Accurate Portraits of Scientific Resources and Knowledge Service Components

Yue Wang, 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 With the advent of the cloud computing era, the cost of creating, capturing and managing information has gradually decreased. The amount of data in the Internet is also showing explosive growth, and more and more scientific and technological resources are uploaded to the network. Different from news and social media data ubiquitous in the Internet, the main body of scientific and technological resources is composed of academic-style resources or entities such as papers, patents, authors, and research institutions. There is a rich relationship network between resources, from which a large amount of cutting-edge scientific and technological information can be mined. There are a large number of management and classification standards for existing scientific and technological resources, but these standards are difficult to completely cover all entities and associations of scientific and technological resources, and cannot accurately extract important information contained in scientific and technological resources. How to construct a complete and accurate representation of scientific and technological resources from structured and unstructured reports and texts in the network, and how to tap the potential value of scientific and technological resources is an urgent problem. The solution is to construct accurate portraits of scientific and technological resources in combination with knowledge graph related technologies.

Key words knowledge service components, scientific resources, pre-training models, deep learning

1 Introduction

With the advent of the cloud computing era, technologies and researches related to big data have also received more and more attention. The cost of creating, capturing and managing information has also gradually decreased, and the amount of data on the Internet has exploded, with more and more scientific and technological resources being uploaded to the network. Different from news and social media data ubiquitous in the Internet, the main body of scientific and technological resources is composed of academic-style resources or entities such as papers, patents, authors, and research institutions. A network of associations, from which a large amount of cutting-edge scientific and technological information can be mined. However, there are a large number of management and classification standards for existing scientific and technological resources. These standards are difficult to completely cover all entities and associations of scientific and technological resources, and cannot accurately extract important information contained in scientific and technological resources. It is an urgent problem to produce a complete and accurate representation of scientific and technological resources and to further tap the potential value of scientific and technological resources. The solution is to construct accurate portraits of scientific and technological resources in combination with knowledge graph related technologies.

Scientific and technological resources involve various entities related to scientific research, such as papers, patents, scholars, institutions and publishing units. The relationship between these entities and other scientific and technological resource entities forms a massive and heterogeneous network of scientific and technological resources. Today, the utilization of scientific and technological resources is to be integrated into knowledge retrieval websites on a large scale to provide search and query services for scientists. These service methods meet the basic needs of scientific and technological resource retrieval, but cannot deeply explore the potential of scientific and technological resources. With the popularization and development of concepts related to natural language processing technology and knowledge graphs, the valuable information contained in scientific and technological resources can be further extracted and utilized.
mation contained in these scientific and technological resources has begun to be mined by more knowledge service platforms. For example, by extracting and analyzing the domain science and technology resource entities and the entity relationship network, the relationship network between each entity can be constructed, so as to construct the knowledge map of the related field; by analyzing the relationship between the entities in the subject domain, it can help users quickly understand the main research results and researchers in each subject area; by accurately clustering the topics of resources, it can help improve the query accuracy. Using knowledge map technology to display complex knowledge fields through data mining, in formation processing, knowledge measurement and drawing road.

2 Acquisition and feature representation of scientific resource texts

Compared with traditional Internet data, scientific and technological resources show more complex features. In terms of extracting textual representation features of scientific and technological resources, statistical models based on word frequency, topic models or word vector representation methods based on deep learning are usually used. TF-IDF\(^3\) utilizes statistical methods to extract text features. The document word weight is calculated by calculating the word frequency and the inverse document frequency, and the document vector representation is constructed by using the weight set of all words in the document, which is a typical text vector representation method. Wu Zhe et al.\(^4\) proposed the TTF-LDA algorithm, which is based on TF-IDF and LDA, and uses the method of topical analysis to process the abstracts of academic literature. Mikolov et al.\(^5\) proposed the Word2Vec model, which uses the CBOW word bag model and the Skip-Gram method to obtain the hidden layer vector representation of a word through the task of predicting the next word. This method is also called the embedding method. Compared with the One-hot representation, the word vectors trained by Word2Vec integrate the semantic information of the context, and use the distance between the word vectors to represent the semantic similarity between words.

With the rapid development of artificial intelligence technology, deep learning technology can also be used for feature extraction of scientific and technological texts, among which, autoencoders can effectively learn the semantic representation of text data. Eisa et al.\(^6\) use deep autoencoder technology to extract lexical feature sets. The network structure of RNN can process the input of different time series, which is very suitable for extracting features from serialized text data, and plays a great role in text processing tasks\(^7\)\(^8\).

