

Profiling and Evolution of Intellectual Property

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Abstract In recent years, with the rapid growth of Internet data, the number and types of scientific and technological resources are also rapidly expanding. However, the increase in the number and category of information data will also increase the cost of information acquisition. For technology-based enterprises or users, in addition to general papers, patents, etc., policies related to technology or the development of their industries should also belong to a type of scientific and technological resources. The cost and difficulty of acquiring users. Extracting valuable science and technology policy resources from a huge amount of data with mixed contents and providing accurate and fast retrieval will help to break down information barriers and reduce the cost of information acquisition, which has profound social significance and social utility. This article focuses on the difficulties and problems in the field of science and technology policy, and introduces related technologies and developments.

Key words Policy Data; Content Extraction; Text Classification; Text Matching; Language Model

1 Introduction

In recent years, with the rapid growth of information data in the Internet, the number and types of scientific and technological resources are also rapidly expanding[1], but the increase in the number and category of information data sometimes increases the cost of information acquisition. For any individual's value standard, the disorganized data means that a large amount of, or even most of the information is not of interest to it, which also means that it takes more time to identify valid information from it. Taking technology-based enterprises as an example, in addition to general papers, patents, etc., policies related to science and technology or that support the development of their industries should also belong to a type of scientific and technological resources. However, such resources are mixed with a large number of other irrelevant policy data. It increases the acquisition cost and difficulty of technology companies. Extracting valuable scientific and technological resources from a huge amount of data with mixed contents and providing accurate and fast retrieval will help to break down information barriers, eliminate information gaps, and reduce information acquisition costs. It has profound social significance and research value.

Policy resources usually come from multiple fields and different disciplines, and the characteristics of multiple data sources lead to inherent difficulties in collecting and obtaining policy resources. For different information sources on the Internet, this means that the collection rules to be set are also different, and a general strategy needs to be designed to solve the problem of labor costs. In addition to the initial collection of web page data, the content of the body of the web page is more important. The content of the body of the web page is the main body of policy resources. Accurate text extraction capability is not only a means of obtaining policy resources, but also the premise of subsequent model algorithm training and learning. The text extraction technology of web
token types, and the difference of the value will affect the extraction effect, which is not very good in actual performance. In 2003, Microsoft Research Asia proposed a visual representation-based web content structure analysis method - VIPS algorithm\(^7\), combined with the DOM tree to process the page\(^8\)\(^9\). On the basis of this algorithm, there is an algorithm combining the improved Hidden Markov Model to realize Web information extraction \(^10\). The webpage text extraction algorithm based on the VIPS algorithm has better performance when facing webpages with a single visual form and a large difference in the code structure level. However, such algorithms require a page to be completely rendered before analysis and extraction can be performed, which consumes a large amount of resources.

Another idea of page text extraction is template-based extraction algorithm\(^11\). The core idea of this kind of algorithm is to assume that web pages are constructed using the same or similar templates, so the same or similar parts between pages are non-text, while pages The part with a large difference is the main text\(^12\)-\(^14\). In practice, it can also be combined with the URL to determine whether the web pages to be extracted have the same structure. However, such algorithms are more suitable for modeling a single data source to achieve content extraction. When faced with multiple data sources, it is very inflexible. If the extraction code is written separately for each data source, it is labor-intensive, and once the website of the target data source is updated or revised, the old algorithm needs to be re-modified.

At present, the best and widely used methods of extraction are generally to use the information of HTML pages to design heuristic strategies for extraction, these heuristic strategies include: text density, synthetic text density, label ratio, path ratio\(^15\) and so on. The paper\(^16\) defines text density as the ratio of all words within a label to the number of all labels. The paper\(^17\) proposes an entropy-based information content density algorithm. The paper\(^18\) proposes a paragraph extractor to cluster HTML paragraph tags and local parent titles to identify main content in news articles. Such algorithms generally use heuristic functions to calculate and score label nodes as the extraction criteria. However, such algorithms often use a single strategy and need to manually determine the threshold, which is not highly adaptable in the face of multiple data sources. The paper\(^19\) proposes an adaptive extraction algorithm based on decision tree to solve this problem, extracts features from each node of the DOM tree, and uses the decision tree algorithm for binary classification judgment. However, this method has many pre-assumptions, such as Only leaf nodes are considered, and only fewer HTML tags are considered.

