, Skip-gram[17,18] is just the opposite, predicting the context based on the current word, which makes up for the inconsistency between the two methods mentioned above and cons including location information. However, Word2vec assumes that the semantics of words are given by frequently occurring contextual information. In the big data of science and technology, there will be polysemy words such as "nuclear" and "apple". "Nuclear" may represent "nucleus" in physics, or it may represent the "core processor" in computer, and may also represent the "kernel function" in artificial intelligence theory.

In 2018, Google announced BERT, which performed well in several natural language processing (NLP) tasks. BERT[20] is essentially a self-supervised learning method based on massive corpus, which can learn a good feature representation for text, where self-supervised learning is supervised learning that runs without human-annotated data[21]. In specific natural language processing tasks, it is also effective to directly use the output of BERT as word-embedding for other tasks. BERT can provide a transfer-learned model[22,23] for other tasks, which is fine-tuned or not fine-tuned according to the task and directly fixed as a feature extractor. The source code and model of BERT were open-sourced on Github on October 31 of the same year[24], and the simplified Chinese and multilingual models were also open-sourced on November 3 of the same year. Although these models can be directly applied to scientific and technological big data to achieve relatively good results, they do not have good adaptability for accurate and effective scientific research results query requirements. BERT is only trained for general knowledge. For some technological entities and proper nouns, the recognition ability is poor, and further training is required on this basis.

An image is only expressed in a computer as a sequence of pixels, which is more difficult to understand than text. In the early days, traditional methods such as Scale Invariant Feature Transform (SIFT)[25] and Histogram of Oriented Gradient (HOG)[26] were used for image feature extraction, and image features were expressed through prior knowledge. These methods have strong interpretability. However, it is not feasible to extract image features for scientific research results query, and traditional methods are only suitable for extracting features for specific tasks. SIFT is suitable for tasks such as image matching and 3D modeling, HOG is suitable for tasks such as pedestrian detection, and LBP is suitable for tasks such as face recognition and photo classification. To form mappings with texts of different modalities, traditional image feature extraction methods do not have such capabilities. Currently, most image recognition tasks are implemented by means of machine learning[27], and
convolutional neural networks\cite{28,29} are a popular direction. Zhang et al.\cite{30} proposed a handwritten English text recognition method based on convolutional neural network and Transformer. Transformer abandoned the Long Short Term Memory Network (LSTM) and switched to a global self-attention mechanism. It combines Transformer and CNN to propose a segmentation-free image recognition model. VGGNet is a convolutional neural network model that repeatedly stacks convolution and pooling layers, which can deeply extract image features. Reference\cite{31} constructed a VGGNet-based classification and recognition method for the main organs of tomato, and used a variety of data augmentation techniques to retrain the network on the basis of VGGNet. Like text feature extraction methods, image feature extraction methods also need to be optimized for specific tasks.

Existing models such as BERT and VGGNet have excellent results in general text and image features, but they cannot meet the query needs of researchers and supervisors when applied to accurate and effective scientific research results query. The scientific and technological resource dataset optimizes the model and combines other technologies on its basis.

2 Cross-media research results query

The key issue of cross-media scientific research results query is how to extract information of the same dimension from different modalities\cite{32}. For example, there is a relationship between the text "polymer" and a picture of "epoxy resin". Epoxy resin is a kind of polymer. There are many ways to realize cross-media query. References\cite{33-36} map resources of different modalities to the same feature subspace, and calculate the feature similarity between them in this feature subspace as the query basis. Canonical Correlation Analysis (CCA)\cite{37} is a traditional feature mapping algorithm that can learn the linear mapping relationship between two sets of variables. Reference\cite{38} provides a cross-modal retrieval method based on deep learning, which proposes a cross-modal Correspondence Autoencoder (Corr - AE), which uses two single-modal autoencoders. And the common correlation of different modes is modeled, and the objective function and optimization algorithm are designed for it. Literature\cite{39} proposed a method of cross-media synesthesia matching of Chinese poetry and folk music based on emotional features, which explored the relationship between multimedia works and emotions, and used emotional similarity to establish the connection between text (poetry) and music. Literature\cite{40} proposes a resource-oriented library cross-media knowledge service, and discusses the innovative model of cross-media knowledge service, with the construction and management of cross-media knowledge map as the core, and cross-media knowledge discovery and innovation as the key, put forward the implementation path of cross-media knowledge service. Reference\cite{41} proposed a cross-media social network topic mining based on deep learning, which explored security topics from the daily rich media of Sina Weibo, and used reinforcement learning, adversarial learning and other methods to realize cross-media search methods in social networks\cite{42}.

