A formal framework for robot to understand compound concepts

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Abstract. Social robots are playing an important role in assisting humans in shopping, caring for the elderly and educating children. However, to accomplish these tasks with high quality, social robots still face huge challenges. One of the main challenges is how robots understand the intentions of human behavior and predict human needs in order to respond appropriately. Most existing social robots determine the intentions and needs of humans based on the postures and actions in a specific scene. We know that it is not enough to understand human intentions and needs based on gestures and actions. It will be more perfect to understand human intentions and needs through natural language communication. To this end, we propose a formal framework for describing robots' understanding of simple and compound concepts. Once the robot has the ability to understand compound concepts, it has the ability to understand some simple knowledge. We first introduce the formal methods of expressing the connotation and extension of simple concepts, and then propose a framework for robots to understand simple concepts, and finally build a formal framework for robots to understand complex concepts. This framework provides a formal method for robots to understand knowledge.

1. Introduction

In the past ten years, the interaction between social robots and humans has made great progress. Especially its outstanding performance in accompany the elderly, assisted education, shopping navigation, catering services, etc., has attracted great attention from researchers and the industry. How to understand human intentions and needs has become a hot topic in social robot research [1]. For example, Islam et al. [2] developed a shopping support robot that can follow customers autonomously. This kind of robot can understand the customer's shopping behavior by observing the customer's posture, and provide appropriate support without disturbing the customer. Filippini et al. [3] proposed to improve the educational robot Mio Amico's ability to understand children's emotions and intentions, and to evaluate children's ability to participate in social activities, so as to realize the natural
interaction between the robot and children. Wächter et al. [4] proposed a framework that integrates functions such as natural language understanding and task planning, so that the robot can understand natural language and generate task plans based on the actual environment to complete complex tasks. The research aims to improve the ability of robots to communicate and collaborate with humans, so as to apply existing knowledge in new environments to solve problems that have not been encountered before. Kotov et al. [5] discussed how robots understand problems, and developed a natural text parser with speech understanding for the companion robot. They see the concept of understanding as a compound phenomenon involving the processing of text and the response of the audience. They also believe that emotional representation space is an important aspect of understanding, and process simulation is a shallow model of text understanding. Demir et al. [6] studied the collaborative performance of a binary search team composed of humans and robots in a simulated Minecraft task environment. The research shows that teams that use natural language and shared mental models perform better than other teams. If the robot can understand natural language to a certain extent, it will help improve the efficiency of cooperation between the robot team and the human team. Eriko et al. [7] proposed a sensory association method to understand the meaning of metaphorical expressions. When interpreting a noun, this method associates people's perception and impression of the noun. Through the application of concept library and large-scale knowledge base association mechanism, the goal of computer understanding metaphor is realized. Zhou et al. [8] proposed a framework for deep understanding, using syntax tree model to realize image recognition and natural language generation. The framework aims to identify the interaction between people and objects in images and describe the interaction process in natural language. Doboli et al. [9] proposed a semantic network representation model that includes functions such as reasoning, decision-making, and design. The model includes features, concepts, categories, goals, rewards, and their relationships. It can be used to represent the application of semantic networks in creative activities. In order to discover and understand the user's intention in web search queries, Roy et al. [10] proposed a word classification framework to divide the words in the search query into content and intention. The content word indicates the subject of the query, and the intention word indicates the result that the user wants. Intelligent processing of intention words can provide users with better pages. In order to solve the difficulties of object-based visual classification algorithms, Sheng et al. [11] proposed a new robot semantic mapping method. This semantic mapping method based on human activity recognition uses semantic information to help robots understand unknown environments. Amaro et al. [12] proposed a representation method for semantic understanding. This method extracts semantic representations by observing human activities, thereby transferring human skills to humanoid robots.

However, the interaction between existing social robots and humans is still in its infancy, its intelligence level is low, and the work it can complete is limited. With the increase of social demand, social robots are facing new challenges in terms of providing higher service quality and more complex tasks. First, robots need more intelligence; second, robots need to establish a natural and intuitive interactive relationship with humans. To this end, this article explores the question of how robots understand knowledge, and proposes a formal framework for social robots to understand compound concepts in order to improve the robot's ability to understand human intentions. This method lays the foundation for the further development of robots to understand more complex knowledge in the future.

2. Robot's understanding of simple concepts

2.1 How do robot understand concept

Concepts can be divided into simple concepts and compound concepts in structure. In constructing a formal framework for robot understanding concepts, it is necessary to determine some of the most basic simple concepts as the basis, and then expand into composite concepts. These simple concepts as the basis are not further decomposed in the formal representation, so they are also called atomic concepts. Descriptive logic has a relatively complete theoretical system for the formal representation of concepts [13], which will not be introduced here. This article focuses on how to build a formal
framework that describes the robot's understanding of simple and compound concepts.

