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Text Reasoning Chain Extraction for Multi-Hop Question Answering

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Abstract: With the advent of the information age, it will be more troublesome to search for a lot of relevant knowledge to find the information you need. Text reasoning is a very basic and important part of multi-hop question and answer tasks. This paper aims to study the integrity, uniformity, and speed of computational intelligence inference data capabilities. That is why multi-hop reasoning came into being, but it is still in its infancy, that is, it is far from enough to conduct multi-hop question and answer questions, such as search breadth, process complexity, response speed, comprehensiveness of information, etc. This paper makes a text comparison between traditional information retrieval and computational intelligence through corpus relevancy and other computing methods. The study finds that in the face of multi-hop question and answer reasoning, the reasoning data that traditional retrieval methods lagged behind in intelligence are about 35% worse. It shows that computational intelligence would be more complete, unified, and faster than traditional retrieval methods. This paper also introduces the relevant points of text reasoning and describes the process of the multi-hop question answering system, as well as the subsequent discussions and expectations.

Key words: multi-hop quiz; text reasoning; document retrieval; intelligent computing; text complex network

1 Introduction

With the rise of deep learning, text reasoning technology based on deep learning has received widespread attention. However, how to make machines master human knowledge and perform interpretable reasoning in the process of text reasoning is a major challenge faced by current technology. With the advent of the age of scientific and technological information, it is particularly important to quickly find the information that customers want in complex information. The knowledge data spectrum is constructed in the form of a tripartite group to store huge information. A tripartite can be expressed as $\{A, B, C\}$: A represents the initial entity; B represents the structural entity; and C represents the relationship that exists between the two. The knowledge data spectrum describes the huge Internet information into understandable meaning expressions in the current world. With strong semantic description, preservation, and expression capabilities, it has received key attention in various academic circles and has become a special research application.

The intelligent question answering system is mainly aimed at the complicated information given by people, allowing users to ask questions in a natural language description method and to collect accurate answers for

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users. Because of the rapid development of knowledge data spectrum technology, the questioning of knowledge data spectrum has become more able to understand semantics. This paper aims to investigate the gap between traditional information retrieval and computational intelligence in text reasoning capabilities through corpus correlation and other computational methods, with the hope of greatly promoting the application and development of text reasoning technology.

Multi-hop knowledge answering reasoning takes the latest research approach and divides these methods into three categories, including embedded multi-hop knowledge question answering reasoning, multi-hop knowledge question answering reasoning asking for directions, and thinking logic multi-hop knowledge question and answer reasoning. The embedded multi-hop knowledge question answering reasoning method is to connect the knowledge data spectrum elements to a relatively low-dimensional continuous vector space and then to analyze the corresponding targets through function operations or encoders. However, the multi-hop knowledge question answering reasoning method of asking for directions first needs to determine the subject entity in the question and then randomly walks on the knowledge graph to find the answer entity. The thinking logic multi-hop knowledge question and answer reasoning method is a hot research method mainly based on first-order logic. This paper classified them to obtain results, as shown in Fig. 1.

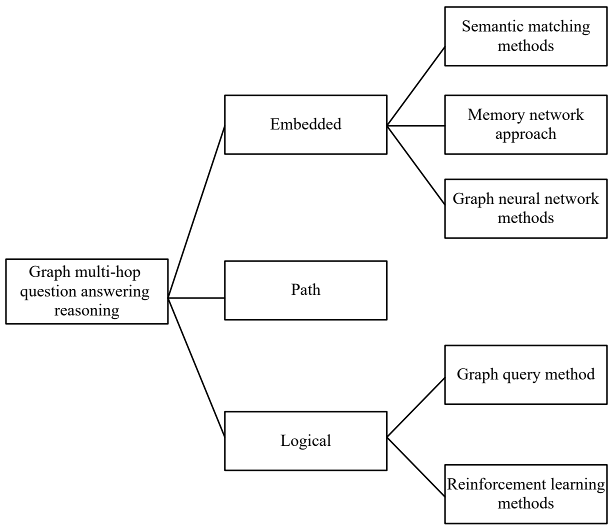

Fig. 1 Classification of multi-hop question answering reasoning methods based on knowledge data spectrum.

2 Related Work

For the study of textual reasoning, Tsai and Wilkinson[1] examined a Chinese teacher. He conducted a group discussion experiment on narrative texts with five Chinese-American students aged 13 to 15 in a Chinese community school classroom. Textual reasoning promotes students' higher-order thinking skills and reasoning processes. The findings suggested that the implementation may change the nature of classroom discussions in Chinese community schools[1]. Reasoning is often based on highly analytical and intuitive processes. Liem[2] studied osteopathic clinical and diagnostic decision-making and showed that the intuition and analytical processes that lead to decision-making are equally important in diagnostic reasoning.