On this basis, in order to solve the problem of RNN gradient disappearance caused by long distance, people improve RNN, construct LSTM and GRU\(^9\) units, and retain long-distance semantic information by integrating memory, forgetting, and output stages, so that the model can be The feature extraction of long text can achieve good results. Although the deep neural network is very useful in the task scenarios of sequence to sequence such as classification, it is not suitable for mapping one text sequence to another text sequence by itself. This problem can be solved by an encoder-decoder architecture, where a multi-layer LSTM network acts as an encoder to convert the input sequence into a fixed-length vector, and another LSTM network acts as a decoder to decode the vector into an output sequence. By training the model, people can use the hidden vector output by the trained model encoder as the semantic vector representation of the text of scientific and technological resources, and then the semantic feature extraction of scientific and technological resources can be realized.

Devlin et al.\(^11\) proposed a Bert pre-training model based on bidirectional Transformer, which maximized the use of multi-head self-attention mechanism to capture contextual semantics and achieved good results in multiple natural language tasks. The Transformer unit\(^12\) proposed by Google is composed of multi-head attention mechanism layers. Using Transformer to replace the common LSTM unit can obtain good parallel computing power and improve the learning efficiency of the model on large-scale corpus. In 2019, Yang et al.\(^13\) proposed the XLNet model. XLNet is an autoregressive language model. Compared with Bert, it optimizes the model pre-training method and fine-tunes it on this basis. It has achieved relatively high performance on many NLP tasks. Good results.
3 Accurate portrait of scientific resources

3.1 Science resource entity and entity relationship extraction

The construction of scientific and technological entity and concept knowledge graph requires entity extraction and entity relationship extraction of scientific and technological resources existing in the network.

In the problem of named entity name recognition, many deep learning methods (convolutional neural network\textsuperscript{[14]}, hybrid neural network\textsuperscript{[15]}) can effectively extract scientific and technological entities from unstructured text\textsuperscript{[16]}. Amplayo\textsuperscript{[17]} proposed several network construction methods for data collection of scarce scientific literature, using the full text of scientific literature and automatically extracting the entities required to build the network. Ma et al.\textsuperscript{[18]} proposed a BiLSTM-CRF entity extraction method based on a feature-based named entity knowledge base to extract entities related to ecological restoration technology. Peng et al.\textsuperscript{[19]} used word vectors to improve the recognition effect of named entity recognition in the social domain. Named entity name recognition also plays a significant role in special fields. Zeng et al.\textsuperscript{[20]} used LSTM combined with CRF model in medical entity name recognition; Cao Yiyi et al.\textsuperscript{[21]} used CNN combined with CRF to analyze potential entities in electronic medical records. Recognition; Cai et al.\textsuperscript{[22]} used the LSTM-CRF model to extract entities from electronic medical records and introduced a self-attention mechanism to improve the performance of the model; Chen et al.\textsuperscript{[23]} proposed a semi-supervised deep learning framework from government literature Extract potential entities from the text in . Wang Ziniu et al.\textsuperscript{[24]} used the BERT model for named entity recognition on the People's Daily dataset and achieved good results. Cheng et al.\textsuperscript{[25]} performed named entity recognition on colloquial texts and context-deficient Chinese short texts by adding entity vectors to the BERT model.

For entity relation extraction, it mainly involves extracting entity relation triples (entity 1, relation, entity 2 ) from unstructured text , which is the next stage of named entity recognition. In order to solve the dependency problem between long-distance words, Zhang et al.\textsuperscript{[26]} proposed to replace CNN with RNN to model entity relations. By replacing the position vector with a simple position label, the model can better capture the semantics of long-distance words. association. Based on the recurrent neural network model, Li et al.\textsuperscript{[27]} used a syntactic parse tree to recursively generate text feature representations from the bottom up, and achieved certain results. However, the problem of gradient disappearance of recurrent neural network in the case of long distances leads to the fact that the model can only use information in a limited range in prediction, and cannot be very effective in relation extraction of long texts.

Zhang et al.\textsuperscript{[28]} proposed an entity relationship classification method based on BiLSTM . While learning bidirectional semantic information, LSTM units such as memory gate and forget gate are used to capture the semantic dependencies contained in long texts, avoiding the gradient of RNN or bidirectional RNN. disappear problem. Dey and Salem\textsuperscript{[29]} proposed a gated recurrent unit GRU, which, as a variant of LSTM, simplifies the overall structure of the model and improves the effect of relation extraction. The attention mechanism was inspired by human vision and played a great role in the field of image processing. Later, the idea of the attention mechanism was introduced into the field of natural language processing, which also showed good results\textsuperscript{[30,31]}. The attention mechanism has been applied many times in speech recognition, knowledge question answering and automatic translation tasks\textsuperscript{[32,33] }, and achieved certain results in the task of entity relation extraction\textsuperscript{[34,35]}. Zhou et al.\textsuperscript{[36]} proposed a BiLSTM entity relationship extraction algorithm based on attention mechanism. Wang Hong et al.\textsuperscript{[37]} proposed a bidirectional LSTM entity relationship extraction model based on the attention mechanism, using BiLSTM to capture the contextual semantic association between words and words, and then using the attention mechanism to associate the output and input of the model, which strengthens the beneficial The key feature of relation extraction improves the effect of entity relation classification.

