Research on Spatial Conceptual Modeling of Natural Language Processing Based on Deep Learning Algorithms

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Abstract. From the point of view of computer science, especially artificial intelligence, the task of natural language understanding is to establish a computer model. This computer model can give the result of understanding natural language like human. An important aspect of natural language understanding lies in how to express knowledge to the computer, how to express knowledge, and how to establish the connection and reasoning between knowledge, that is, how to apply the brain's association, reasoning and selection process to the model of language processing. The physical structure and logical structure of modern computers are very clear, but what we need is a set of feasible formal thinking mechanism to enable machines to process natural language information. Deep learning is one of the areas of machine learning that is close to AI. It is analyzed by simulating human brain learning nerves. Deep learning is derived from the study of artificial neural networks and is a structure for learning deep nonlinear networks. By presenting complex function approximations, the input data is distributed and represented, and the ability of the data samples to focus on the essential characteristics of the data set is revealed.

1. Introduction

In recent decades, after statistical-based models have become non-mainstream methods of natural language processing, artificial neural networks, which are typical representatives of statistical methods, have not received enough attention in the field of natural language processing [1]. Of course, all this has changed since Hinton and others proposed in 2006 to learn deeply. Deep learning is the fastest growing field in the field of machine learning, which is to build deep neural networks to simulate the mechanism of human brain to explain and analyze data such as learning images, voice and text [2]. Strictly speaking, deep learning is another name for learning method based on deep neural network. The reason why in-depth learning has received high attention in academia is because of its breakthrough achievements in a series of important tasks of artificial intelligence [3]. At present, some achievements have been made in the application of natural language processing combined with depth learning model, and it has become one of the research hotspots [4]. Therefore, the concept of natural language processing space based on deep learning technology has very important research significance and application value [5].

With the advent of the multimedia era, the demand for visualization and convenience of human-machine communication has developed rapidly [6]. How to eliminate the obstacles of automatic conversion of natural language and graphic scenes has become a research hotspot in the 21st century [7]. Spatial concept modeling is a very basic problem in the study of Wenjing conversion. The research on automatic and effective natural language description space concept modeling method has important theoretical significance and practical value for natural language understanding and context conversion research. At present, we use natural language to describe spatial relationship as the research object, and gradually put together a set of spatial concept modeling scheme based on natural language description,
and deeply study the construction of spatial ontology library and spatial relationship extraction technology [8]. On this basis, the space placement of objects based on the two-step method is studied and realized [9]. The visual evaluation method based on t-test evaluates the scene of the space concept modeling prototype system, verifies the effectiveness of the small-scale space ontology library, and realizes the feasibility goal of the space concept modeling scheme based on natural language description [10].

2. Basic concepts and structural models of in-depth learning

2.1 Basic concepts of in-depth learning
The concept of deep learning originates from the study of artificial neural networks and is a structure for learning deep nonlinear networks. By showing the approximation of complex functions and using the distributed representation of input data, the ability of learning the essential characteristics of data set in data sample set is finally shown. Deep learning can more simulate neural activities in the neural layer, and combine low-level features to synthesize more abstract high-level attribute feature categories to better show data distribution characteristics. The theory of depth learning was put forward by Hinton in 2006. Through unsupervised greedy step-by-step training algorithm of depth net, it can provide better guidance for solving optimization problems related to depth structure.Lecun et al. proposed one of the earliest real multi-layer structure learning algorithms, namely convolutional neural networks. The training error rate is reduced by the relative number of parameters of the spatial relationship, and the training performance is improved. The problems that need to be solved by deep learning have some common features, such as the problem of insufficient depth, the process of understanding, layer by layer, and so on.

