

Research Article

Research on the Disease Intelligent Diagnosis Model Based on Linguistic Truth-Valued Concept Lattice

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Uncertainty natural language processing has always been a research focus in the artificial intelligence field. In this paper, we continue to study the linguistic truth-valued concept lattice and apply it to the disease intelligent diagnosis by building an intelligent model to directly handle natural language. The theoretical bases of this model are the classical concept lattice and the lattice implication algebra with natural language. The model includes the case library formed by patients, attributes matching, and the matching degree calculation about the new patient. According to the characteristics of the patients, the disease attributes are firstly divided into intrinsic invariant attributes and extrinsic variable attributes. The calculation algorithm of the linguistic truth-valued formal concepts and the constructing algorithm of the linguistic truth-valued concept lattice based on the extrinsic attributes are proposed. And the disease bases of the different treatments for different patients with the same disease are established. Secondly, the matching algorithms of intrinsic attributes and extrinsic attributes are given, and all the linguistic truth-valued formal concepts that match the new patient's extrinsic attributes are found. Lastly, by comparing the similarity between the new patients and the matching formal concepts, we calculate the best treatment options to realize the intelligent diagnosis of the disease.

1. Introduction

Intelligent diagnosis technology began in the 1980s, it has become a very active research field, and its characteristic is to apply the technical achievements of artificial intelligence to the field of intelligent diagnosis. Based on the conventional diagnosis, artificial intelligence promotes the expert experience and knowledge processing to logical reasoning or self-learning, self-diagnosis, self-processing, and system reconstruction. As a branch of computer science, artificial intelligence is a subject that makes computer simulate some thinking process and intelligent behavior of human. It has been widely used in many fields such as robot, economic and political decision-making, control system, and simulation system and has achieved fruitful results. Artificial intelligence technology has the characteristics of behavior ability, perception ability, thinking ability, uncertainty information

processing, network intelligent management, and writing ability. It can improve the relevant intelligent diagnosis and management in many fields through a great quantity of data analysis and classification that human experts are difficult to complete, such as mechanical fault intelligent diagnosis, process equipment intelligent diagnosis, disease and pest intelligent diagnosis, and human disease intelligent diagnosis. From the way of information description and communication, concepts can be looked as the smallest unit of human basic thinking and an important component of artificial intelligence. In different fields such as knowledge representation, knowledge management, and machine learning, researchers analyze concepts from different perspectives and viewpoints, forming different formal description methods of concepts. Based on Birkhoff's contribution to lattice theory [1], Professor Wille established a conceptual hierarchy model according to the dependence

or causality of knowledge body in connotation and extension and first proposed concept lattice as a mathematical theory in 1982 [2, 3].

As a powerful tool for big data knowledge discovery in artificial intelligence, concept lattice has been successfully applied to digital book and literature retrieval, software engineering, knowledge discovery, and other fields and has achieved good economic and social benefits [4–10]. In the medical field, Cole and Eklund [11] have applied the concept lattice method to analyze and visualize the medical database with 1962 attributes and 4000 prescription abstracts; Liu Ling et al. [12] have also studied the application of concept lattice in the intelligent diagnosis of diseases. In these studies, the disease information in the case base is completely determined. Its essence is to build a concept lattice for each patient's disease information. Each node in the lattice represents the symptom-degree pair of the disease and assigns the corresponding weight to each symptom and degree, so as to form a case base. Then, the query information entered by the new patient is expressed as a concept lattice, and the final diagnosis result is given by calculating the inclusion degree of query concept lattice and each concept lattice in case base. However, due to the large number of existing patients and their disease information, the number of concept lattices constructed in case base is even larger. At the same time, some correlations among concept lattices generated by the similarity of disease information among patients are not considered. When calculating the inclusion degree of concept lattices of new patients' disease information and each concept lattice in the case database, the computation is too large, and the structural advantage of concept lattice Hasse graph is not used in the whole process. And besides, there exist a large amount of uncertain medical disease information described in natural language, which makes the current artificial intelligence technology difficult to play its higher value [13, 14].

In order to make better use of artificial intelligence technology to solve the problem of disease intelligent diagnosis with uncertain natural language information, based on the previous work [15–18], this paper continues to study the linguistic truth-valued concept lattice (LTV-CL) and applies it to medical intelligent diagnosis. LTV-CL is a mathematical model based on the linguistic truth-valued lattice implication algebra (LTV-LIA). It is different from classical concept lattice and fuzzy concept lattice in that its value range is no longer binary $\{0,1\}$ and interval value $[0,1]$, but a complete lattice composed of natural languages. This complete lattice, namely, LTV-LIA, can be used to describe the uncertainty linguistic information through the nodes on the complete lattice to directly express the natural language.