3 Text Feature Representation and Classification Methods of Science and Technology Policy Resources

Computers cannot understand text data directly, so it is necessary to encode text data features into a form that computers can understand. Feature extraction and representation of text data is an important part of text mining, and there are many studies and theories. TF-IDF is a weighting technique that uses statistical methods to extract keywords. It calculates the importance of a word in the entire corpus by measuring term frequency (TF) and inverse document frequency (IDF). Filter some common but irrelevant words while retaining important words that affect the entire text. TD-IDF often has good performance and performance, but it also has some shortcomings, such as not considering the order in which the symbols appear in the text collection, and cannot reflect the position information of the symbols, etc., and a word with a slight morphological change will also be recognized
is costly. The most important thing in applying deep learning to solve large-scale text classification problems is to solve text representation, and then use network structures such as Convolutional Neural Networks (CNN)\cite{40}/Recurrent Neural Networks (RNN)\cite{41} to automatically obtain feature expression capabilities. Eliminate cumbersome manual feature engineering and solve problems end-to-end. Mikolov proposed the use of FastText for efficient text classification in 2016\cite{42}. The principle is to average all word vectors in the sentence, and then directly connect to the softmax layer, while adding some n-gram feature skills to capture local sequence information\cite{43}. FastText does not consider word order information, and the capture of local sequence information is insufficient. CNN initially achieved great success in the field of images, the core of which is that it can capture local correlations, which can be used to extract key information similar to n-grams in sentences in text classification tasks. Although TextCNN has good performance in many tasks, CNN has the problem of fixed filter_size field of view. On the one hand, it cannot model longer sequence information, and on the other hand, hyperparameter adjustment is very cumbersome. Therefore, Recurrent Neural Neural (RNN) has become a more commonly used technology. RNN can better express context information, and Bi-directional RNN can capture variable-length and bidirectional n-gram information in text classification tasks. The literature\cite{44} describes the design of RNNs for classification problems. In recent years, the development of text classification has continued. There is a text classification method TextRCNN\cite{45} that uses a recurrent convolutional neural network to improve TextCNN; CharCNN\cite{46} uses a character-level convolutional neural network\cite{47} for classification; HAN\cite{48} uses a method to obtain attention weights, used to identify and classify important words for classification; TextGCN\cite{49} proposes to do text classification based on graph neural network\cite{50}, using the entire dataset/corpus to build a large heterogeneous graph, the graph contains two types of nodes, one is the document node (text to be classified), the other is word nodes (all deduplicated words in the dataset/corpus), and uses a graph convolutional network to jointly learn word and document embeddings.

4 Text Matching and Retrieval of Science and Technology Policy

Accurate query is inseparable from the measurement of semantic similarity of text\cite{51}, which can also be called semantic matching. Traditional text matching technologies include BoW\cite{52}, TF-IDF\cite{53}, BM25\cite{54}, Jaccard\cite{55}, SimHash and other methods, which can mainly solve the matching problem at the lexical level, but are difficult to deal with the limitations of word meaning and structure. With the rapid development of the field of deep learning, more and more researches have been devoted to applying deep neural network models\cite{56} to natural language matching tasks in recent years, thereby reducing the cost of feature engineering. From the perspective of the development of matching models, they can be divided into single-semantic models\cite{57}, which encode two sentences and calculate the similarity without considering the local characteristics of the phrases in the sentences; multi-semantic models\cite{58-60}, which interpret sentences to be matched from multiple granularities, considering Local features such as words and phrases; matching matrix model, considering the pairwise interaction of the sentences to be matched, and extracting features with a deep network after the interaction, which can obtain deeper relationships between sentences. From the essence of matching models, they can be divided into two types: representational and
configurability of multi-data source index by means of XML configuration to solve the problem of unified retrieval of multi-data sources. The literature[73] designs an efficient way to build Boolean queries based on Lucene.