Existing cross-media query systems do not integrate cross-media and deep semantics, and only search based on keywords or perform clustering\cite{43} and topic mining based on cross-media similarity, which is insufficient. At present, the research on data query of cross-media scientific research results is not mature, so how to effectively learn the semantic information of cross-media scientific research results has become an urgent problem to be solved.

3 Ranking learning of scientific research results

With the development of various big data technologies and the continuous increase of data, manual sorting and scoring are no longer suitable for sorting after information retrieval. Google 's ranking of web pages now considers more than 200 ranking factors, and it is almost impossible to give a human score. Machine learning is suitable for such occasions. Applying machine learning techniques to ranking, learning to rank\cite{44-46} emerges. PageRank and HITS\cite{47} are more classical ranking algorithms, but they cannot effectively combine user behavior information. L2R (Learning to Rank)\cite{48}\cite{49} came into being in order to better solve the ranking
problem. It is a supervised ranking learning algorithm that can automatically optimize the ranking model according to the feedback information to achieve personalized ranking. L2R mainly consists of three forms: single document (PointWise), document pair (PairWise) and document list (ListWise). The PointWise method transforms the ranking problem into a multi-classification or regression problem. In PairWise, documents and queries appear in pairs, and they are sorted according to their correlation. The ListWise method trains an optimal scoring function to score and sort. Based on the existing Listwise research, the literature proposes a weighted voting method using the topic similarity between documents, which further improves the accuracy of sorting. Reference proposed a new sorting framework based on matrix decomposition, clustering and outer product-based deep neural network, which can solve the problems caused by the complex network structure while taking advantage of the neural network. The literature fully mines the user's historical behavior data, weights the user's historical behavior based on the attention mechanism, builds a deep interest network, and completes accurate personalized retrieval and CTR prediction functions. Reference uses the convolutional neural network to further process the feature vector to complete more accurate sorting learning. It proposes a multi-channel convolutional neural network to act on the document list sorting learning method (ListCNN). The model is trained on the list level, each query has a corresponding document list, and the essence is to reorder on this list. An online ranking learning method that balances speed and quality is introduced. The goal of online ranking learning is to obtain an optimal ranking model through interaction with users. When ordering needs to be learned from user behavior, unlike other LTR methods, there is a quality-versus-speed trade-off when choosing a model. Complex models are more expressive and can find more results, while simple models train faster and can optimize the model with less user interaction. Simple models converge to suboptimal models. It finally proposes a velocity-mass balance model for cascaded multi-leaf gradient design. The organic combination of both, fast learning and high-quality convergence is achieved by using cascades.

4 Cross-media Scientific Research Achievement Query System

With the continuous development of the Internet and the continuous enhancement of scientific research and innovation capabilities, the number of scientific research achievements has increased year by year. The performance of massive scientific research results data query on traditional databases can no longer meet the needs of efficient retrieval. Lucene is a full-text search engine based on an inverted index. Lucene mainly includes three modules, indexing, searching and management. It analyzes and processes a large number of documents according to the indexing module and divides them into terms, thereby constructing an inverted index table. Lucene will rank documents that are highly relevant to the query in the query results, which is calculated according to a score function. Reference provides a solution for multi-data source index configuration. Reference designed an efficient method for Boolean query based on Lucene. Today's data volume Lucene can no longer be well satisfied, and Lucene-based distributed search engines Solr and ElasticSearch have emerged. They provide powerful distributed retrieval capabilities through mechanisms such as distributed indexing, failover, and load balancing. Reference designed a distributed search system based on ElasticSearch combined with intelligent recommendation.

Existing scientific research results query systems such as the National Science and Technology Achievement Information Service System can query scientific research results based on keywords, and the query results can be filtered according to the three-level application industry, the source of the results, and the completion time. Aminer, a big data mining service platform for scientific and technological information established by the team of Professor Tang Jie from the Department of Computer Science and Technology of Tsinghua University, analyzes and mines various academic information based on researchers, scientific literature and academic activities. It contains more than 100 million researchers, 8 million knowledge concepts,
300 million paper results and massive citation relationships, and it also opens data for all researchers to use. Although Aminer has massive data and rich functions, its pertinence is not strong enough. When researchers and supervisors want to know the scientific research results of a certain scholar, they cannot inquire about their scientific research projects, and do not make statistical summaries of their work over the years.

5 Conclusion

Existing cross-media query systems do not integrate cross-media and deep semantics, and only search based on keywords or perform clustering and topic mining based on cross-media similarity, which is insufficient. At present, the research on data query of cross-media scientific research results is not mature, so how to effectively learn the semantic information of cross-media scientific research results has become an urgent problem to be solved, and the ranking problem based on retrieval also needs to be solved urgently.

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