Semantic Analysis and Construction of English Discourse Based on Intelligent CAD Tutoring Systems

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Abstract: In recent years, Neural network (NN) semantic analysis, as one of the intelligent CAD tutoring technologies, has become one of the hot tasks in English natural language processing. However, due to the limited development time of this task and the complex overall architecture, there is a lot of room for improvement in all parts of the system models. Meaning is the main content of discourse communication, and semantics is the essential attribute of discourse. Discourse semantics is the study of the meaning of language complex beyond sentences. At present, the semantic expression methods are mainly based on the hypothesis of statistical distribution, using massive texts and statistical modeling to represent the semantic information in natural language as a vector form with sparse high dimensions or dense low dimensions. In essence, the research object of semantic disambiguation is language. Therefore, applying the research results of linguistic phenomena and essence to semantic disambiguation will promote the development of semantic disambiguation to a deeper and wider extent. This paper adopts the technology and method of artificial NN, which has been widely used in the field of natural science, and makes use of the characteristics of NN, such as self-organization, adaptability, and high fault tolerance. Through the learning of large-scale real corpus, a semantic disambiguation model for English modal verbs may be constructed. The model finally achieves a disambiguation accuracy of 78% and achieves a relatively ideal result.

Keywords: Intelligent CAD Tutoring; Neural network; English semantics; Discourse analysis
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1 INTRODUCTION

With the development of natural language processing, people have made remarkable achievements in terms of words, phrases, and sentences. Discourse relationship refers to the semantic and logical relationship between two text units, such as causal relationship, turning relationship, juxtaposition relationship, etc. [1]. According to whether it contains discourse connectives, discourse relations are divided into explicit discourse relations and implicit discourse relations.[2]. Word sense disambiguation is a question of determining the meaning of words. In the field of traditional computational linguistics, semantics is usually defined in artificially constructed lexical semantic knowledge bases, such as various dictionaries and well-known WordNet [3].

The concept of artificial intelligence was first proposed in the 1950s. Generally speaking, artificial intelligence can be divided into two main schools. The first school is devoted to making machines behave like human beings and have human-like intelligence when dealing with various actual scenes. [4]. The topic of this paper belongs to the first genre. In fact, since the goal of making machines with human intelligence was conceived, it has experienced decades of development, and great breakthroughs have been made in many application fields [5]. All along, the research of cognitive intelligence is the core subject in the field of artificial intelligence. Its goal is to make machines have the cognitive understanding of natural language and the ability to make high-level cognitive reasoning on this basis [6]. At the same time, the reasoning problems involved in common sense scenarios can no longer be solved simply by simple operations such as knowledge base queries, but more efficient reasoning techniques are needed. In the past, semantic research on English modal verbs focused on semantic classification, syntactic features, and functional description. The research on semantic disambiguation of English modal verbs is limited to the description of semantic categories, syntactic features, and contextual features. [7].

In our previous work, we mainly studied the comprehensive analysis and semantic understanding of multimodal image features and achieved good results in image clustering and retrieval applications. However, its limitation is that it largely depends on the initial features selected manually while ignoring the automatic selection and optimization of features [8]. Although there are so many feature extraction technologies, it is still unable to solve the "semantic gap" between the low-level visual features of the image and the high-level semantics of the image [9]. Therefore, the traditional feature extraction methods have certain limitations and can not express the image features well [10]. This paper studies AMR semantic analysis based on NN. The idea of the NN method is derived from the simulation of the working process of the human brain. NN method generally refers to the machine learning method that uses NN, including multi-layer nonlinear transformation, to learn the abstract representation of data. In recent years, NN methods have been widely used in various related tasks in the fields of speech recognition, image processing, and natural language processing, and they have achieved great success.

This paper studies the semantic analysis of English discourse, which is structured as follows:

The first chapter is the introduction. This part mainly introduces discourse relations and related corpora, traditional supervised machine learning algorithms, related knowledge of deep learning, and systematic evaluation indicators of this paper. The second chapter is a summary of relevant literature, summarizing its advantages and disadvantages and putting forward the research ideas of this paper. The third chapter is the method part, focusing on the Convolutional NN(CNN), long-term and short-term memory NN, and NN based on the attention mechanism used in the semantic classification of emotional discourse relations. At different data sets and different semantic levels, the effectiveness of the NN based on the attention mechanism proposed in this paper is verified. The fourth chapter is the experimental analysis. In this part, experiments are carried out on data sets to analyze the performance of the model. Chapter five, conclusion and prospect. This part mainly reviews the main contents and results of this research, summarizes the research conclusions, and points out the direction of further research.

