Research on Intellectual Property Resource Profile and Evolution Law

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Abstract In the era of big data, intellectual property-oriented scientific and technological resources show the trend of large data scale, high information density and low value density, which brings severe challenges to the effective use of intellectual property resources, and the demand for mining hidden information in intellectual property is increasing. This makes intellectual property-oriented science and technology resource portraits and analysis of evolution become the current research hotspot. This paper sorts out the construction method of intellectual property resource intellectual portrait and its pre-work property entity extraction and entity completion from the aspects of algorithm classification and general process, and directions for improvement of future methods.

Key words Intellectual Property; Resource Profile; Named Entity Recognition; Evolution Analysis; Deep Learning

1 Introduction

As the most important information carrier and knowledge source of research results and technological innovation, patent is the main object of intellectual property analysis. The research on intellectual property in this paper also focuses on patents. With the rapid development of science and technology and the acceleration of technological iteration, the number of patents has also exploded. Analysis and mining of intellectual property resources mainly based on patents, mining technology concepts, technology application fields and other information from a large number of patent data, and then grasping the development status and trends of technology, which is helpful for enterprises to identify technology opportunities[1], seize market opportunities[2], adjust claims to improve authorization opportunities[3], and enhance the core competitiveness of enterprises.

Patent literature requires a strong professional background to understand its content, and its analysis work mostly relies on patent analysts[4]. With the rapid increase in the number of patents, interdisciplinary technologies continue to emerge, and it is difficult to quickly and comprehensively understand technologies only by manual analysis, development. Patents contain a large number of specialized vocabulary and technical terms, which are characterized by precise language, complex semantic information, and high information density, which pose challenges to the accurate extraction of key information in patents. At the same time, there are complex and rich connections among intellectual property entities such as technical concepts, applicants, and involved fields, and changes in these relationships can reflect the fine-grained changes and development of intellectual property rights. When traditional patent analysis and data mining methods analyze important information such as technical concepts and research topics in patents, there is a serious loss and fragmentation of semantic information[5], and they lack the use of the relationship between intellectual property entities, making it difficult to capture knowledge. The development and change of property rights in subdivision fields.

With the development of artificial intelligence and big data technology, data profiling[6] technology has been more and more widely used. Data portraits can comprehensively use the extracted entity information and relationship information in metadata to obtain highly refined feature representations, and use features to mine data patterns. Construct intellectual property resource portraits for intellectual property resources, transform unstructured patent text data into structured expressions such as entity-relationships that are easily accepted by people, effectively organize high-density technical information in patents, and enhance deep semantic relationships between patents.

This paper mainly introduces the main technologies used in the construction of intellectual property resource portraits and the existing technology evolution law
proposed an entity name recognition method based on iteratively dilated convolutional neural network (IDCNN), using IDCNN network instead of LSTM network. In recent years, as Transformer has been widely used in other tasks of natural language processing and achieved excellent results, improved models based on Transformer\cite{30,31} are also increasingly used in named entity extraction.

2.2 Entity completion method

After entity extraction from patent text, massive knowledge consisting of a large number of entities and relationships can be obtained, but due to the lack of some key entity categories, the degree of perfection of this knowledge is low\cite{32}, such as in the abstract of patent text. In the information, more than half of the patents did not clearly indicate the area covered in the abstract. This requires prediction of missing entities and relationships in the graph to complete graph knowledge\cite{33}.

There are mainly two types of entity completion methods. One is to use the graph structure information of the existing graph to generate the feature representation of the triplet\cite{34,35}, and combine the given entity relationship with all possible entities to form candidate triples. Set of groups, calculate the score of each triple, and obtain the completed entity according to the score. Si Jiaqi\cite{36} proposed a knowledge graph completion based on text enhancement, introducing the source text of entity-relationship triples, respectively representing the triples and source texts, fusing the two features to form the final representation, and then using the fusion Feature representations make predictions of entity-relationship triples.

The other category is to assign existing attributes to entities with missing attributes through classification based on the fact that entities with missing attributes and similar entities with existing attributes share the same concept. For example, when predicting tail entities based on head entities and relations, the tail entities can be determined by classifying the given head-entity relations into a set of head-entity relations with the same tail entities. This method is suitable for nodes that contain textual information. Based on the premise that entities with missing attributes and entities with existing attributes share the same concept, She Qixing et al.\cite{37} used the probability and statistical model based on Bayesian network, through the dependency between the concept and attribute of the hypernym and the relationship between the entity and the hypernym. Concept dependencies, recommending known attributes to entities lacking attributes. Yang Yifan et al.\cite{38} used the above-mentioned attributes in the introduction text to train the classification model to determine whether the extracted named entity is an alias, so as to realize the completion of the character alias. Pan Luming\cite{39} used multi-label text classification to predict the type information of entities missing by using the type information to be predicted as a column.

2.3 Portrait of intellectual property resources

In recent years, more and more scholars have paid attention to the importance of scientific and technological resource information\cite{40,41}. However, compared to common user profiles\cite{42} and scholar profiles\cite{43}, scientific and technological resource profiles face more challenges. On the one hand, user portraits and scholar portraits can be constructed using public datasets. In the social media analysis scenario, Liang et al.\cite{42} used Twitter data to construct user portraits, and Tang J et al.\cite{44} established an AMiner data platform based on three types of data: researchers, scientific literature, and academic activities. It provides a data basis for the study of scholar portraits. In contrast, scientific and technological resource portraits lack public datasets, and the data are widely distributed on the Internet, so an automated method for obtaining technological resources from massive data and constructing portraits is required\cite{45}. On the other hand, the construction of scientific and technological resource profiles requires accurate identification of valid information from the acquired scientific and technological resources\cite{46}. However, the accuracy of the existing user profile and scholar profile methods is limited, which makes the construction of scientific and technological resource profiles more difficult.

In the construction of scientific and technological resource portraits, the existing methods mainly include the construction method based on ontology, the construction method based on topic, the construction method based on profile matrix, and the construction method based on semantic mining. European scientists used the system Euro-CRIS to build a unified description model CERIF\cite{47} to build a portrait of
clusters through keyword co-occurrence matrix, and displayed trend analysis of cluster members' influence through patent distribution. Tan Tingting[69] and Wei et al. [70] used LDA to perform topic clustering on patent data, and determined the evolution path according to the similarity between topic words.

4 Conclusion

The resource portrait method for intellectual property mainly extracts technical keywords from patent text through entity extraction method, and then converts unstructured patent text into a structured representation of a set of intellectual property entities after entity completion. The evolution law of intellectual property is mainly analyzed by methods such as cooperation network analysis and keyword analysis to mine the evolution law of hot spots and cooperation. The evolution law of technology development and technology path is mostly analyzed by methods such as topic clustering.

At present, there are supported patent mining technologies in different fields of patent analysis, but these patent mining technologies also have certain defects, which still need to be improved. More in-depth research can be focused on the following aspects:

(1) In the analysis of the evolution law of intellectual property, the trend of popularity only considers the frequency of co-occurrence, and indicators such as time decay, applicant influence, and patent influence can be introduced, so that the popularity can more comprehensively reflect the change of patent influence.

(2) In the construction of intellectual property knowledge graph, the types of entity relationships can be enriched, the entity fusion algorithm based on deep learning can be introduced, the accuracy of entity recognition can be improved, and the triple data of patent entity relationship can be constructed more accurately, thereby improving the accuracy of entity recognition. Accuracy of high intellectual property knowledge map and resource portrait.

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