Construction Model and Evaluation of Dynamic Knowledge Map for Deep Learning

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Abstract. The related technologies of knowledge map have been widely applied in many fields, such as search engine, intelligent question and answer, language understanding, recommendation calculation, big data decision analysis and so on. Deep learning originates from the research of artificial neural network, which uses deep network to learn knowledge from massive data. Its advantage is that it can obtain features without manual work. It is one of the current research hotspots to integrate the method of deep learning into the application of knowledge map. In this paper, a dynamic knowledge map reasoning method based on multi-relationship cyclic events is proposed, and an improved multi-relationship proximity aggregator is used to fuse the neighborhood information of target entities to obtain a more accurate representation of entity neighborhood vectors. It improves the speed of manual annotation, reduces the time and labor cost of manual annotation, and improves the migration ability of event extraction system.

Keywords: Deep Learning, Dynamic Knowledge Map, Deep Confidence Network, Entity Extraction

1. Introduction

Knowledge represents the thinking and behavior patterns inspired by human beings in the process of solving problems. At present, the research object of knowledge map is entities and relationships between entities, which has achieved remarkable research results. However, the limitation of knowledge map lies in the limitation of its knowledge base, and the knowledge map has made slow progress in the inference expansion of its rules [1]. Faced with the huge amount of company data with scattered sources and various formats, traditional methods such as statistical reports, regulatory inquiries, manual search and processing of information, manual identification and disposal have gradually become unsuitable, and the ability of machines to process and analyze data needs to be
improved. Knowledge map has become one of the indispensable and important technologies to realize artificial intelligence at cognitive level.

It is impossible to reason the evolution process of knowledge map in time. Therefore, adding time information to knowledge map to construct dynamic knowledge map is a rising research direction in recent years. Dynamic knowledge map can not only alleviate the data sparse problem of large-scale knowledge map, but also improve the computational efficiency, which is of great significance to relation extraction, knowledge map completion and knowledge reasoning [2]. Applying deep learning to the extraction of knowledge units and the relationship between them can provide a good foundation for drawing knowledge maps; At the same time, graph database uses graph data structures such as nodes, edges and attributes to represent and store information, which is more suitable for storing knowledge maps.

2. Deep learning and dynamic knowledge map acquisition

2.1. Relation extraction

The purpose of relation extraction is to extract semantic relations between marked entity pairs in sentences. Traditional relation extraction mainly classifies text relations based on feature engineering classifier model. From a broader perspective, any knowledge representation based on graph can be regarded as a knowledge map. From the perspective of computer science, building a knowledge map includes four stages: information extraction, knowledge representation, knowledge fusion and knowledge reasoning [3]. The basic work of establishing an analysis framework is to select a deep learning model, and then develop a system based on this analysis model. For the events in knowledge extraction, it can be described as an event that appears in a certain place or region at a fixed time or time segment, with specific participants and more than one specific action, and often takes sentences as the division of events. The core of graph neural network is to realize the operations similar to traditional deep learning on graph data, such as convolution and pooling, so as to realize the learning of network structure.

Translation-based methods usually embed entities and relationships in knowledge map into a low-dimensional vector space, in which the embedding vector of the head entity plus the embedding vector of the relationship should be equal to the embedding vector of the tail entity. You can collect all kinds of entities, synonyms of entities, homonyms, concepts of entities, their contextual relationships and categories corresponding to entities through the relationship of its article pages [4]. The entity description is used as a supplement to the triple structure information, and the information fusion from different sources is realized. The purpose is to fully learn the semantic information of entity description, alleviate the data sparsity problem of knowledge map, and improve the representation ability of the model.

2.2. Event extraction

There are static and dynamic knowledge maps. Static knowledge maps are knowledge-oriented maps, while dynamic knowledge maps are activity-oriented dynamic things maps, which can track learners' mastery of knowledge. Traditional machine learning methods still rely on traditional external natural language processing tools such as dependency analysis, syntactic analysis and part-of-speech tagging
in the process of feature extraction, resulting in error accumulation. In the event knowledge map, this definition is also applicable, and the definition of master-slave event is added. Widely promoted the development of most research directions, such as relation extraction, entity extraction, knowledge representation learning, knowledge map completion, knowledge reasoning and so on.

Basic tasks in the field of natural language processing include lexical analysis, syntactic analysis and semantic analysis. Syntax analysis takes over the lexical analysis at the bottom, and makes use of semantic analysis after syntactic transformation. Knowledge map pays more attention to the relationship between entities in the real world, and pays attention to the hidden objects or things behind strings, rather than just the meaningless strings themselves. Many attributes are hidden in some semi-structured tables or lists, and one or more patterns can be constructed by pattern learning to realize automatic information extraction, but it needs to be improved by manual adjustment or new patterns [5].

3. Knowledge unit and its relationship recognition based on deep trust network

3.1. Deep confidence network

In the training process of deep confidence network, first, each layer of RBM network will be trained unsupervised to map the intrinsic features of data samples to different feature spaces, and then supervised training will be used to classify the previously learned feature combinations. Each entity and relationship is represented as a vector, and then the multi-dimensional matrix is used to obtain the relationship between entities and relationships. And use the score function of TransE to predict the entity.