Because the concept is a basic component of knowledge, we must understand the concept from the level of understanding knowledge, instead of separate the concept for discussion. Knowledge understanding can be divided into four levels from primary level to advanced level: (1) Retelling understanding, that is, being able to describe knowledge literally; (2) interpretative understanding, that is, being able to analyze and summarize the internal relations of knowledge; (3) critical understanding, that is, being able to comment on knowledge; (4) creative understanding, that is, being able to innovate knowledge. Considering that there is a big gap between human and robot in understanding the innate conditions of knowledge, this paper only discusses the concept of robot understanding at the level of retelling understanding and explanatory understanding.

At present, there is not much progress in the research on how robots understand concepts. There is neither a recognized definition nor a specific framework or model for how to verify whether a robot understands a certain concept. Therefore, how to explain that the robot understands a certain outline is the core issue we need to pay attention to. In fact, when humans describe a concept of how to understand, they also have different views and different expressions. However, the concept has two basic characteristics that everyone recognizes, namely connotation and extension. Connotation refers to the meaning of a concept, that is, the unique attributes of the things or objects reflected by the concept. Extension refers to things or objects that have the attributes reflected by the concept. Therefore, to understand a concept, you must understand its connotation and extension. This is the most basic requirement for understanding the concept. This article proposes three conditions to determine whether a robot can understand a concept:

**Condition 1:** The robot knows the connotation of the given concept, that is, the robot knows what the essential attributes of the given concept are.

Specifically, the robot can query the essential attributes of a given concept in its own knowledge base. These essential attributes can be stored in the knowledge base of the robot in advance by the designer, or obtained by the robot through learning. When the robot finds the essential attributes of the concept and can retell the content in a certain language, we say that the robot has the ability to retell the concept.

**Condition 2:** The robot knows the extension of a given concept, that is, the robot knows which objects are within the scope of the given concept.

In other words, the robot has the ability to judge whether an object is within the scope of a given concept. This task can be accomplished by a computer vision system or other recognition system installed on the robot.

**Condition 3:** The robot knows the function of a given concept, that is, the robot can use the connotation and extension function of the given concept to solve related problems or complete related tasks.

For example, if the robot understands the concept of "cup", then when the owner says he wants to drink water, the robot knows to get the cup and then to fill the water. Conversely, when the owner says he wants a cup, the robot knows that the owner wants to use the cup to hold water, drinks, wine and other liquids.

The above three conditions are considered to be that the robot has a preliminary understanding of the given concept.

### 2.2 Framework for robots to understand simple concepts

We build a framework for robots to understand simple concepts based on first order logic (FOL).

Some commonly used symbols and their meanings are the same as those in FOL or description logic (DL). Since robots need to have certain cognitive abilities in the process of understanding conceptual attributes, we give robots some simple cognitive abilities. The purpose and meaning of several concepts and symbols commonly used in this article are explained as follows:

- **Simple concepts:** basic concepts used to construct other composite concepts, usually expressed by P, Q.
The domain of concept P: the value range of the extension of P (that is, the object described by the concept), represented by D.

The connotation of the concept P: describe the essential attributes of the concept, expressed by Con(P). In the formal description, Con(P)={A₁, A₂, ..., Aₙ} or Con(P)=A₁ ∧ A₂ ∧ ... ∧ Aₙ, where the formulas A₁, A₂, ..., Aₙ represent all essential attributes of p.

The extension of the concept P: the object described by the connotation of the concept P, expressed by Ext(P). In the formal description, Ext(P)={x | x∈D and x has all the attributes of P}.

**Definition 2.1** Suppose A is a formula in FOL, R is a robot, and KB is R's knowledge base, then R knows A if and only if A is in KB. Symbolized as:

\[ \text{Know}(R, A) \iff A \in KB. \] (1)

Among them, \( \text{Know}(R, A) \) means that the robot R knows A.

Definition 2.1 means that the robot knows and only knows the knowledge in its knowledge base.

**Definition 2.2** Let the predicate formula P represent a simple concept, and Con(P) represents the connotation of P. If Con(P)∈KB, the robot R is said to know the connotation of the concept p, denoted as \( \text{Know}(R, \text{Con}(P)) \).

An equivalent of Definition 2.2 is that if the robot R knows all the essential properties of the concept P, then R knows the connotation of P. vice versa.

In discussing the concept of robot understanding, we assume that the robot is equipped with multi-functional sensors that can recognize all objects related to the task in the robot environment.