In the actual diagnosis process of human diseases, each patient's condition is generally expressed in natural language, which to a large extent has inevitable uncertainty. Doctors need to make a comprehensive consideration of the current symptoms of the patient's condition, the onset time of the disease, the patient's age, gender, occupation, personal disease history, and family disease history, and other pieces of information and then give the final diagnosis result combined with their previous experience. Based on this

application background, in this paper, we regard the patient's disease characteristics as attributes, divide them into intrinsic attributes and extrinsic attributes in accordance with the attribute characteristics, and establish the LTV-CL which is the case database by the partial order relationship between extrinsic attributes and patients. Secondly, the matching algorithm between extrinsic attributes is given and several matching linguistic truth-valued formal concepts close to the condition of new patients can be found in the case database. Finally, the matching operator between intrinsic attributes is proposed; through the matching algorithm of intrinsic attributes, the matching degree between new patients and each matching formal concept is calculated and compared; the matching formal concept with the highest matching degree is determined. Combined with the diagnosis cases of matching formal concept in case database, the final treatment scheme of new patients is given.

In this paper, we summarize the artificial intelligence technology used in the disease intelligent diagnosis model in Section 1, expound the three important steps that the classic concept lattice model follows in the diagnosis process (namely, the construction of case base, the knowledge representation of new patients and the intelligent diagnosis based on matching algorithm), and compare and analyze the differences of the diagnosis model in this process; we mainly introduce the early theoretical basis of this paper, LTV-CL in Section 2; we study the formation process of intelligent diagnosis model based on the LTV-CL one by one and focus on the method and algorithm of case database formation in Section 3; we mainly study the extrinsic and intrinsic attribute matching between new patients and case database and give the phase in Section 4. Finally, we summarize the whole paper and discusses the approaching research direction in Section 5.

2. Research Framework

The diagnosis of human diseases is a significant field of artificial intelligence technology in the applied study of intelligent diagnosis. This research field has been formed since the early 1970s. The artificial intelligence technology involved is mainly represented by expert system, neural network, fuzzy diagnosis, and so on. In the branches of artificial intelligence, expert system is the most widely used, and it is also the most easy to combine with other disciplines and has obtained unprecedented development opportunities and space. The traditional medical diagnosis expert system is a production rule system. Its knowledge base is composed of many if-then rules. It completes the diagnosis process through pattern matching. The disadvantages are as follows: when there are too many rules in the knowledge base, it will lead to contradictions before and after the system reasoning; the medical diagnosis expert system based on fuzzy algorithm uses the theory of fuzzy mathematics and replaces the probability statistical methods with the fuzzy mathematical model. It can solve the highly complicated and nonlinear problems which are difficult to describe with the general mathematical model. The medical diagnosis expert system based on a neural network can not only keep the original

characteristics of the expert system but also have the characteristics of neural network. It can make a reasonable judgment on the complex problems according to the learned knowledge and the experience of dealing with the problems and give a more satisfactory answer or give a more effective forecasting to the future. In recent years, many scholars have studied the intelligent diagnosis model based on concept lattice. The whole process of diagnosis involves three key steps. While the diagnosis model of LTV-CL in this paper makes a reasonable intelligent diagnosis with uncertainty natural language information, there exist fundamental differences in the realization of these three steps. For convenience, the diagnosis model based on classic concept lattice is recorded as model A, and the diagnosis model based on LTV-CL is recorded as model B as follows.

2.1. Construction of Case Base (See Section 3). Model A represents the knowledge of each disease in medical experts or medical books as a concept lattice structure. Its essence is the knowledge representation of a patient about the symptom expression degree of the disease. Each node in the structure represents the symptom-degree pair of the patient. The object set in its corresponding formal context is composed of the symptom presented by a patient. The attribute set is composed of the degree value of each symptom. The case base is a collection of many concept lattice structures. Model B proposed in this paper is only represented by one concept lattice. The object set in the formal context is composed of a large number of patients with the same disease, while the attribute set is composed of the symptoms and symptom values displayed by the patients. Each node in the concept lattice structure is a patient symptom-value pair. In the construction of case base, compared with model A, the construction of concept lattice is greatly decreased in quantity, and each node can be used as a necessary reference to directly give the final diagnosis results in the feature matching of patients to be diagnosed.