In the hidden variable model, entities are represented as vectors, relations as matrices, and relations are regarded as second-order relations between entities, and the interaction between entities and relations is obtained, and its score function is shown in formula (1).

$$f_r(h,t) = h^T M_r t$$

(1)

The single-layer neural network model introduces the nonlinear transformation of neural network. It connects $h$ and $t$ as the input layer of nonlinear hidden layer, and then the linear output layer outputs the corresponding score as shown in formula (2). In which $f(x)$ is a common nonlinear activation function.

$$f_r(h,t) = u_r^T f(M_r^T h + M_r^t t + b_r)$$

(2)

The temporal method of deducing atlas represents time, entity and relationship in the same vector space, and constructs a scoring function similar to TransE for knowledge reasoning [6]. The main task of syntactic dependency analysis is to determine the syntactic structure of sentences and the dependencies between words. The relational path is regarded as the transformation between entities representing learning. At the same time, a path constrained resource allocation algorithm is designed to measure the reliability of the relational path, and entities are represented by semantic combination of relational embedding.

3.2. Relationship recognition of named entities
The purpose of dynamic knowledge map is to obtain the vector representation of all entities and relations of the triplets in the low-dimensional continuous space by learning the semantic information of measuring the triplet structure in the knowledge map. Entity relation refers to the semantic relations between entities, in which these semantic relations can be explicit or implicit. It can better solve the problem that the existing dynamic atlas model is difficult to reason highly concurrent events at multiple time points, and model the time correlation of dynamic atlas in the whole time domain. The data processing and knowledge reasoning module provides data model and relational model support; The vector representation of entities and relationships is obtained by minimizing the matrix of tensor multiplied by entities and relationships. Structured knowledge is extracted from Web data and stored in database. The key technologies involved are entity extraction, relation extraction, knowledge processing and so on.

In the experiment, the named entity recognition program based on deep trust network is written by using the deep learning package Theano in Python. The model consists of three hidden layers, and each layer has 1500 nodes. 80% of the data were used for training and 25% for testing. After comparing the experimental results (see Table 1) with the artificial neural network, it is found that the results of the deep confidence network are higher than those of the artificial neural network using shallow learning, which reflects the advantages of deep learning.

| Algorithm                  | Accuracy (%) | Recall rate (%) | F value |
|----------------------------|--------------|-----------------|---------|
| Depth confidence network   | 76.5         | 71.9            | 77.5    |
| Artificial neural net      | 71.8         | 70.3            | 72.1    |

The type of event trigger determines the type of event. Therefore, identifying the event trigger word can complete the event recognition. One way to complete knowledge map is to infer new knowledge from existing knowledge and complete missing links. Dynamic knowledge map can be used to solve this problem. Knowledge is shared and transmitted among learners. Instead of passive recipients, learners actively participate in discussions and seek information in the process of knowledge acquisition. They are committed to achieving common learning goals. Therefore, the advantage of knowledge map is to quickly delineate the attention range of an event. Promote the evolution of knowledge system. Finally, the knowledge presentation module uses the graph database to draw the knowledge map.

Multi-relationship proximity aggregator is an aggregation model, which is used to obtain the proximity information of the target entity under each timestamp, and aggregate the acquired proximity information to obtain the feature representation of the proximity field of the target entity [7]. The knowledge map only contains correct facts, and the unobserved facts are considered to be wrong. Based on this situation, it is considered that only the correct facts are contained in the triplet set of knowledge map. Then, the machine learning model can be used for processing, the similarity of feature vectors can be calculated, and the case relations can be classified. For example, unstructured data can be used normally only after being processed by natural language technology in most cases. The vector space representations are learned for them, and the true values of triples are fitted by the calculation between the vector space representations, so as to complete the knowledge map.
4. Evaluation of dynamic knowledge map construction model

4.1. Overall framework of model

In this paper, a dynamic knowledge map model based on convolution cyclic neural network and entity description is designed. There are two representations for each entity in the model, which are the representation based on triple structure and the representation based on entity description. In the recognition of entity relationship, entity pairs are regarded as analysis data, and character features, entity type features, relative position of entity pairs, context window features and other features are generally selected for discrimination. The accessibility query and substructure query of atlas are carried out by atlas retrieval technology. Reverse reasoning on the query results to get accurate data. Query the relevant matching data records in the specific knowledge base, and judge the authenticity of the new knowledge according to the score of correctness statistics. The core of this method lies in the number of words in the dictionary, forward and reverse reading directions and pattern matching rules. Dictionary-based word segmentation methods include forward and reverse maximum matching method, minimum segmentation method, bidirectional maximum matching method and so on.

Dynamic knowledge map drawing goes through three important steps: entity extraction, entity relation extraction and knowledge map visualization, as shown in Figure 1.