**Definition 2.3** Suppose P represents a simple concept, and Ext(P) represents the extension of concept P, and D represents a universe of discourse; if R can identify whether d is the extension of P for any element d in D, then R knows The extension of P, denoted as \( \text{Know}(R, \text{Ext}(P)) \).

Definition 2.3 shows that if the robot can distinguish which elements in the domain D meet the conditions described by a given concept and which do not, then it can be considered that the robot knows the extension of the concept.

**Definition 2.4** Suppose P represents a simple concept, and R is a robot, then R understands P if and only if R knows the connotation of P and the extension of P, which is represented by the symbol

\[ \text{Und}(R, P) \iff \text{Know}(R, \text{Con}(P)) \land \text{Know}(R, \text{Ext}(P)) \] (2)

3. Robot's understanding of compound concepts

In the previous section, we proposed a formal framework for describing simple concepts that robots understand. Next, we discuss how the robot understands compound concepts. Compound concepts are constructed on the basis of simple concepts, including "conjunctive concepts of connotation" and "negative concepts". The composition of compound concepts is more complicated than the composition of compound propositions. Any two propositional formulas can constitute a legal propositional conjunction. However, we cannot combine any two attributes into a meaningful concept. For example, "high foot glass with handle" is a meaningful compound concept. "Low alcohol red wine" is also a meaningful compound concept. But "red wine with handle" is a meaningless concept. Generally speaking, we only discuss the concept of compound in a certain scope. For example, within the scope of the extension of the cup, we discuss the composite concepts of "high foot glass with handle" and "blue plastic cup without handle". Strictly speaking, we discuss the compound of subordinate concepts within the scope of the superordinate concept, and each sub-component concept in the compound concept has the same domain.

For example, let P denote "low alcohol wine" and Q denote "red wine", then we have that P and Q both are simple concepts, and PAQ is a compound concept, which means "low alcohol red wine".

**Definition 3.1** Suppose that P and Q are two simple concepts. On the basis of their common superordinate concept, the connotation attributes of these two concepts are combined to form a composite concept, which is called the conjunction concept of P and Q, and denoted as PAQ.

For example, let P denote "low alcohol wine" and Q denote "red wine", we have that P and Q are simple concepts, and PAQ is a compound concept which means "low alcohol red wine".

**Theorem 1** Let P and Q be two simple concepts, and R is a robot, if \( \text{Und}(R, P) \) and \( \text{Und}(R, Q) \),
then \( \text{Und}(R, PAQ) \).

Proof: Assuming \( \text{Und}(R, P) \) and \( \text{Und}(R, Q) \). By definition 2.4, we have \( \text{Know}(R, \text{Con}(P)) \land \text{Know}(R, \text{Ext}(P)) \) and \( \text{Know}(R, \text{Con}(Q)) \land \text{Know}(R, \text{Ext}(Q)) \). a) We first prove \( \text{Know}(R, \text{Con}(PAQ)) \). Let \( \text{Con}(P)=\{A_1, C_1, C_2, \ldots, C_n\} \), \( \text{Con}(Q)=\{B_1, C_1, C_2, \ldots, C_n\} \), where \( \{C_1, C_2, \ldots, C_n\} \) is the essential attribute of the superordinate concept of \( P \) and \( Q \), that is also the common essential attributes of the two, \( A_1 \) is the unique essential attribute of \( P \), and \( B_1 \) is the unique essential attribute of \( Q \). By definition 2.2, \( \text{Con}(P)=\{A_1, C_1, C_2, \ldots, C_n\} \subseteq \text{KB} \), and \( \text{Con}(Q)=\{B_1, C_1, C_2, \ldots, C_n\} \subseteq \text{KB} \), then we have \( \text{Con}(PAQ)=\{A_1, B_1, C_1, C_2, \ldots, C_n\} \subseteq \text{KB} \). Again by definition 2.2, we have \( \text{Know}(R, \text{Con}(PAQ)) \). b) Then prove \( \text{Know}(R, \text{Ext}(P \land Q)) \). Because \( \text{Con}(P \land Q)=\{A_1, B_1, C_1, C_2, \ldots, C_n\} \), \( \text{Ext}(P \land Q)=\text{Ext}(P) \cap \text{Ext}(Q) \subseteq \text{Ext}(P) \). From \( \text{Know}(R, \text{Ext}(P)) \) and definition 2.3, we have \( \text{Know}(R, \text{Ext}(PAQ)) \). According to definition 2.4, we have \( \text{Und}(R, PAQ) \).

Next, we will discuss negative concepts. In general, we use positive statements to describe simple concepts, and use a negative word together with simple concepts to represent negative concepts.