2.2. Knowledge Representation of New Patients (See Section 4). For the same new patient, in model A, we need to build our own query concept lattice according to the disease information of the new patient before matching, while in the model B, we only need to express the disease information of the patient in the form of node sequence pair, without building the concept lattice, which greatly reduces the computing time and complexity in the knowledge representation.

2.3. Intelligent Diagnosis Based on Matching Algorithm (See Section 5). In model A, by calculating the inclusion degree between the query concept lattice and the case database one by one, the candidate concept lattice that meets the requirements in the case database is screened out, then a second match with the query concept lattice is made, and the similarity between them and the query disease is calculated by the weight of the candidate disease to find the most similar disease. In the two matching algorithms in model B,

firstly, the candidate concept nodes are selected from the concept lattice of case base through the matching between the incomparable intrinsic attributes, then the most similar concept nodes are found through the similarity calculation of the variable extrinsic attributes, and the final diagnosis results and treatment methods are given through the concrete value of similarity and the treatment cases of the most similar concept nodes. Compared with model A, model B can not only find similar diseases but also calculate the severity and treatment plan of the patients to be diagnosed by matching algorithm. In addition, model B also considers extrinsic disease attributes and intrinsic inherent attributes, so that different inherent attributes (such as age, gender, and weight of the patients with incomplete consistency) with the same degree of disease attributes are considered. The doctors can directly give specific treatment plans including drug dosage in different patients.

3. Linguistic Truth-Valued Concept Lattice

The two theoretical bases of the LTV-CL are classical CL and LIA. Please refer to the literature for details.

Definition 1 (see [1]). The formal context is defined as a data table structure $K = (A, B, I)$ consisting of sets A and B and a binary relation $I \subseteq A \times B$. $\forall a \in A$ is called an object of A and $\forall b \in B$ an attribute of B , respectively. The relationship aIb is read: the object a has the attribute b . For a set of objects $X \subseteq A$, X^* is defined as the set of features shared by all the objects in X ; that is,

$$X^* = \{b \in B \mid aIb \forall a \in X\}. \quad (1)$$

Similarly, for $Y \subseteq B$, Y^* is defined as the set of objects that possess all the features in Y ; that is,

$$Y^* = \{a \in A \mid aIb \forall b \in Y\}. \quad (2)$$

Definition 2 (see [1]). A formal concept of the context $K = (A, B, I)$ is defined as a pair (X, Y) with $X \subseteq A$, $Y \subseteq B$ and $X^* = Y$, $Y^* = X$. The set X is called the extent and Y the intent of the formal concept (X, Y) .

Definition 3 (see [1]). Let $L(K)$ denote the set of all formal concepts of the context $K = (A, B, I)$; for any two formal concepts $C_1 = (X_1, Y_1)$ and $C_2 = (X_2, Y_2)$ in $L(K)$, an order relation on $L(K)$ is defined as follows:

$$(X_1, Y_1) \leq (X_2, Y_2) \iff X_1 \subseteq X_2 \text{ (or } Y_2 \subseteq Y_1), \quad (3)$$

the formal concept C_1 is called a subconcept of the formal concept C_2 , and C_2 is called a superconcept of the formal concept C_1 . The concept lattice associated with the formal context described in Table 1 is shown in Figure 1.

Example 1. A formal context $K = (A, B, I)$ and its Hasse diagram of the concept lattice are depicted as Table 1 and Figure 1, where $A = \{1, 2, 3, 4\}$ and $B = \{a, b, c, d, e\}$.

In Figure 1, the formal concepts generated according to the partial order relation are $\{1234, \emptyset\}$, $\{13, ce\}$, $\{14, be\}$,

TABLE 1: Formal context (A, B, I) .

	a	b	c	d	e
1	1	1	0	0	1
2	1	0	0	0	1
3	0	1	1	1	0
4	0	0	1	0	1

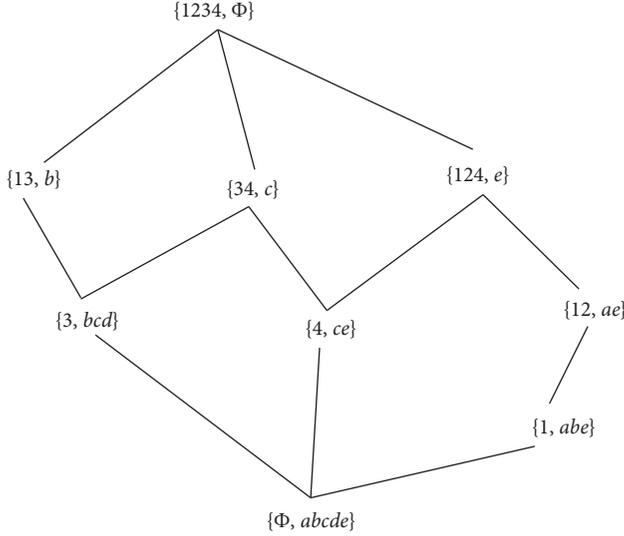


FIGURE 1: Hasse diagram of concept lattice.