2 RELATED WORK

Discourse semantics is an interdisciplinary research field involving many related disciplines, such as discourse analysis, discourse linguistics, semantics, psycholinguistics, discourse understanding, cognitive linguistics, natural language processing, and so on. On the whole, the semantic research of discourse has a long history. This is a macro theory of discourse semantics put forward in the framework of discourse analysis. From the ontological point of view, the entity of discourse semantics has not been clearly put forward because the previous discussions of discourse semantics are all carried out as a topic of psychology or discourse analysis and only stay at the level of analyzing psychological phenomena or language phenomena, without defining the entity concept of discourse semantics at the level of philosophy and methodology.

Ambridge B and others designed the first system jamr to convert natural language sentences into AMR graphs. They proposed the first aligner to match the segments of words in a sentence with the corresponding concept nodes in the AMR graph and obtained an alignment result. On this basis, the semantic analysis system is trained for many subsequent works [11]. Groom n et al. Transformed Chinese discourse relations into English discourse relations from a bilingually aligned corpus and obtained artificially synthesized implicit discourse relations data. Similarly, they use a multi-task NN model for semantic recognition. Their multi-task model is relatively simple. A multi-layer fully connected NN is used to realize the semantic classification of a single task, and then the parameters between the main task and the auxiliary task are shared to realize the knowledge sharing between the main task and the auxiliary task [12]. Xiong Q uses a NN-based multitasking framework. They use CNN to realize the semantic recognition of implicit discourse relations between the main task and the auxiliary task and use an additional CNN to realize the knowledge sharing between the main task and the auxiliary task. In order to improve the performance, they also take the manually extracted discourse relationship features as the input of the NN [13]. Rachel H et al. Obtained a large amount of synthetic implicit discourse relation data according to explicit discourse connectives in the unlabeled data set, which is used as the training data of auxiliary tasks in multi-tasks, and the labeled implicit discourse relation data is used as the main task data set [14]. Meng y uses CNN to obtain the vector representation of two arguments respectively and then uses a cooperative NN based on mouth mechanism to realize the information interaction between arguments [15]. He proposed to automatically mine the syntactic features in the syntactic parsing tree based on the kernel holding method and combine them with other features (such as connective features, argument order distance, etc.) for semantic recognition of implicit discourse relationships [16]. Dapkus P analyzes the syntactic structure and dependency of implicit discourse relations and improves the recognition performance by introducing the structural features of sentences [17]. Inspired by the English discourse relations of pdtb, Shrivastava and others put forward a set of annotation methods for Chinese discourse relations [18] through in-depth analysis and combining the differences between English languages. The network structure of face recognition proposed by Rosewelt et al. uses about 120m training parameters. The reason why these large-scale network structures are so powerful is mainly due to the trainable model with a large number of parameters and the large training data set [19]. Huang Z believes that systemic functional linguistics regards discourse semantics as a study of the meaning of discourse beyond clauses and regards discourse as "a system in which text/discourse producers achieve social goals through the interaction between text/discourse (products) and their consumers" [20].

3 METHODOLOGY

3.1 Semantic Expression Method of Words Based on Multi-Source Information and NN Modeling

The semantic expression of natural language aims to solve the problem of how to make machines express and understand the semantics of natural language efficiently and reasonably. In computational linguistics, the study of semantics is ubiquitous. At first, semantic expression research is a semantic knowledge base method represented by the knowledge base defined by artificial experts. The most representative one is WordNet Knowledge Base. The semantic knowledge base defines the semantics of common words well, which has great research value. However, the existing semantic knowledge base expresses and defines semantics in the form of natural language. In the semantic expression of natural language forms, because of the complexity of natural language, it often brings great challenges to the semantic understanding of machines. Therefore, the current mainstream semantic expression methods usually express the semantics of words in the form of mathematical vectors, which machines easily process. They use natural text as the main source of information, and based on the statistical distribution hypothesis of word context, they learn semantic modeling. However, these methods, because they only rely on the context of words for semantic learning, often have some problems, such as inaccurate semantic estimation. Therefore, in order to solve the problems existing in the current mainstream semantic expression methods, this paper proposes two new semantic modeling methods. The first one is a semantic modeling method that integrates massive text and lexical-semantic knowledge. This method will learn from the advantages of existing semantic expression methods and learn the semantic information of words from the rich context provided by massive texts. The second is the semantic modeling method under the supervision of part-of-speech-related information. In the process of modeling and learning the semantics of words, this paper uses the part-of-speech information of words, designs the corresponding part-of-speech related weights, and provides a more accurate and effective information supplement for the expression of context. In some specific experiments, this method has also achieved good results.