**Definition 3.2** If a positive statement is used to describe the connotation of a concept, the concept is called a positive concept; and a negative statement is used to describe the connotation of a concept, then the concept is called a negative concept.

The formal representation of negative concepts is more complicated. In FOL, usually a negative word "not" is added in front of a proposition symbol to indicate the negation of the proposition. For example, suppose the formula \( P \) means "\( c \) is a plastic cup", then \( \neg P \) means "\( c \) is not a plastic cup". From the meaning of \( \neg P \), as long as \( c \) is not a plastic cup, \( \neg P \) is considered true. For example, if \( c \) is a glass or \( c \) is a saucer, then \( \neg P \) is true. But when discussing the formalization of negative concepts, simply adding a negative word in front of the positive concepts cannot fully express the meaning of the negative concepts.

For example, "plastic cup" is a positive concept, and "non-plastic cup" is a negative concept. The essential attributes of "plastic cups" are "cup" and "plastic products", while the essential attributes of "non-plastic cups" are "cup" and "not plastic products". It is easy to see that both the positive concept "plastic cup" and the negative "non-plastic cup" contain the essential attribute "cup", and the negative concept "non-plastic cup" only negates the attribute "plastic product", but does not negate the attribute "cup". Therefore, when formalizing negative concepts, we should clearly indicate which attribute the negative words in negative concepts negate.

**Definition 3.3** Suppose \( P \) is a simple concept, \( \text{Con}(P)=\{A_1, C_1, C_2, \ldots, C_n\} \), where \( \{C_1, C_2, \ldots, C_n\} \) is the essential attribute of the superordinate concept of \( P \), and \( A_1 \) is the unique essential attribute of \( P \). The negative concept of \( P \) is represented by \( \neg P \), which refers to the things that do not have the attributes of \( A_1 \) in the superordinate concept of \( P \). That is, \( \text{Con}(\neg P)=\{C_1, C_2, \ldots, C_n\} \cup \{A_1\} \), \( \text{Ext}(\neg P)=\text{D-Ext}(P) \).

For example, suppose \( P \) stands for "plastic cup" and \( \neg P \) stands for "non-plastic cup". \( \text{Con}(P)=\{A_1, C_1, C_2, \ldots, C_n\} \), where \( A_1 \) represents "plastic products", \( \{C_1, C_2, \ldots, C_n\} \) represents the essential properties of "cup", then the extension of \( P \) is the set of all plastic cups, and the extension of \( \neg P \) is the set of all cups that are not made of plastic.

**Theorem 2** Let \( P \) be a simple concept, \( R \) is a robot. If \( \text{Und}(R, P) \), \( \text{Und}(R, \neg P) \).

Proof: Assuming \( \text{Und}(R, P) \), by definition 2.5, we have \( \text{Know}(R, \text{Con}(P)) \land \text{Know}(R, \text{Ext}(P)) \). Let \( \text{Con}(P)=\{A_1, C_1, C_2, \ldots, C_n\} \), \( \text{Con}(\neg P)=\{C_1, C_2, \ldots, C_n\} \cup \{A_1\} \), where \( \{C_1, C_2, \ldots, C_n\} \) is the essential attribute of the superordinate concept of \( P \), and \( A_1 \) is the unique essential attribute of \( P \). By definition 2.2, \( \text{Con}(P)=\{A_1, C_1, C_2, \ldots, C_n\} \subseteq \text{KB} \). Thus \( \text{Con}(\neg P)=\{C_1, C_2, \ldots, C_n\} \cup \{A_1\} \subseteq \text{KB} \). Again by definition 2.2, we have \( \text{Know}(R, \text{Con}(\neg P)) \). On the other hand, according to \( \text{Know}(R, \text{Ext}(P)) \) and definition 2.3, the robot \( R \) can recognize the attributes \( \{A_1, C_1, C_2, \ldots, C_n\} \) of \( P \). By definition 3.3 it is deduced that \( R \) can recognize the attributes \( \{C_1, C_2, \ldots, C_n\} \cup \{A_1\} \) of \( \neg P \). So we have \( \text{Know}(R, \text{Ext}(\neg P)) \). According to definition 2.4, we have \( \text{Und}(R, \neg P) \).
4. Conclusion

In this paper, we propose a formal framework for robots to understand composite concepts. First, we introduce the necessary conditions for robots to understand a concept, and give the specific method of formalizing the connotation and extension of a simple concept. Secondly, we gave a formal definition of the connotation and extension of a simple concept that the robot knows. Next, we defined a formal framework for robots to understand a simple concept. Finally, a framework for robots to understand composite concepts is defined. The conjunctive concept and the negative concept are the two most basic compound concepts. On this basis, more complicated compound concepts can be constructed for further study.

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