Multi-hop neurophilosophy is understood as a different field of philosophy in terms of applying computational intelligence to multi-hop question answering, such as the philosophy of neuroscience, the philosophy of artificial intelligence, or the elimination of materialism. This interpretation of terminology is due to the still incomplete understanding of the subject area of the subject. Bezlepkin and Zaykova[3] analyzed the terms "philosophy of neuroscience" and "philosophy of artificial intelligence", and provided variants of their distinction. It was concluded that the overall use of the term "neurology" should be abandoned[3]. In order to synthesize prior work to procure, corroborate, contextualize, and identify key strategies required for learning from multiple texts, the study of List and Du[4] examined multiple text-processing and written-response compositions of students under three different heuristic conditions. The results showed that students who were instructed on purchasing not only obtained more document information but also included more information in their notes. Drivers appeared to be consciously choosing and rejecting certain traffic situations suitable for texting. However, it was still unclear which situational characteristics the driver considered when making this decision. Petzoldt and Schleinitz[5] were looking at how to better understand drivers' reasoning when deciding to text and how the surrounding environment affected that reasoning.

For the role of artificial intelligence in text reasoning, Schlottfeldt et al.[6] believed that intelligence is a complex behavioral phenomenon that needs further research on a biological basis. Using a cognitive working memory task, it investigated differences in P300 Electroencephalogram (EEG) patterns in multi-hop question answering between average and high-intelligence Brazilian children. The latencies and amplitudes of these peaks were analyzed by repeated measures Analysis of Variance (ANOVA), and the groups differed in response time but with different levels of response accuracy[6]. For text reasoning in artificial intelligence and data mining, Kotelnikov[7] discussed general scenarios for building different artificial intelligence and data mining systems. This scheme interpreted various intelligent techniques as various kinds of reasoning[7].

3 Method of Text Reasoning Chain Extraction

3.1 Introduction to textual reasoning chains

Text representation is the basis of text exploration. Modern text is usually represented by the vector space model method. Although this method has the advantages of strong practicability, simple operation, etc., it is irrelevant to the assumed special words, so it is easy to cause the relationship between words and the loss of text content information. When dealing with a large amount of data information, there are also problems requiring high-dimensional performance and looseness, which can easily lead to the correlation between words and the omission of internal information of the text. Besides, when processing big data information, there is also the problem of requiring high-dimensional characteristics and loose characteristics. These problems all have a certain negative impact on the subsequent literature mining and exploration[8]. However, in recent years, due to the new discovery of the complex network characteristics of words in traditional Chinese, relevant researchers have also carried out in-depth research on the characteristics of complex network texts, focusing on the research on the interrelationship between words and, on this basis, constructing a research platform for complex text networks. This method can locate the words in the text at the nodes in the complex network and define the relationship between them as the edge to preserve the semantic connection between the words. According to whether it affects the weight of the edge, it can be divided into two kinds of networks, unweighted network and weighted network. Although the method of complex network is used, which can well store the correlation between text information and words, its main disadvantage is that in the construction of complex text networks, the construction method of edges can only be the co-occurrence method of numbers and words, and its effect is relatively limited. Moreover, most construction methods cannot be realized, because the calculation of semantic relationship between words is mainly based on the method of corpus, which cannot reflect the actual and objective semantic connection between the numbers and words due to the high degree of influence of the corpus, causing deviations in the text structure and affecting the results of complex network text expression[9].

In view of the above problems, at the beginning of the research, this paper adopts the correlation calculation method which is different from the coexistence frequency words in the text expression method of the redundant network. Using Wikipedia as the data source, other related data such as categories, meanings, and their connections are extracted for related calculations to accurately estimate the semantic connections between words, so as to build the relevant calculation method of the text-weighted redundant network and improve it to improve accuracy. Combining with the characteristics of the weighted degree of the nodes in the redundant network, a text operation method different from the redundant network is proposed. The experimental results showed that the redundant network had a better effect on the text representation than the vector space template text representation[10].

3.2 Text-related theory

3.2.1 Single text lengthy network description

A verbose network can be a system covered under content and structure, where a single or special phenomenon is called a node, and the relationship under study is called an edge connection. It simplifies the system as a whole through a view. The elements in the process are called morphemes, and the relationship between words and words is defined as correlation[11]. Generally, the relationship between the two includes: coexistence, concept, and grammatical relationship. In Table 1, 1 means the relationship is covered, and 0 means no coverage relationship. The redundant network coverage relationship is shown in Table 1.

3.2.2 Quantification of word-meaning relationships

Relationships in words are generally divided into three

Table 1 Redundant network coverage.

Relationship between nodes	Single text-heavy network	Complex text-heavy network	Word relation quantification
Co-occurrence relationship	1	1	0
Concept synonym	1	1	0
Syntactic relation	0	0	1

types, approximate, related, and sibling relationships. Generally appearing in the dictionary, the common method in the corpus is the approximate relationship, which is also a common processing method. Not counting the connection of measurement, the similarity of words and the connection of semantics are also different. The two represent different meanings have different properties. With interchangeability and irreplaceability, their meanings will also reflect different meanings in the text. The words are interchangeable. The semantics are irreplaceable, and their connection also determines whether they have the same properties. The two are also similar in meaning and do not have contradictions, but they are independent. They are generally irreplaceable such as general causal words. It has the characteristics of mutual intervention, such as mutual contradictory or independent words, causal correlation, etc. The relationship between them is generally irreplaceable, such as landslides and ground fissures.