![Flow chart of dynamic knowledge map construction](image)

Figure 1. Flow chart of dynamic knowledge map construction

The problem of traditional methods lies in the lack of granularity of semantic understanding of text, such as coarse-grained emotional analysis of text, but unable to identify the object targeted by this emotion; However, there is no uniform standard for studying the relationship between two entities or more than two entities in one sentence [8]. Only the neighborhood information corresponding to the target entity to be predicted is reserved, which avoids the influence of neighborhood information of other non-target entities and makes the neighborhood information obtained by aggregator more accurate. Convolution cyclic neural network firstly extracts the features of entity description by convolution operation and maximum pooling operation, then extracts the word order information in entity description by cyclic operation, and finally obtains the semantic representation of the whole entity description.

4.2. Sequential event encoder
Dynamic knowledge map is essentially composed of events with time series, which has strong time dependence before and after events. Knowledge map constructs ontology, which is beneficial to the standardization of knowledge and subsequent processing such as query. The entity features here are similar to the word features identified by named entities, except that the character table based on words is changed into the character table based on entities. The model convolutes and loops the entity description, and can obtain the effective features and the context vector of the entity description. Knowledge map can assist public opinion analysis system to better understand semantics, and can analyze the objects targeted by text emotions by linking entities to entities in knowledge base; In this method, each word is regarded as an individual, and the words are formed into words by using the maximum entropy model, and the results with the highest scores are scored. The application range and accuracy of this method are higher than those of dictionary-based word segmentation method.

This system displays the results to users through Web pages. In the following, 2000 questions are randomly selected from the test set of Web Questions data set as the system input to test the operation response delay. Selected test cases and results are shown in Table 2.

| Use cases or others | Start event                                      | End event                                      | Response delay (ms) |
|---------------------|-------------------------------------------------|------------------------------------------------|--------------------|
| Problem pretreatment| Search request received in background           | Pretreatment of the problem is completed       | 803                |
| Problem understanding| The background receives the problem preprocessing result | Encode and express the problem dependency tree | 662                |
| Query statement generation | Problem coding completed                   | Generate query statements                  | 715                |
| Generation of answer information | Query statement generation completed       | Output the display results                   | 724                |

Table 2. Performance test cases

The role of pooling layer is down sampling, which reduces the number of parameters and improves the robustness of the model by removing unimportant samples. For example, when judging whether a person can form a role relationship with an institution, the entity pair must satisfy the requirement that one entity is a person name type entity and the other entity is an institution name type entity. In order to capture longer time-dependent information, time series event encoder uses long and short memory network [9]. Finally, the conceptualized knowledge in the domain is transformed into formalization, and a standardized ontology structure is formed. An input sequence is encoded into a context vector at the encoding end, and another output sequence is obtained at the decoding end based on the context vector. At the same time, the approximately aligned entity pairs are iteratively constructed and added into the entity alignment seed set to enhance the effect of the model.

One-step reasoning of knowledge map refers to deducing the missing components in fact triples based on observed knowledge. The embedding of entities and relationships is studied in a unified vector space, and the alignment is realized by the structural information of knowledge map. Learning
annotation model through large-scale corpus. With the development of deep learning, the deep neural network model combined with semantic understanding makes the task of named entity recognition achieve better results than before.

4.3. Vector space alignment module

In the vector space alignment module, corresponding vector representations are obtained from two vector spaces according to the aligned entity seed sets of two knowledge maps. The encoder mainly encodes an input sequence into a vector with a fixed length. For each time of the input sequence, a fixed-length hidden state vector expressing its own information can be obtained. Therefore, knowledge represents the distributed vector obtained by learning, which can be directly used for knowledge reasoning. By summarizing and inducing the rules of words in the training corpus, the model turns the task of word segmentation into the task of word classification, and uses the maximum entropy model to deal with it. From the perspective of algorithm, there are two different scenarios: one is based on rules, and the other is based on probability. Ensure that feature information is retained as much as possible when feature vectors are mapped to different feature spaces.

Relative position feature of entity pair: the relative position feature of entity pair can describe the positional relationship between two entities in the entity pair. The model calculates the score for each triplet in the knowledge map. For a correct triplet, the lower the score, the better. For a negative sample generated by a negative sample, the higher the score, the better. Adding neighborhood information of non-target entities affects the extraction of neighborhood features of target entities, which leads to the decline of prediction accuracy. If these features depend on the preprocessing of corpus, the better the preprocessing is, the better the recognition effect of entity relationship is.

5. Conclusion

To sum up, the future knowledge map will complement deep learning at more levels, and enhance the interpretability of deep neural networks. In this paper, the deep learning algorithm is introduced into the construction of dynamic knowledge map, and two machine learning tasks, named entity recognition and entity relationship recognition, are adopted to solve the two difficult problems of knowledge unit extraction and knowledge unit relationship extraction. The multi-relationship proximity aggregator is used to fuse the proximity information of the target entity, and the temporal correlation between events is obtained by using the time sequence event encoder. For a specific triple relationship, the attention mechanism will pay more attention to the relationship-related features in the entity description and assign a larger weight to them, thus representing the different semantics of the entity in different relationships.

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