2.2 Structural Model of Deep Learning
According to the application of models and technologies, depth learning classifies models into three categories, namely, generative depth model, differentiated depth model and hybrid model. Generative model shows the high-order correlation characteristics of data by describing the joint probability distribution of observed data and corresponding categories. At the same time, it is different from the traditional neural partition network in that observation data labels are obtained through joint probability distribution, so that the prior probability and the posterior probability can be better predicted. Convolution neural network belongs to discrimination training, a real practical training algorithm of multi-layer network structure. Through the inspiration of neurons with the same parameters acting on the visual system structure, an invariable feature is generated at different positions on the upper layer. A hybrid model is the goal of distinguishing better, usually using a generated structure output. Hybrid structural model learning—generating and discriminative parts. Discriminative tasks are often used in existing typical generative units and are applied to classification tasks. Pre-training allows ownership values to be optimized by using a generative model in combination with other typical discriminative learning algorithms.

3. Advantages of Deep Learning in Natural Language Processing

3.1 Deep learning helps to develop new models
A good example is the use of a cyclic neural network that can learn and judge the output of ultra-long sequences. This method allows NLP practitioners to get rid of traditional modeling assumptions and achieve the most advanced results. Yoav Goldberg pointed out in his monograph "Neural Network Methods for Natural Language Processing" on NLP in-depth study that complex neural network models such as cyclic neural networks can bring new NLP modeling opportunities. He believes that in 2014 or so, the field has begun to see some success in the conversion from a linear model with sparse inputs to a nonlinear neural network model with dense inputs. Other changes are more advanced, requiring researchers to change their thinking and bring new modeling opportunities. In particular, a series of
methods based on cyclic neural networks alleviate the dependence on the ubiquitous Markov assumptions in the sequence model, allowing conditions on arbitrary long sequences and producing efficient feature extractors. These advances have contributed to breakthroughs in language modeling, automated machine translation, and other applications.

Building a probabilistic language model is to calculate the probability distribution of words. The problem can be simplified to calculate the conditional probability distribution of current words through context words, as shown in Eq. 1:

\[
S_j = \frac{1}{\sum_{i=1}^{n}(S_i)}(0 < (S_j) \leq 1)
\]  

Where: Sj represents the words in the vocabulary; N represents the probability distribution of the word r.

3.2 Developing and training end-to-end model capabilities for natural language problems

End-to-end model can not only improve the performance of the model, but also bring better development speed and simplicity. Neural machine translation is a large-scale neural network that attempts to learn to translate one language into another. In this network, we can train and optimize the whole end-to-end machine translation process. This trend away from manual customization model and towards end-to-end, sequence-to-sequence prediction model has always been the trend of speech recognition. The system that does this is called a neural machine translation system. Designing end-to-end models instead of designing processes for specialized systems is also a trend in speech recognition. Each component of speech recognition can be replaced with a neural network. The major chunks in the automatic speech recognition process are speech processing, acoustic models, pronunciation models, and language models. But because each component has its own neural network and different errors, it doesn't work well together. So this gives us the motivation to try to train the entire speech recognition as a large model. Depth learning The various types of errors in the end-to-end model vary with the training process, as shown in Figure 1.

![Fig. 1 The Change of Errors in End-to-End Model with Training Process in Depth Learning](image)

The conditional probability distribution of a word vector can be expressed as:

\[
E_2 = E_1 = \frac{E_m}{1 - \sqrt{v_f} (1 - E_m / E_f^2)}
\]

Where: Em=E3(-E(E2;f2)
For each layer of RBM training is to use the maximum likelihood estimation method to maximize the log-likelihood function of the word vector probability distribution:

$$HD = \frac{1}{L} \sum_{i=1}^{L} A_i \oplus B_i$$

HLBL language model training uses the method of contrast divergence in Eq. 3.