In the exploration of lexical related operations at home and abroad, it is mainly based on the corpus method, which is based on a large range of lexical data for statistics. Computational information such as frequency and probability effects in the corpus are important parameters for operations related to lexical meaning. In addition, in the algorithm of understanding, it is mainly to replace the meaning of words according to the relationship between words. This requires understanding its similarity. Similarity is a relationship related to sense, not words, so when we measure it, we measure it based on a certain meaning of a word, such as bank being similar to fund. However, we will calculate similarity based on both words and meanings. According to the operation method on the concept of the word, it can be obtained whether it is replaceable. However, both the current number of occurrences in the dictionary and the iteration speed are low, resulting in unsatisfactory application, so the calculation is mainly performed on the similarity[12].

The current methods to connect their relationships are mainly covariance, information exchange, and coexistence frequency. Coexistence frequency is a common method for word relatedness currently. Its principle is as follows. According to the frequency of two similar words appearing in the thesaurus, they show a proportional relationship, with the same increase and the same decrease.

$$W_{ij} = \log\left(1 + \frac{\mathrm{fre}(t_i, t_j)}{\mathrm{fre}(t_i) + \mathrm{fre}(t_j) - \mathrm{fre}(t_i, t_j)}\right) \tag{1}$$

where $\mathrm{fre}(t_i, t_j)$ represents the number of occurrences of these two feature word generation unit windows. $\mathrm{fre}(t_i)$ and $\mathrm{fre}(t_j)$ represent the total number of times t_i and t_j existing in the text, respectively. If the $\mathrm{fre}(t_i, t_j)$ is larger, it means that the two characteristic words are more related, and the closer they are to synonyms. If $\mathrm{fre}(t_i, t_j)$ is smaller, it means that the correlation between the two words is very small, which can be said that there is no relationship.

However, there are still problems in the calculation process, as shown in Table 2 (0 means not conforming and 1 means conforming).

(1) According to the operation result, the final result is 0, indicating that the results do not match.

(2) The result of the correlation degree is interfered by the few words, causing the result of the correlation operation to be close to 0, which is also inconsistent with the result. It also can be excluded.

(3) In the case where the value obtained by the operation result is relatively small, it is not conducive to distinguishing the relationship.

Therefore, as can be seen from Table 2, the compliance of the operation results is not very ideal, and the results are compliant only when the correlation is disturbed.

3.3 Text complex network model construction

3.3.1 Textual complex network correlations

The words in the text directly form a text according to the existence of a certain relationship, not in a free

Table 2 Result of the operation conforming to the situation.

Result of the operation	In line with the situation	Non-compliance	Suitable
Result is zero	1	0	0
Correlation is disturbed	0	0	1
Operation value is too small	0	1	0

state. In particular, sentences with specific meanings in the text can only have the function of transmitting information after being combined so as to form new sentences with new meanings, such as paragraphs and whole sentences. The traditional model does not have the relationship between words, which can easily lead to insufficient expression of the meaning of the whole sentence. In the complex text network, the newly-built weighted network is the most accurate and objective, which can express the correlation between sentences and perform correlation operations through Wikipedia[13].

In this paper, the text-weighted complex network is formally expressed as

$$G = (N, E, W) \tag{2}$$

where N represents the set of nodes. Then Eq. (3) can be got as follows:

$$N = \{n_1, n_2, n_3, \ldots, n_k\} \tag{3}$$

where $\{n_1, n_2, n_3, \ldots, n_k\}$ represents the feature-related words after preprocessing. E represents the set of edges in the weighted complex network, as shown in Eq. (4).

$$E = \{e_{ij} = (n_i, n_j) | n_i, n_j \in N\} \tag{4}$$

where E represents the weight set of the edge, as shown in Eq. (5).

$$W = \{w_{ij} \mid i, j = 1, 2, \ldots, k\} \tag{5}$$

where w_{ij} represents the weight of edge e_{ij}. The complex network text representation process is shown in Fig. 2. Constructing a new text requires weighted network nodes and edge connections and the corresponding characteristic words. Their relationship is mutual influence and close. The weight plays a decisive role in the association between words, and the larger the value is, the greater the correlation will be.

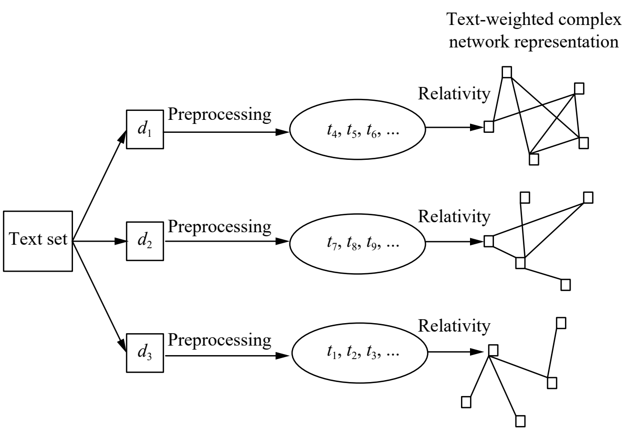

Fig. 2 Complex web text representation process.