The previous research work mainly focused on the subtasks of discourse analysis, such as the identification of discourse connectives, the semantic identification of explicit discourse relations, argument tagging, and the semantic identification of implicit discourse relations, which can be regarded as the research of isolated components in discourse analysis. Specifically, (1) In the explicit discourse relationship, for PS case (argl is in the previous sentence of the sentence where the Discourse Connective is located) and SS case (argl is in the sentence where the Discourse Connective is located), considering the different textual and grammatical characteristics of large and arg2, extract different features for large and arg2 respectively, and construct different argument extractors to mark arguments; (2) This paper introduces more features to improve the classification performance of the text parser.

Figure 1 shows the framework of the English discourse parser system designed in this paper, which consists of 10 components. Firstly, the explicit discourse parser is used to identify the explicit discourse relationship in the text. For texts with explicit connectives: (1) Connective classifier: judge whether the connectives are discourse connectives or not. (2) Argl position classifier: determining the relative position of Argi, that is, judging whether Argl is in the sentence where the discourse connectives are located (SS) or in the sentence before the sentence where the discourse connectives are located (PS). (3) For SS, use the SSA RGL extractor and SSA ARG2 extractor to mark ARGL and ARG2, respectively. (4) For PS, use PSA RGL and PS ARG2 extractors to mark ARGL and ARG2, respectively. (5) After obtaining the arguments of explicit discourse relations, this paper uses an explicit semantic classifier to identify the semantics conveyed by explicit discourse relations.

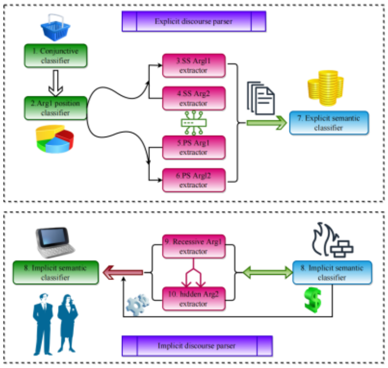


Figure 1: Framework of English text parser system.

Then, for each pair of adjacent sentence pairs in each paragraph that are not recognized as explicit discourse relations: (1) Use implicit semantic classifier to identify the implicit discourse relations contained in each sentence pair; (2) Because of the textual relationship of enteral semantics, the former sentence is directly regarded as argl and the latter as arg2. Therefore, if the output of the implicit semantic classifier is entered, this paper uses the first sentence in the sentence pair as large and the last sentence as arg2. Otherwise, implicit argl extractors and implicit arg2 extractors are constructed to extract argl and arg2 for non-enterl relationships in implicit discourse relationships, respectively.

3.2 English Semantic Analysis Based on NN

Reasoning is an important field of research in artificial intelligence. In the past decades, this topic has been paid close attention to, and academic circles have done a lot of exploration work in the field of reasoning. This paper will not examine traditional logical reasoning but focus on the current mainstream field of probabilistic reasoning. At present, the mainstream probabilistic reasoning methods mainly include Bayesian Networks' Markov Logic Networks and other graph models. Taking Bayesian Networks as an example, this method models natural events in a predefined graph structure and calculates the posterior probability of events based on Bayesian theory. However, the existing methods, in actual tasks, will face great efficiency and scalability problems due to the increasing number of possible events to be handled. Continuous vector space, which has good semantic smoothing ability. Therefore, this paper can effectively organize and link a large number of discrete natural events involved in reasoning through the current mainstream semantic expression model. Based on the idea of semantic expression in continuous space, a series of similar works have been produced in academic circles at present. The representative work is the representation modeling of the knowledge base. The main goal of this paper is to use NN to calculate the conditional probability between any two discrete events and E_2, namely $\Pr(E_2|E_1)$. Therefore, Nam model can be used as a general framework for probabilistic reasoning. As shown in Figure 2.