It is an effective method to construct the semantic representation layer of scientific and technological big data based on the pre-trained model. The BERT pre-training model is an encoder that uses a bidirectional Transformer\textsuperscript{[38]}. Compared with the traditional model, the Bert model uses Masked LM to capture the word-level
semantic representation in the text during the pre-training process, and obtains the semantic representation of the text based on Next Sentence Prediction. Sentence-level semantic representation. By using Bert, we can use large-scale corpus to pre-train the Transformer model before performing specific downstream task coding, and then fine-tune it under specific downstream tasks based on the pre-trained parameters to achieve better results.

Transformer introduces the self-attention mechanism, which learns the relationship within the sentence, the relationship within the target sentence, and the relationship between the source sentence and the target sentence, and proposes a multi-head attention mechanism, using the structure of full Attention. For the position of the word, Transformer uses the position encoding mechanism to preprocess the data, which increases the parallelism of the model and achieves better experimental results. In the Transformer architecture, the Encoder uses two sub-layers, one is a multi-head attention layer, which uses self-attention to learn the relationship within the source sentence. The other is the feedforward network layer, which uses a simple fully connected network to perform a simple linear transformation on the vector at each position based on the ReLU activation function, and then generates the output of the encoder and passes it to the decoder. The encoding process is computed in parallel, which greatly improves the efficiency compared to the original encoder-decoder model.

3.2 Entity extraction of scientific and technological subject words

In the construction of scientific and technological resource portraits, keyword extraction technology can be used to construct the correlation between scientific and technological keywords and scientific and technological achievements. Keyword extraction can extract some of the most relevant words in the text. In the era of poor retrieval performance, in order to improve the retrieval speed, keywords are often used as the retrieval basis for the entire article, so as to avoid traversing the article during retrieval. Therefore, the keyword item can still be seen in the paper. At the same time, keywords themselves play an important role in NLP fields such as text classification, clustering, and text summarization. In the text clustering task, the convergence time spent on clustering can be reduced by exploiting similar keywords between texts. By knowing the keywords in a piece of text, you can roughly know the main content and topic of the text.

The keyword extraction task can be realized by a simple keyword assignment algorithm, and a huge keyword library can be prepared. For a given text, by searching and matching the words in the text, several keyword libraries related to the text can be found. As the keyword set of the current text, the effect of this method depends on the quality of the keyword library, and the extraction ability of some new words in the text is poor. The second method is keyword extraction, which extracts existing words in the text as keywords of the text. This method is not affected by the quality of the keyword library and is more meaningful in practical use.

Keyword extraction is also divided into word extraction and phrase extraction. For a given text, the text is first divided into words of length 2–3 by Jieba word segmentation or SnowNLP word segmentation, and the process of keyword extraction is from the word segmentation results. Select a few words as the extraction result. For phrase extraction, it may involve algorithms such as splicing words into phrases or generating phrases. Phrases contain richer semantic information than words and are more valuable for reference.

The algorithm of keyword extraction includes the statistical TF-IDF algorithm. During the training process, the word frequency and inverse document frequency of each word in the text are calculated as the weight of the word, and the first few words with the largest weight are extracted from the text as the weight of the word. The result of keyword extraction. At the same time, some methods based on word graph can achieve language-independent keyword extraction, avoiding the problem of poor keyword extraction due to the vocabulary generated by the training process that does not contain words in the predicted text.

3.2 Relation extraction in the field of scientific and technological achievements

The relationship between scientific and technological achievements and subject areas is an important part of the portrait of scientific and technological resources. For hierarchical subject areas, you can use hierarchical multi-label classification to
associate scientific and technological achievements with specified subject area nodes. Hierarchical multi-label classification is a special form of multi-label classification. In ordinary flat multi-label classification, each label is isolated, but in hierarchical multi-label classification, each label may have its parent label and child label, with a certain level structure. Therefore, compared with the flat multi-label classification, the hierarchical multi-label classification has a label set with semantic association information between different levels. These associations can be used as a direction to optimize the hierarchical multi-label classification. At the same time, due to these associations, the hierarchical multi-label classification also faces the difficulties and challenges of data skew and complex evaluation indicators. The current hierarchical multi-label classification algorithms are mainly divided into flat methods \cite{53}, local methods \cite{54}, global methods \cite{55} and hybrid methods\cite{56}. Hierarchical multi-label classification is a special form of text classification problem. Compared with the classic multi-label classification problem, the labels of hierarchical multi-label classification are organized in a hierarchical structure, so hierarchical multi-label classification includes differences between different levels. connection relationship.