New words, popular words, abbreviations, or specialized words that appear in modern times cannot be recognized by general dictionaries because these do not appear in traditional databases. Wikipedia can solve the problem very well. Because of its extensive knowledge and database, it has a high degree of stability and is also in line with the principle of operation, which can make it get rid of the dependence on the corpus, making the calculation result more realistic.

(1) Mapping t_i and t_j in Wikipedia is defined as topic concepts c_i and c_j. When the mapped words t_i and t_j are repeated, the resulting definition is redefined.

(2) When the concept cannot be obtained by calculating the relationship value, quantization is performed, and the coexistence frequency cannot be determined.

If the result of the operation in Step (1) is consistent, the judgment method of the concept connection distance can be obtained as follows:

(1) Link distance

The concept of link distance is defined as c_i and c_j, and the distance formula between them is calculated as

$$D_{\text{link}} = \frac{\log(\max(|O|, |Q|)) - \log(O \cap Q)}{\log(|W|) - \log(\min |O|, |Q|)} \tag{6}$$

where D_{link} is the semantic distance between concepts c_i and c_j. O and Q are concept sets that are linked to concepts c_i and c_j in Wikipedia, respectively. W is a collection of all concept explanation pages in Wikipedia. The symbol "$|\cdot|$" means to take the number of entities in the set[14].

(2) Category distance

In the future, the factors that affect the correlation are reduced, and on this basis, the obtained distance is used to determine its correlation. Determine the category to which it belongs and use the minimum distance as the category distance. The equation for calculating the category distance between them is shown as

$$D_{\text{cat}}(c_i, c_j) = \log(\min(d_{ij}) + 1) \tag{7}$$

where D_{cat} represents the different minimum distances in the two classes. d_{ij} represents the distance between i and j. The result is calculated as a function to make the variation more even, preventing too much variation.

3.3.2 Correlation calculation method

Taking the above two factors into consideration, the conceptual semantic distance calculation method between concept c_i and concept c_j defined in this paper is formally expressed as a linear combination of link distance D_{link} and category distance D_{cat} as shown in Eq. (8).

$$D(c_i,c_j)=\alpha D_{\text{link}}(c_i,c_j)+(1-\alpha)D_{\text{cat}}(c_i,c_j) \tag{8}$$

where α is the adjustment coefficient, and the value is between (0, 1].

$$R(c_i,c_j)=\frac{1-\alpha}{D(c_i,c_j)+1} \tag{9}$$

Finally, the similarity between the two is taken as the final result of the correlation and used as the calculation method of the weighted network.

3.4 Computational intelligence and neuroscience

The network structure of associative memory is particularly attractive due to its computational speed and linearity in computational intelligence and neuroscience with learning properties. Although several artificial neural network architectures have been proposed to solve the problems in system identification and control, from the perspective of real-time adaptability, they cannot all be competent, and there are dimensional problems. Because such real-time systems contain linear combinations of functions with certain properties, usually the single output of an associative memory network is equal to a linear combination of M basis functions. The basis function output is again nonlinear and depends on the input of the network, and at the same time, there is a dense support for the partial reconstruction of the basis function[15]. Therefore, some signals close together in the input space will activate adjacent basis functions and produce similar outputs. It is for this reason that this network is called "associative memory". Learning in an area of the input space will not interfere with the knowledge related to distant areas. A new structure called multi-resolution associative memory network is designed. The support of each basis function includes several lattice units. For example, a hat-shaped basis function contains 9 two-dimensional lattice supports. This can solve the dimensionality problem of the network, and the trapezoidal-based associative memory network can be well used in real-time adaptive situations[16]. Intelligent hybrid systems are divided into four categories, fusion system, change system, combination system, and association system, as shown in Fig. 3, which shows the relationship between the features and the significance of intelligent computing[17].

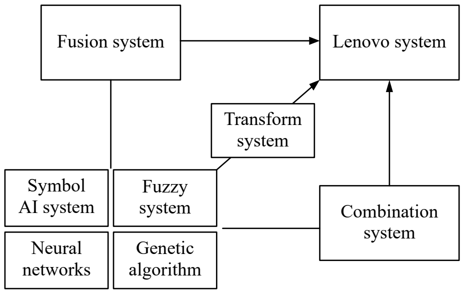

Fig. 3 Smart hybrid system category.