4. Typical Application of Deep Learning in Natural Language Processing

4.1 Natural Language Processing Oriented Deep Learning Platform Tool

Compared with the achievements made in the fields of image and voice, in-depth learning has not made a major breakthrough in natural language processing. However, it has also been applied in many related fields, such as part-of-speech tagging, syntactic analysis, word meaning learning and affective analysis, and has achieved good results. There are many deep learning platforms for natural language processing. According to different development languages, they can be divided into algorithm libraries or frameworks based on different programming languages such as Python, C++, C or Java. According to the different neural network models, they can be divided into components such as RBM/DBN, convolutional neural network, circular neural network and recursive neural network. According to different functional objectives, they can be divided into function libraries/toolkits that provide basic functions for deep learning, and different application frameworks for domain-oriented tasks based on function libraries. At present, there is no obvious breakthrough law in how to combine deep learning with the specific tasks of existing natural language processing. Therefore, this is the focus of research at this stage.

Evaluating a language model can be judged by calculating the confusing value of the model. The lower the confusing value, the better the effect of the model. The calculation of the confusing value is as shown in Eq. 4:

$$S(r_k) = \sum_{r \neq r_k} w(r_k)D_r(r_k, r)$$

4.2 Prospects of Research on Deep Learning in Natural Language Processing

The research work of in-depth learning for natural language processing is still in its infancy. Although the existing deep learning algorithm models such as recurrent neural network, recurrent neural network and convolutional neural network have played a significant role, there has been no significant breakthrough. There should be a very broad space for research on the construction of in-depth learning models suitable for natural language processing. In the current research on depth learning models, the difficulty is the optimization and adjustment of parameters in the process of model construction. Such as the depth of network layers, regularization problems and network learning rate. Generally speaking, the training speed of depth learning model is much slower than that of linear model. In addition, the larger the data set, the better the training results. This is very consistent with the current mainstream big data application trend. But this may also create obstacles to the optimization of learning models. Will the research enthusiasm for a better learning model be weakened in the pursuit of big data training?

5. Spatial Concept Modeling Based on Natural Language Description

5.1 Spatial Conceptual Modeling Prototype Framework

At present, conceptual modeling systems can be divided into two categories: script-based prototype systems and natural language-based prototype systems. The modeling system based on fixed-format phrases and similar high-level languages belongs to the prototype system based on scripts. Dialogue-based or text-based modeling systems belong to natural language-based systems. The script-based modeling system involves little or no understanding of the front-end natural language and mapping of discrete data to continuous data. The main focus is to solve the back-end scene modeling
problem, which is mainly determined by the clear format and clear meaning of the scripts it handles. The natural language-based modeling system mainly involves three aspects: the natural language understanding technology of the front end, the scene generation technology of the back end, and the mapping of natural language discrete data to continuous data of the graphic scene. The mapping of natural language discrete data to continuous data of graphic scenes should be based on the core problem of natural language modeling system, and it is also the current bottleneck problem. The main solution is the knowledge-based method. The sample mean and distribution based on the space modeling experiment are shown in Table 1.

| Evaluation conditions | Scene set | A     | B     | C     | D     | E     | F     | Average score |
|-----------------------|-----------|-------|-------|-------|-------|-------|-------|---------------|
| Closed test           | Subjective| 0%    | 44.14%| 55.26%| 0%    | 0%    | 0%    | 71.65         |
|                       | System    | 0%    | 16.65%| 48%   | 27.56%| 7.79% | 0%    | 58.42         |
|                       | Random    | 0%    | 0%    | 33.25%| 55.32%| 11.43%| 0%    | 48.86         |
| Open test             | Subjective| 0%    | 16.65%| 66.65%| 16.7% | 0%    | 0%    | 63.29         |
|                       | System    | 0%    | 16.65%| 48%   | 35.35%| 0%    | 0%    | 60.81         |
|                       | Random    | 0%    | 0%    | 16.65%| 48%   | 35.35%| 0%    | 41            |

5.2 Implementation of Spatial Conceptual Modeling Process

On the basis of known Chinese POS tagging results, conceptual modeling is a process of extraction and quantification. For a given chapter of the scene to be generated, it is first cut into substrings to obtain a substring set. Then, for each substring, the spatial expression boundary is identified cyclically to obtain a set of spatial expression boundaries. The boundary markers, position prepositions and position words are respectively identified within the boundaries of each spatial expression, thus the spatial expression extraction is completed and the spatial expression set is obtained. For each spatial expression, all corresponding projectiles are identified respectively to obtain spatial relations and form a set of spatial relations. For each spatial relationship, the spatial semantic disambiguation of the orientation words is first performed. Then calculate the range of the area corresponding to the emitters, and finally get the position and orientation of each shot based on the genetic algorithm. Loop through each spatial relationship in turn to get the coordinates and orientation of all entities. The entire conceptual modeling process is built around spatial relationships, so it is important to design a data structure that can express chapter-level spatial relationships.