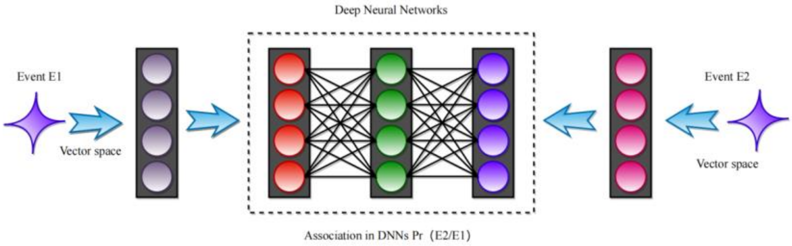


Figure 2: Main technical framework of Nam model.

Figure 2 shows the general framework of the NAM model for linking two discrete events E_1 and E_2. In the technical framework shown in the figure, based on the semantic expression model, two events will be represented respectively in the corresponding low-dimensional continuous space. On this basis, the deep NN will be used to model the association relationship between events. The NN takes the event theory as input and calculates the probability of another event $\Pr(E_2|E_1)$. In fact, the physical meaning of conditional association probability $\Pr(E_2|E_1)$ will be different in different tasks. Table 1 shows an application scenario of NAM model.

Application	E_1	E_2

Language modeling	h	ω
Causal reasoning	$cause$	$effect$
Knowledge triple classification	e_i, r_k	e_j
Lexical entailment	W_1	W_2
Textual entailment	D_1	D_2

Table 1: Typical application scenarios of NAM model.

In the language model, the event E_1 corresponds to the history above, h, while the subsequent possible event E_1 corresponds to the next word ω that appears immediately above. The value of a word may contain several different values, which are mainly determined by the dictionary. In causal reasoning, E_1 and E_2 will correspond to "cause" and "effect" respectively.

Suppose there are N_d observation samples, each of which corresponds to an event pair. This paper does not regard its table as a sample. Concentrated samples include positive samples and negative samples. Each sample corresponds to one label, the label of positive sample is $y_n = 1$, and the label of negative sample is $y_n = 0$. Meanwhile, the set of all positive samples is represented as D^+, and the set of negative samples is represented as D^-. Based on the unique distribution hypothesis in the field of statistical relational learning, the training objective function of NAM model can be expressed as follows:

$$\varsigma(\Theta) = \sum_{x_n^+ \in D^+} \ln f(x_n^+;\Theta) + \sum_{x_n^- \in D^-} \ln(1 - f(x_n^+;\Theta)) \tag{1}$$

3.3 Radial Basis Function NN

In the task of natural language processing, we need to model sentences. Here, it is necessary for the model to be able to model the context persistently. At present, we widely use recurrent NN in many tasks in the field of natural language processing. Its network structure contains cycles and supports the persistence of information. RNN has many variants, such as long-term and short-term memory networks, GRU, etc. In the semantic analyzer based on transition, we need to predict the transition action that is most likely to be executed in the transition state according to the transition state. Previous studies have used NN as the classifier of this transition system, and it has proved to be very effective.

In order to overcome the poor applicability of BP NN in English semantic analysis, radial basis function (RBF) NN is introduced. As shown in formula (2),

$$\begin{aligned}
&h_j = \exp\left[\frac{\left\|x - c_j\right\|^2}{2b_j^2}\right] \\
&c = \left[c_{ij}\right] = \begin{bmatrix} c_{11} & \dots & c_{1m} \\ \dots & \dots & \dots \\ c_{n1} & \dots & c_{nm} \end{bmatrix} \\
&b = \left[b_1, \cdots, b_m\right]^T \\
&y_m = \sum_j^m w_j h_j
\end{aligned} \tag{2}$$

As shown in formula (3),

$$E(t)=\frac{1}{2}(y(t)-y_m(t))^2 \tag{3}$$

First, update the weight w, as shown in equation (4).

$$\begin{aligned}\Delta w_j(t) &= -\gamma\frac{\partial E}{\partial w_j}=\gamma(y(t)-\gamma_m(t))h_j\\ w_j(t) &= w_j(t-1)+\Delta w_j(t)+\delta(w_j(t-1)-w_j(t-2))\end{aligned} \tag{4}$$