The research of neural computing science is mainly based on the research of neural network, making full use of the new progress in other fields and carrying out comprehensive research on the overall theory. It discusses how various comprehensive intelligent systems with neural network information system as the main body work more effectively and realize intelligent information processing with brain style, with the goal of biological intelligence and "planning" the brain. The computational intelligence conference also covers neuroscience (brain science), cognitive science, information science (information processing), nonlinear science (chaos), etc., especially the content of information processing, such as time sequence analysis, system and model identification, image and signal processing, data fusion, data analysis, optimization methods, etc. The conference uses them as the themes of the paper grouping sessions in a large number, indicating that modern information processing methods have been effectively and widely used in computational intelligence research. Therefore, neurocomputational science is a new theory and new method of intelligent information processing with the knowledge processing and expression of the human brain, which is studied from the perspective of information science and using computational methods. It can develop intelligent information processing theories and comprehensive integration methods with some neuro-computation properties of the human brain so that information processing and information representation can be raised to a high level and promote the development of various disciplines. There are high strategy and creativity, as well as obvious exploration and feasibility. Meanwhile, attention should be paid to the combination of neural, fuzzy, and evolutionary computing, i.e., computational intelligence, and the use of modern information processing and nonlinear theory, as well as the use of current small-scale neural networks and computational intelligence systems, which is designed to be a huge complex intelligent information processing system (neural computer) that can synthesize and integrate the intelligent behavior of the brain. Therefore, the content of neural computing scientific research is far broader than that of neural network and computational intelligence, and the comprehensive integration of knowledge and technology is higher[18].

The function mapping is performed according to the symbol of the specific two, and Eq. (10) is obtained after mapping the input information:

$$N_{i_1} = O_{i_1},\ i = 1, 2, ..., n_1 \tag{10}$$

The second step modulates the obtained function expression as

$$O_{i_2} = \frac{1}{1+\mathrm{e}^{-\alpha I_{i_2}}},\ i = 1, 2, ..., n_2 \tag{11}$$

According to the algorithm and grammar rules of the following formula, the input will be obtained.

If N_{1_3} is $X_1\,(O_{1_2})$, N_{2_3} is $X_2\,(O_{2_2})$, and N_{3_3} is $X_3\,(O_{3_2})$, then O_{1_3} is Y_1.

X_1, X_2, and X_3 are fuzzy variables. Y_1 is the fuzzy output. Then match the output according to Eq. (12):

$$O_{J_4} = \sum_{i=1}^{n_3} W_{ij} O_{i_3}, j = 1, 2, ..., n_4 \tag{12}$$

The output of the previous step is modeled to obtain Eq. (13):

$$O_{i_5} = \begin{cases} 1, & \text{for } O_{i_4} \geqslant \theta_i; \\ 0, & \text{for } O_{i_4} < \theta_i \end{cases} \tag{13}$$

A brief description of the computational methods of neuroscience is provided here for follow-up supplements.

3.5 Basic process of neuroscience and multi-hop question answering system

3.5.1 Retrofit and expansion

The concept and the first sememe in its definition are reclassified into a hyponymous relationship, and the concept is defined by the sememe. Sememe has the smallest connotation and relatively large extension. In essence, using sememe to label concepts is equivalent to classifying concepts. If the first meaning in the concept definition is regarded as the upper level of the concept, the concept can be incorporated into the corresponding feature file as its subclass to form a complete hierarchical structure. When some verb concepts are redefined, some verb concepts are very incompletely defined while some are only explained by a single sememe. Sememe itself is not defined, and this way determines that it is impossible to really distinguish concepts or to carry out effective reasoning[19]. In order to overcome this shortcoming, use *Modern Chinese Dictionary*, take into account the original definition of HowNet, and use its knowledge system description language Knowledge Database Mark-up Language (KDML) to redefine these verb concepts. After taking the first meaning of the definition of a noun concept as its upper position, the rest of it describes the attributes of the concept. If the original definition is not detailed and accurate enough, the *Modern Chinese Dictionary* should be referred to add or change the original attributes to facilitate reasoning[20].

Each verb concept can find the necessary role framework in the event feature file according to its first defined seme. After the trigger is added by the event meaning, the necessary role frame can be filled in by activating the trigger. The necessary roles of many sememes are the same, and the rules for filling in the frames are similar. These sememes are grouped into sememe classes, and the necessary roles of the sememe classes and the relevant rules reflecting the semantic relationship in the rule base are used to build a text graph for the input text. There are roughly two cases for filling in the role value: One is directly determined by the dependency relationship, and the other is given according to the range of the value. In addition to the dynamic roles in the necessary role framework, there may be other semantic relations between words. The determination of these semantic relations is completed by some rules that reflect the characteristics and connotations of semantic relations[21].

3.5.2 Output representation

This paper only deals with text reasoning and does not involve grammatical analysis, syntactic analysis, and lexical analysis. It is assumed that the input has been processed in these aspects, and there is no relationship such as classification, remarks, word disambiguation, or coexistence.

For example, a little goat came to a green meadow.