After y is normalized by softmax, the output of the model is the probability of the standard classification label to which the word vector belongs. The training of the model can be expressed as finding the maximum value of θ for the following equation (5), where S is the weight attenuation penalty.

$$S_j = \frac{1}{\sum_{i=1}^{n} (S_i^j)}(0 < (S_j^j) \leq 1)$$

Eq. 5 can be directly optimized by random gradient descent method. In the process of optimizing the supervised neural network for this layer, the parameters of the entire depth neural network are fine-tuned to optimize the feature extraction capability of the neural network.

6. Summary

Natural language is an abstract condensed representation of human knowledge. In the process of expression, people will omit a lot of things due to the existence of background knowledge, which makes the expression of natural language more concise, but it also brings great challenges to the processing of natural language. In-depth learning will be a major issue in the field of natural language processing in the future. At present, in-depth learning has been widely used in natural language processing, sweeping all applications of natural language processing. There are in-depth learning models in almost all aspects such as word segmentation at the bottom, language model, syntax analysis, etc. at the top, semantic understanding, dialogue management, machine translation, knowledge question and answer, etc., and
good results have been achieved. The advantage of deep learning is the pre-training through large-scale unsupervised data, which effectively improves the performance of the depth model. Therefore, how to combine the linguistic prior knowledge with the excellent statistical ability of the depth model to obtain better performance is the future research direction.

References
[1] Vidyasagar V B R, Abirami S. Conceptual modeling of natural language functional requirements[J]. Journal of Systems and Software, 2014, 88:25-41.
[2] Ditzler G, Polikar R, Rosen G. Multi-Layer and Recursive Neural Networks for Metagenomic Classification[J]. IEEE Transactions on NanoBioscience, 2015, 14(6):608-616.
[3] Booth J, Eugenio B D, Cruz I F, et al. Robust Natural Language Processing for Urban Trip Planning[J]. Applied Artificial Intelligence, 2015, 29(9):859-903.
[4] Hoffman P, Binney R J, Lambon Ralph M A. Differing contributions of inferior prefrontal and anterior temporal cortex to concrete and abstract conceptual knowledge[J]. Cortex, 2015, 63:250-266.
[5] Clarke, Alex. Dynamic information processing states revealed through neurocognitive models of object semantics[J]. Language, Cognition and Neuroscience, 2015, 30(4):409-419.
[6] Rizzo D. Miscanthus spatial location as seen by farmers: A machine learning approach to model real criteria[J]. Biomass & Bioenergy, 2014, 66(7):348-363.
[7] Chen C F, Liu C M. The definition of urban stormwater tolerance threshold and its conceptual estimation: an example from Taiwan[J]. Natural Hazards, 2014, 73(2):173-190.
[8] Sandeep P, Narasimha B, Chuan-Hoo T. A Modeling Language for Conceptual Design of Systems Integration Solutions[J]. ACM Transactions on Management Information Systems, 2018, 9(2):1-25.
[9] Linden D V D, Proper H A, Hoppenbrouwers S. Conceptual Understanding of Conceptual Modeling Concepts: A Longitudinal Study among Students Learning to Model.[J]. Lecture Notes in Business Information Processing, 2014, 178:213-218.
[10] Bartzke G, Huhn K. A conceptual model of pore-space blockage in mixed sediments using a new numerical approach, with implications for sediment bed stabilization[J]. Geo-Marine Letters, 2015, 35(3):189-202.