The flat method removes the association between the hierarchical labels\cite{57}\cite{58}, transforming the problem into a general multi-label classification, for non-leaf nodes in the hierarchical label, any text that is classified as a sub-label will be automatically classified as its ancestors node. The flat method ignores the relationship between hierarchical labels (parent-child relationship and level relationship), and its effect is generally poor.

The local method constructs a classifier for each hierarchical label, and constructs the global classification result by training multiple classifiers, selecting the classifier and pushing down the label depth according to the prediction result of the classifier. The types of local methods are LCN \cite{59}, LCPN \cite{60}, LCL \cite{61}.

The global approach builds only one classifier \cite{62} on the hierarchical labels to handle all categories simultaneously. These global methods are modified based on the planar method. Most of them are implemented in neural networks\cite{63} and deep learning\cite{64,65,66}. The computational cost of the global method is lower than that of the local method, which avoids the problem of error propagation caused by the hierarchical structure of the local method, but it cannot be obtained from the hierarchical structure. information, the fitting of the hierarchical information is insufficient.

The hybrid method combines the advantages of the local method and the global method\cite{67}, and utilizes both the hierarchical label information and the global information, and the two parts are processed uniformly based on neural network technology\cite{68}\cite{69}. Hybrid methods are now more and more popular among researchers, and good classification results can be obtained by combining local information to design the architecture of neural networks.

4 Science Resources Knowledge Service Components

In the development and design of the knowledge service system, Xu Tongyang\cite{70} analyzed the current situation of archives knowledge service and believed that the intelligent question answering system is an effective way to process archives data. Based on the current demand for multi-source archive data, an intelligent question answering model for knowledge service is designed. Xu Kaiying\cite{71} developed and designed the knowledge service of the university library by relying on the huge knowledge collection of the university library. Based on the advantages of subject resources and talents in colleges and universities, it provides professional library knowledge services for college students, and improves the efficiency of students' acquisition of knowledge. Wang Chao \cite{72} expounded the connotation and characteristics of the knowledge service of the smart library, analyzed and excavated the constituent elements of the library knowledge service system, designed the overall structure of the library knowledge service system, and proposed the basic structure of the library knowledge service system. concept. Huang Shanshan et al.\cite{73} designed and implemented a university library knowledge service system based on big data related technologies, adopted a targeted management model, effectively created a scientific and perfect information resource guarantee system, and established a high-quality knowledge service system and management. Team, so as to realize the professional knowledge service mode centered on user needs. Ye Fei\cite{74} implemented the
construction of university library smart space with knowledge service as the orientation. Through the integration and interconnection of multiple spaces, it can effectively solve the knowledge exchange barriers existing in the construction of university library space, and promote the transformation and upgrading of the university library service system. Based on system dynamics, Shen et al. [75] analyzed the system structure of the development of knowledge services of think tanks, clarified the internal dynamic elements and their interaction relationships, and constructed a theoretical model of the development mechanism of knowledge services of think tanks. In terms of service components, Guo Peng et al. [76] proposed a Web Service-based smart service framework SSF (Smart Service Framework), which decouples functional modules through component-based logic design and improves the reuse rate of modules. And scalability, user-friendly data processing. Wang Run [77] implemented an automated service publishing discovery model based on distributed technology [78]. Tang Liwen [79] discussed the production and design of space launch site service components from the perspective of products, introduced load balancing technology, and designed a high-availability launch site service component set, which provided more information for the rapid construction and iteration of space launch site information services. A way to load application modules. Wang Zhendong [80] carried out component analysis and component development for the scientific research office information system. Based on the Justep x5 architecture platform, he defined the macro component description resource method. The developed system confirmed the rationality and feasibility of the business component description system.

5 Conclusion

With the development of big data technology, the amount of data in the Internet has exploded, and technological resources related to technology and academic fields are also flooded on the Internet. Scientific and technological resources are mainly composed of entities closely related to academic resources such as papers, patents, authors, institutions, publishing units, etc., and contain a large amount of text information. How to construct a complete and accurate representation of scientific and technological resources from structured and unstructured scientific and technological resources, and further tap the potential of scientific and technological resources Value is a pressing issue. The solution is to construct an accurate portrait of scientific and technological resources in combination with knowledge graph related technologies, and to construct a knowledge graph of technological resources based on the portrait.

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Yue Wang was born in 1997, is a Master candidate in Computer Science of Beijing University of Posts and Telecommunications. His research interests include nature language processing, data mining and deep learning.

Zhe Xue 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.