Its form is a form tree. As shown in Fig. 4, its word meaning is selected from the *i*-th in the series *n*. Judging the relationship between words according to the output is conducive to filling the role frame. For example, the frame of “come and arrive” is about to arrive or have arrived, and the dependent words are

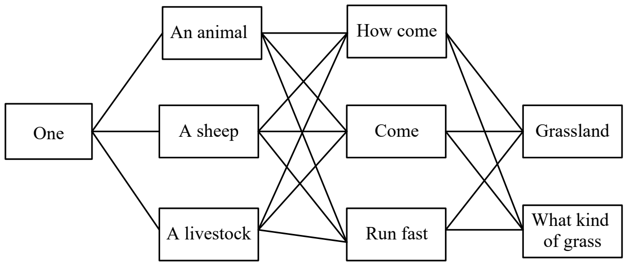

Fig. 4 Example of text representation.

"sheep" and "grass".

Its selection can be multi-directional and has a lot of beating. It can be inferred from "the sheep are about to reach the grass" that they may be hungry, but it cannot be inferred that "the sheep has reached the grass" or that "an animal is about to reach the grass". Its selection is unstable. This is the principle of text chain reasoning, and the meaning cannot be distorted at will so that there is no reasoning[22].

3.5.3 Generate inference

To reason about subsequent things according to the conditions in which the text occurs, it is necessary to construct the meaning model in the text first. It is decomposed according to the meaning, and then all the possible results obtained are fused together to obtain all the possibilities of the model after inference, which is called the text library. Because everything obtained in the text library may not necessarily make the text smooth, some redundant and unsuitable ones need to be deleted to obtain useful text. The reasoning steps are shown in Fig. 5.

Text retrieval is a technology that mainly helps users find the information they need in complex texts. As a part of information retrieval, commonly used document retrieval is generally divided into three categories, retrieval model based on set theory, retrieval model based on algebra, and retrieval model based on probability theory, mainly including Boolean model, vector space model, probability model, reference analysis model, etc. The general retrieval method is engine search. In the library, some systems emerge and evolve into one of the indispensable tools. The general process of text retrieval is that the establishment of a search engine, which means that when the user needs to find a file, a device similar to start-up helps the user to find relevant information. The search of the search engine is a process of conveying the information obtained by the user through the search in the database to the user after being processed by the system. In contemporary search systems, multilingual search, fast search, and personalized search have been implemented to provide users with convenience.

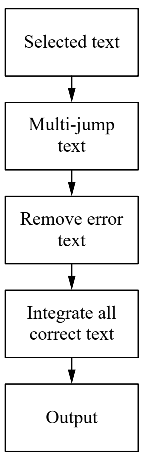

Fig. 5 Reasoning steps.

4 Text Reasoning Chain for Multi-Hop Question Answering

Through information retrieval, users can find most of the words or phrases that are synonymous with the source word. Then they can make a judgment based on the retrieved words, looking at its accuracy, reaction speed, answer breadth and completeness, and question and answer jumping, as shown in Fig. 6. In response to these problems, a comparison is made between intelligent and traditional text reasoning, and their advantages and disadvantages are comprehensively considered.

The advantage of traditional text reasoning is that the length of the encoded vector is the length of the dictionary. The encoding ignores the order in which words appear. Although this encoding method calculates the number of times words appear in the text, it is not possible to distinguish commonly used

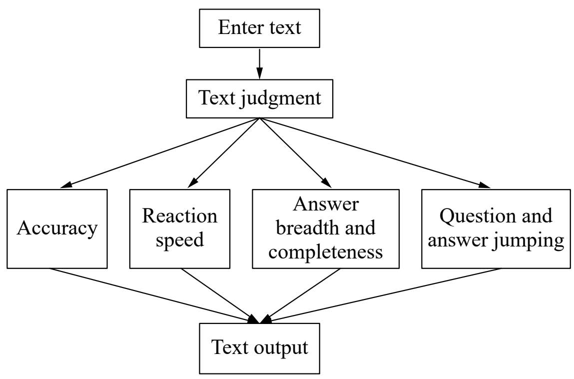

Fig. 6 Retrieval judgment flowchart.

words solely through the attribute of "occurrence times".

The advantages of intelligent text reasoning are simple implementation, easy algorithm understanding, and strong interpretability. The disadvantage is that it cannot reflect the positional information of words. When extracting keywords, the positional information of words should be given higher weights.

This paper compared and analyzed artificial text reasoning and intelligent text reasoning to judge the gap between them and their applicability in application. Now text reasoning uses its background knowledge, regards the process of reasoning as a logical search, and then converts the text into a logical expression. Meanwhile, possible problems are avoided, each stage is clearly visible, and a good viewing window can be obtained. The comparison chart of the accuracy of traditional multi-hop reasoning and intelligent multi-hop reasoning is shown in Fig. 7.

From the comparison chart, it can be found that the accuracy of traditional multi-hop reasoning is generally about 60%, which is about 16% less than that of intelligent multi-hop reasoning, and the accuracy of intelligent text reasoning is improved by 16%. It further illustrates that intelligent text reasoning will be more widely used in applications. With the development of contemporary technology, intelligence will become more and more popular, and the application of traditional aspects will also decrease, which will gradually be replaced by intelligence. Traditional multi-hop reasoning will only be used in a small area, showing that the accuracy of intelligence in artificial intelligence will be more perfect in the follow-up.