Next, update the width b, as shown in equations (5) and (6),

$$\Delta b_j(t)=-\gamma\frac{\partial E}{\partial b_j}=\gamma(y(t)-y_m(t))w_jh_j\frac{\left\|x-c_j\right\|^2}{b_j^3} \tag{5}$$

$$b_j(t)=b_j(t-1)+\Delta b_j(t)+\delta(b_j(t-1)-b_j(t-2)) \tag{6}$$

Finally, the center coordinates c are updated, as shown in equations (7) and (8),

$$\Delta c_{ji}=-\gamma\frac{\partial E}{\partial c_{ji}}=\gamma(y(t)-y_m(t))w_jh_j\frac{x-c_{ji}}{b_j^2} \tag{7}$$

$$c_{ji}(t)=c_{ji}(t-1)+\Delta c_{ji}(t)+\delta(c_{ji}(t-1)-c_{ji}(t-2)) \tag{8}$$

In equations (4) to (8), γ is the learning rate of the model, and δ is the momentum factor of the model. Its range is (0,1), which is used to adjust the speed of gradient decline in the process of model learning and avoid falling into the local optimal solution in the process of learning.

4 RESULT ANALYSIS AND DISCUSSION

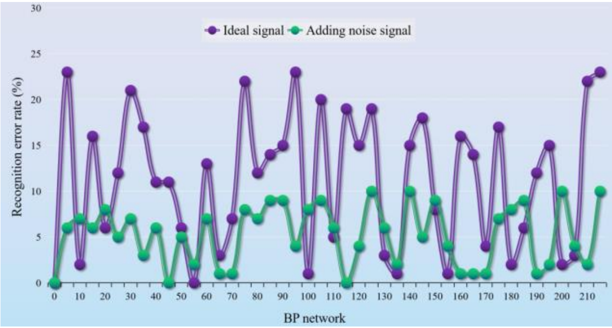
For pdtb data set, the experimental results of binary classification based on NN method and benchmark system on the first semantic level of implicit discourse relations are shown in Table 2.

	Comp.	*Cont.*	*Exp.*	*Exp.*	*Temp*
Benchmark system	38.71	52.52	69.45	70.43	26.25
CNN	34.21	56.21	67.12	78.21	23.01
LSTM	32.15	56.14	66.34	77.12	30.55
Bi-LSTM	33.51	58.59	64.22	72.23	29.98
Attetion	34.59	52.33	63.59	79.54	34.29

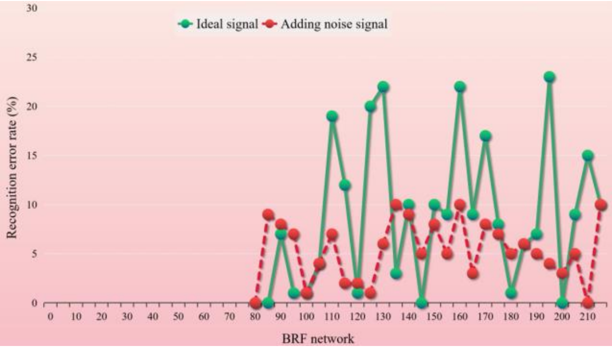
Table 2: Experimental results of binary classification based on NN method on RBF, F1(%).

From the table, this paper can draw the following conclusions: (1) In the model based on NN, CNN achieves better performance than LSTM/BI-LSTM. The possible reason is that CNN can better extract N-gram features from sentences. The word (or phrase or fragment) pairs between two arguments play an important role in the final classification of discourse relations, such as antonym pairs; (rise, fall), (good, bad), etc. (2) Comparing the experimental results of LSTM and BI-LSTM, it is found that the performance of BI-LSTM is generally higher than that of LSTM. This is consistent with the research of "Yi Huan Zhu Qiao" because BI-LSTM considers both forward and backward context information, while LSTM only considers forward information. (3) Introducing an attention mechanism into BI-LSTM greatly improves classification performance. The NN based on attention mechanism (ATTENTION) is superior to the NNs using simple splicing methods (CNN, LSTM, and BI-LSTM).

In order to better evaluate the performance of the RBF network, BP NN is used for a comparative simulation test. Figure 3 (a) and (b) respectively show the change in recognition error rate of BP and BRF networks for the training set with the noise level.