Because search tasks are often carried out in massive corpora, the processing power of single or multi-machine cannot meet the needs of efficient retrieval, and distributed retrieval services are becoming more and more popular. Lucene-based distributed search engine servers Solr and ElasticSearch provide powerful retrieval capabilities through mechanisms such as distributed indexing, load balancing, and failover and recovery[74-76]. The literature[77] designs a distributed intelligent search system based on ES, and builds an intelligent recommendation function on this basis.

5 Conclusive

In view of the characteristics of scientific and technological resources in the policy field under the scenario of big data of science and technology, this paper summarizes related technologies and progress from three aspects: The data structure of science and technology policies is inconsistent, and the data extraction methods of relevant pages are summarized to achieve unified extraction of multi-source policy data; Data features of texts, summarizing related text feature expression methods and text classification techniques; Summarizing related similarity calculation methods and ranking learning methods for the features of scientific and technological policy resources obtained by extraction and mining.

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References

[1] Yang J, Du J, Shao Y. Construction Method of Intellectual-property-oriented Scientific and Technological Resources Portrait[J]. Journal of Software 33, no. 4 (2021): 0-0.
[2] Xue Z, Du J, Du D, et al. Deep low-rank subspace ensemble for multi-view clustering[J]. Information Sciences, 2019, 482: 210-227.
[3] Shah P, Pandit H B. A Review: Web Content Mining Techniques[J]. Data Engineering for Smart Systems, 2022: 159-172
[4] Pujar M, Mundada M R. A Systematic Review Web Content Mining Tools and its Applications[J].
[5] Zhao H, Liu Q, Zhu H, et al. 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.
[6] Zachariasova M, Kamencay P, Hudec R, et al. A Novel Imaging Approach of Web Documents Based on Semantic Inclusion of Textual and Non–Textual Information[J]. AASRI Procedia, 2014, 9: 31-36.
[7] Cai D, Yu S, Wen J R, et al. Vips: a vision-based page segmentation algorithm[J]. 2003.
[8] 8. 吕芳. 基于视觉特征的钓鱼网页相似性计算技术研究 [D]. 哈尔滨工业大学, 2015.
[9] 9. 沈怡涛. 基于视觉特征和文本结构分析的中文网页自动摘要技术研究[D]. 华东师范大学, 2014.
[10] 10. 李伟男, 李书琴, 景旭, 等. 基于模拟退火算法和二阶HMM的Web信息抽取[J]. 计算机工程与设计, 2014, 35(4): 1264-1268.
[11] 11. Bar-Yossef Z, Rajagopalan S. Template detection via data mining and its application[C] //Proceedings of the 11th international conference on World Wide Web. 2002: 580-591.
[12] 12. 杨一柳. 基于模板的网页信息抽取技术研究[J]. 浙海大学学报：自然科学版, 2013, 34(3): 320-322.
[13] 13. 顾韵华, 高原, 高宝, 等. 基于模板和领域本体的 DeepWeb信息抽取研究[J]. 计算机工程与设计, 2014, 35(1): 327-332.
[14] 14. 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.
[15] 15. Wu G, Li L, Hu X, et al. Web news extraction via path ratio[C] //Proceedings of the 22nd ACM international conference on Information & Knowledge Management. 2013: 2059-2068.
[16] 16. D. Song, F. Sun, L. Liao, “A hybrid approach for content
[36] Yabo Y., Wenzhong Y., Huiting Y., et al. Research on Short Text Classification Algorithm Based on Convolutional Neural Network and KNN[J]. Computer Engineering, 2018.