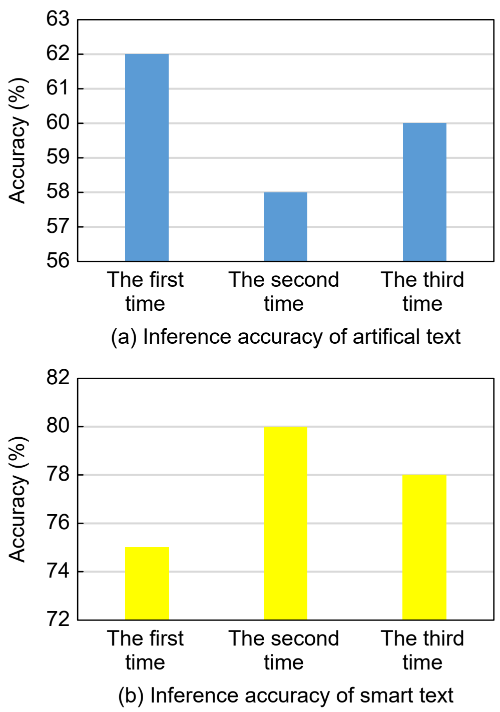

Fig. 7 Comparison chart of artificial and intelligent text reasoning accuracy.

For the text reasoning of multi-hop question and answer (Q&A), the accuracy of the reasoning is also related to the jump of question and answer. Because for the multi-jump question and answer, it is changeable and uncertain, it is still difficult to find related words or words according to the pulsation, especially for the traditional method. It seems to be slightly better for intelligence to find the words it needs on the multi-break pulsation, as shown in Fig. 8.

From Fig. 8, it can be seen that in the traditional text jump experiment, the text jump in the first experiment was 0.56, the text jump in the second experiment was 0.4, and the text jump in the third experiment was 0.52. In the text jump experiment proposed in this paper, the text jump in the first experiment was 0.8, the text jump in the second experiment was 0.78, and the text jump in the third experiment was 0.82. This proves that the computational intelligence proposed in this paper will be more complete, unified, and faster than traditional retrieval methods. From the comparison chart, it can be

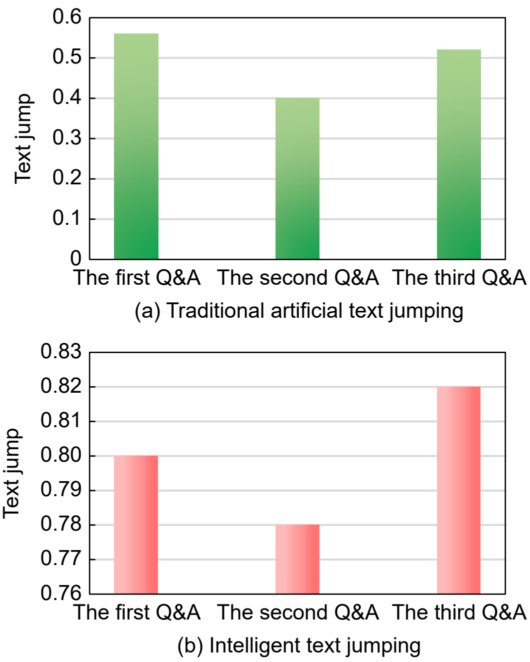

Fig. 8 Text jumping contrast.

seen that the jump of the traditional text is relatively small, because the brain needs a certain reaction time within a limited time in the traditional way. In addition, according to the text in the search to find words that match words or words in short sentences, the jump is still limited, and the jump of the text under traditional calculation is still not enough. Compared with the traditional method, the jumping of intelligent text is about 20% higher. If the jump is greater, it means that in a limited time, more matching words can be found, and the computer will search and find faster in the thesaurus. Moreover, the word memory capacity of the human brain is much less than that of the computer thesaurus. This also leads to the fact that in terms of text jumping, smart text will be more used in practice, and more matching texts will be found.

In the case of more and more developed modern technology, people have expectations for the response speed of the instrument: Do not be slow and pursue faster. The same is true for multi-hop quiz. For multi-jump question and answer, after the development of intelligent neuroscience, people's reaction speed has also increased. The question and answer speed on artificial and intelligent is compared, as shown in Fig. 9.

By comparing the two sets of response speed data, it can be seen that the speed of response and reasoning is faster in computing science compared to the traditional method. The difference between the two is about 0.8 s, and the response speed is increased by 75%. Computer intelligence can be said to be superior in response speed. Due to the need for calculation, the traditional text reasoning method takes a certain amount of time to enter the system, but computer intelligence does not require this step and can directly enter the system. The words needed for reactive text reasoning can be automatically combined and edited, which is faster than that. That is why intelligence is popular. Human brain's response can not keep up with the speed of the computer. With the subsequent development, multi-hop question and answer text reasoning will become faster and faster.