(a)



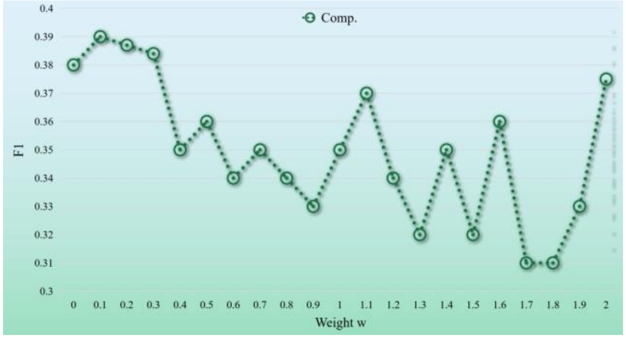
(b)

Figure 3 Relationship between word vector dimension and F1 training time.

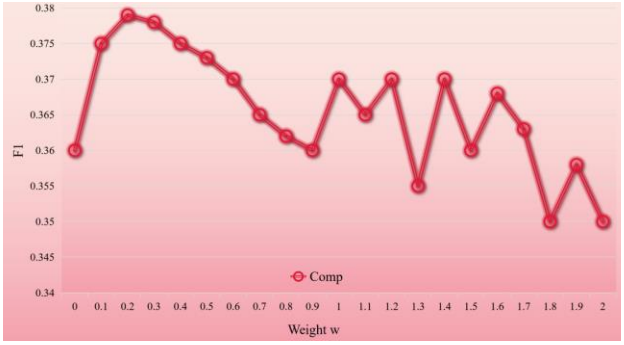
In Figure 3, the solid line is the change of the error rate during the test with the test data set plus noise after training with the ideal signal.

In the training process of the CNN model, different regularization methods have different effects on the experimental results in this paper. On the cifar-10 dataset, this paper uses cifar 10_ Net CNN. This is a CNN with three convolution layers and two full connection layers. Through the experimental comparison of different regularization methods, the regularization method with the best performance is selected. The performance of the multi-task NN model is generally better than that of the single-task model. This shows that using the multitasking method and a large number of synthetic implicit discourse relation data can help improve the performance of semantic recognition of implicit discourse relation and thus make up for the shortage of manual annotation data. Fig. 4 shows the change in the performance of the four dichotomous models on the PDB dataset with W in the weighted sharing model.

From the experimental results, it is found that with the increase in the amount of training data, the test effect improves, which is in line with the training law of the model. At the same time, the man model performs better than the DNN model.



(a)



(b)

Figure 4: In the weighted sharing model, the performance of two binary classifications on the PDB dataset changes with W.

Furthermore, this paper makes a bolder knowledge transfer learning experiment. After training the basic model, this paper will not only update the relation code but also update the linkage parameters of the whole network when training the target knowledge type with its corresponding data. The experimental results based on this configuration include the results on two sets. One is the performance of the model on the test set corresponding to the target knowledge type, as shown in Figure 5.

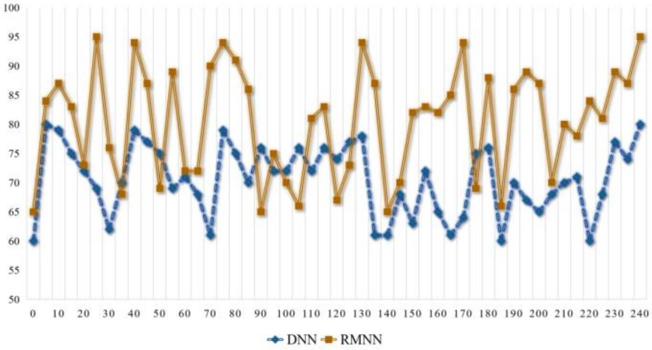


Figure 5: Experimental results of updating all parameters in knowledge transfer learning.

It can be seen from the results in Figure 5 that this strategy can quickly improve the performance of the model on the target type. The lifting speed of DNN is obviously faster than that of RMNN, and the highest performance reaches 94.6%. However, on the test set corresponding to the remaining 13 knowledge types, DNN reduced its performance from 85.6% to 75.5%. Actually, this also means that DNN has some shortcomings in controlling over-fitting. Comparatively speaking, the RMNN model is more stable, which improves the accuracy of the target type from 77.9% to 90.8%, while not seriously reducing the performance of the model on the remaining types (only from 85.9% to 82.0%).