[37] Sabbah T., Ayyash M., Ashraf M. Hybrid Support Vector Machine based Feature Selection Method for Text Classification[J]. The international arab journal of information technology, 2018, 15(3a):599-609.

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

[39] Fang Y., Deng W., Du J., et al. Identity-aware CycleGAN for face photo-sketch synthesis and recognition[J]. Pattern Recognition, 102: 107249, 2020.

[40] Zhou D.X. Universality of deep convolutional neural networks[J]. Applied and computational harmonic analysis, 2020, 48(2): 787-794.

[41] Sherstinsky A. Fundamentals of recurrent neural network (rnn) and long short-term memory (lstm) network[J]. Physica D: Nonlinear Phenomena, 2020, 404: 132306.

[42] Joulin A., Grave E., Bojanowski P., et al. Bag of tricks for efficient text classification[J]. arXiv preprint arXiv:1607.01759, 2016.

[43] Kim Y. Convolutional neural networks for sentence classification[J]. arXiv preprint arXiv:1408.5882, 2014.

[44] Liu P., Qiu X., Huang X. Recurrent neural network for text classification with multi-task learning[J]. arXiv preprint arXiv:1605.05101, 2016.

[45] S. Lai, L. Xu, K. Liu, and J. Zhao, “Recurrent convolutional neural networks for text classification,” in Proceedings of the Twenty-Ninth AAAI Conference on Artificial Intelligence, January 25-30, 2015, Austin, Texas, USA, pp. 2267 – 2273, 2015.

[46] X. Zhang, J. J. Zhao, and Y. LeCun, “Character-level convolutional networks for text classification,” in Advances in Neural Information Processing Systems 28: Annual Conference on Neural Information Processing Systems 2015, December 7-12, 2015, Montreal, Quebec, Canada, pp. 649 – 657, 2015.

[47] Li W., Jia Y., Du J. Recursive state estimation for complex networks with random coupling strength. Neurocomputing, 2017, 219: 1-8.

[48] Z. Yang, D. Yang, C. Dyer, X. He, A. J. Smola, and E. H. Hovy, “Hierarchical attention networks for document classification,” in NAACL HLT 2016, The 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, San Diego California, USA, June 12-17, 2016, pp. 1480 – 1489, 2016.

[49] L. Yao, C. Mao, and Y. Luo, “Graph convolutional networks for text classification,” in The Thirty-Third AAAI Conference on Artificial Intelligence, AAAI 2019, The Thirty-First Innovative Applications of Artificial Intelligence Conference, IAAI 2019, The Ninth AAAI Symposium on Educational Advances in Artificial Intelligence, EAAI 2019, Honolulu, Hawaii, USA, January 27 - February 1, 2019, pp. 7370 – 7377, 2019.

[50] Shi C., Han X., Song L., et al. Deep collaborative filtering with multi-aspect information in heterogeneous networks[J]. IEEE transactions on knowledge and data engineering, 2019, 33(4): 1413-1425.

[51] Yang Y., Du J., and Ping Y. Ontology-based intelligent information retrieval system[J]. Journal of Software, 2015, 26(7): 1675-1687.
[73] Ran Li. Simulation of Boolean Query Implementation Strategy in Lucene[A]. 西南石油大学 (Southwest Petroleum University). 第七届计算与信息科学国际学术会议论文集[C], 西南石油大学 (Southwest Petroleum University), 西南石油大学计算机科学学院, 2019:9.

[74] 窦晓峰, 陈胜, 麦联叨, 由建宏. 应用分布式索引提高海量数据查询性能[J]. 计算机系统应用, 2014, 23(06): 259-261.

[75] Vijaya K P N, Raghunatha R V. A PRACTICAL APPROACH TO WORKING OF WEB SEARCH ENGINE[J]. International Journal of Computer & Electronics Research, 2013, 2(1).

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

[77] 曾亚飞. 基于Elasticsearch的分布式智能搜索引擎的研究与实现[D]. 重庆大学, 2016.