Moreover, the human brain is also limited in answering and does not have the breadth of the computer. The average human brain may say a dozen similar words or sentences at a time, but the computer can respond immediately and say many similar words or sentences. As long as it is needed, the computer can skip immediately and automatically and retrieve the vocabulary. As shown in Fig. 10, the number of words that the computer makes answer skipping in the specified time is compared, and the breadth and completeness of the answer are compared.

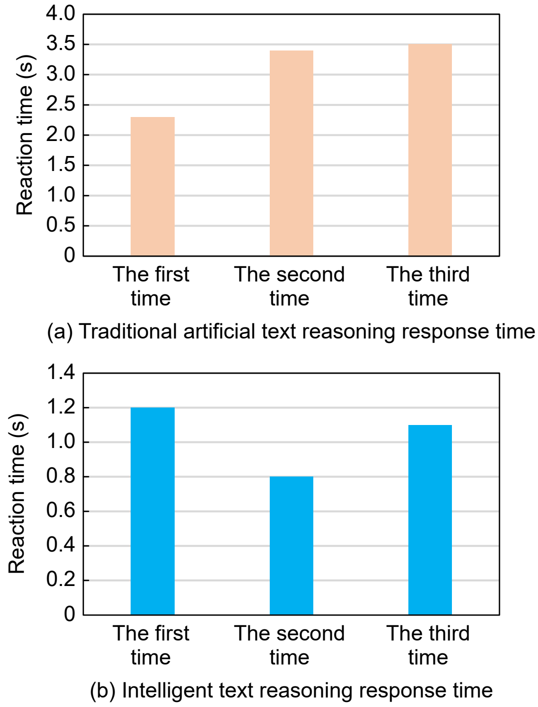

Fig. 9 Text reasoning response speed comparison chart.

By comparing the number of words that make answer jumps in the specified time, it is found that the number of words in traditional multi-hop reasoning only accounts for half of intelligence. It also can be found that when the intelligence calculates and edits these data, it takes a short time and is relatively complete, which is 100% higher than that of manual work. The difficulty of multi-hop question and answer is greatly accelerated, and the text reasoning is also more complex, so there is a lot of room for improvement for people. It shows that the data of the current text thesaurus have surpassed the brain by a lot and that intelligence is being used more and more widely on the road of science and technology.

5 Discussion

With the rapid development of modern technology, many of us are using computers to solve various problems. This paper mainly introduces the text reasoning chain of multi-hop question answering and compares the advantages and disadvantages of manual work. When it comes to building text networks, it is not enough. One can use the text reasoning chain to perform multiple accurate operations in order to select

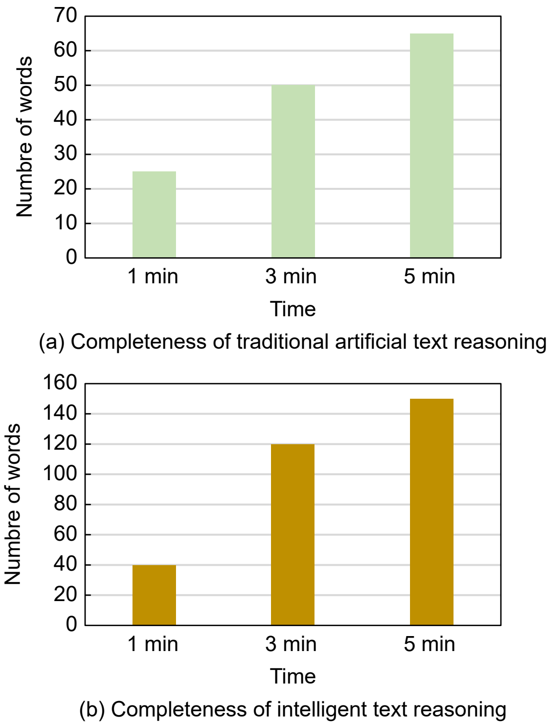

Fig. 10 Textual reasoning completeness comparison.

the desired text. The different elements in it can be refined, classified into other forms, and then sorted out in the database. If the text is automatically classified and the words retrieved before are memorized, this will enrich the database and bring about a more convenient way of text reasoning. This paper did not consider which of the specific task's characteristics is more effective than the other two, such as the advantages and disadvantages of word2vec, glove, and elmo trained word vectors. We need to use the benefits brought by technology, but the correct use of it is the key. Computing technology in the future will be faster and more convenient.

6 Conclusion

This paper mainly studies and expounds the text reasoning connection and its related theoretical knowledge. It also compares the intelligence and artificial aspects of the text reasoning of multi-hop question answering. The study found that artificial intelligence is not enough in intelligent reasoning and search, and the human brain network neural network has not yet met expectations in terms of text reasoning compared with computers. After the use of computational intelligence, its retrieval efficiency, speed, and search breadth are greatly increased, which is also a collision between human network nerves and computer intelligence. This paper only compares the text reasoning of multi-hop question answering. However, in the future, in more in-depth fields, computational intelligence will play a greater role in other aspects and explore more unknown areas. When selecting word vectors, in the future, this paper should consider the characteristics of specific tasks, the advantages and disadvantages of the trained word vectors, and which one is much better than the other two.

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