The other is the performance on the remaining CN14 test set except the target knowledge type, as shown in Figure 6.

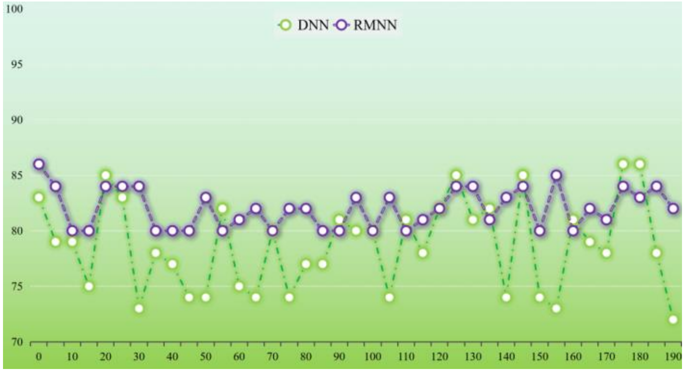


Figure 6: Test result B of updating all parameters in knowledge transfer learning.

In the previous content, this paper proposes three pieces of work, namely, natural semantic expression with words as the core granularity, common sense reasoning with Event Association modeling as the core, and automatic construction of common sense knowledge on massive texts. In fact, these three pieces of work are not separated but closely connected. In the field of artificial intelligence, the most famous cognitive intelligence evaluation task is the Turing test proposed by Alan Turing in the last century. This simplification enables Turing to convincingly explain that "Thinking machine" is possible. Although in the process of research and analysis of the Turing test, some programs claimed to have passed the Turing test. However, later, it was found that this software tended to mistakenly guide testers to think that they behaved like humans by avoiding problems, cheating, and other means. Therefore, the problems existing in the Turing test have gradually been a concern for researchers, and the most critical problem among them. The reason is that the Turing test needs to introduce human subjective evaluation instead of providing an objective evaluation standard. Winograd "schema" challenge "evaluation was proposed by Levesque et al., which is abbreviated as WSC in this paper. This task aims to examine the machine's ability to think in a common sense. The specific evaluation mode is based on the standard reference resolution problem. Compared with the Turing test, the evaluation is more efficient and reasonable because it does not rely on manual subjective evaluation. As the evaluation organization said, it is very time-consuming and difficult to design a large number of WS test problems in a short time, which is why the current public test set only contains more than 200 problems. At the same time, due to the complexity of solving the WS problem, only a small amount of work has been publicly reported that experiments have been carried out on it "Bailey et al. Schiller", "Sharma et al.". These works use traditional logical reasoning methods, and only solve a small number of WS testing problems. In order to clarify the performance of the Nam model on WS tasks in more detail, this paper compares and analyzes the result performance of the Nam model under different model sizes. This paper also gives the statistical significance test results of each model and random guess. It can be seen from the results that all Nam models of different sizes have achieved an accuracy of more than 60%. At the same time, their corresponding significance test results are less than 0.05. This proves that the neural association model trained based on the set of causal phrases automatically constructed in this paper is stable on the Winograd schema test set. Further, when the number of hidden layers is set to 3, the model achieves the optimal performance.

5 CONCLUSIONS

Cognitive intelligence is not only the frontier field of artificial intelligence research but also a hot field that has received extensive attention due to the rapid development of computer and big data technology. Natural language semantic expression and common sense reasoning are the key tasks in realizing the cognitive intelligence of machines. However, the current methods of natural language semantic expression and common sense reasoning still have some problems, such as low accuracy and poor generalization. A reasoning method based on a knowledge-enhanced semantic model is proposed. The semantic word vector technology is used to integrate common knowledge into the word vector construction process, and unsupervised semantic feature extraction and reasoning are realized in the absence of task-related training data. The system constructed by this method achieved the best performance in the Winograd Schema Challenge evaluation in 2016. This paper mainly studies discourse analysis based on deep NN, including the construction of an English discourse parser, a Chinese discourse parser, semantic recognition of implicit discourse relations based on NN, and semantic recognition of implicit discourse relations based on multi-task NN.

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