$\{23, a d\}$, $\{24, b d\}$, $\{34, de\}$, $\{124, b\}$, $\{234, d\}$, $\{1, bce\}$, $\{2, ab d\}$, $\{3, ac de\}$, $\{4, b de\}$, and $\{\emptyset, abc de\}$.

Human intelligence actions are always involved with uncertainty information processing which always exists not only in the processed object itself but also in the course of the object being dealt with. As one of the basic tools of human thinking, natural language is the way that people often use to express uncertainty information such as randomness, fuzziness, and incompatibility. It is also a very important research content in the field of artificial intelligence. In this paper, we use LIA to express uncertainty information and use the LTV-LIA to depict the uncertainty natural language information.

Definition 4 (see [19, 20]). Let (L, \wedge, \vee, O, I) be a bounded lattice with an order-reversing involution $'$, I and O the greatest and the smallest element of L , respectively, and $\longrightarrow: L \times L \longrightarrow L$ a mapping. $(L, \wedge, \vee, ', \longrightarrow, O, I)$ is called a quasilattice implication algebra if the following conditions hold for any $x, y, z \in L$:

- (1) $x \longrightarrow (y \longrightarrow z) = y \longrightarrow (x \longrightarrow z)$;
- (2) $x \longrightarrow x = I$;
- (3) $x \longrightarrow y = y' \longrightarrow x'$;
- (4) $x \longrightarrow y = y \longrightarrow x = I$ implies $x = y$;
- (5) $(x \longrightarrow y) \longrightarrow y = (y \longrightarrow x) \longrightarrow x$.

Definition 5 (see [19, 20]). A quasilattice implication algebra is called a lattice implication algebra, if the following conditions hold for any $x, y, z \in L$:

- (1) $(x \vee y) \longrightarrow z = (x \longrightarrow z) \wedge (y \longrightarrow z)$;
- (2) $(x \wedge y) \longrightarrow z = (x \longrightarrow z) \vee (y \longrightarrow z)$.

Definition 6. Let $(L, \wedge, \vee, ', \longrightarrow, O, I)$ be a lattice implication algebra; if $L = \{l_1, l_2, \dots, l_n\}$ is a set of linguistic truth values, then $(L, \wedge, \vee, ', \longrightarrow, O, I)$ is called a linguistic truth-valued lattice implication algebra (LTV-LIA), recorded as L .

Definition 7. Let $K = (G, M, L, F)$ be a formal context with natural language, that is, a LTV-context, G a finite nonempty objects' set, and M a finite nonempty attributes' set. L is a LTV-LIA, and F is a relation between G and M ; that is, $F: G \times M \longrightarrow L$.

Let G be a nonempty objects' set and $(L, \wedge, \vee, ', \longrightarrow, O, I)$ a LTV-LIA. Denote the set of all the L -fuzzy subsets on G as L^G , for any $A_1, A_2 \in L^G$ and $A_1 \subseteq A_2 \Leftrightarrow A_1(g) \leq A_2(g) (\forall g \in G)$; then, (L^G, \subseteq) is a partial order set.

Let M be a nonempty objects set and $(L, \wedge, \vee, ', \longrightarrow, O, I)$ a LTV-LIA. Denote the set of all the L -fuzzy subsets on M as L^M , for any $B_1, B_2 \in L^M$ and $B_1 \subseteq B_2 \Leftrightarrow B_1(m) \leq B_2(m) (\forall m \in M)$; then, (L^M, \subseteq) is a partial order set.

Theorem 1. Let $K = (G, M, L, F)$ be a linguistic truth-valued formal context and L a linguistic truth-valued lattice implication algebra; define mappings f_1 and f_2 between L^G and L^M ,

$$\begin{aligned}
 f_1: L^G &\longrightarrow L^M, \\
 f_1(A)(m) &= \bigwedge_{g \in G} (A(g) \longrightarrow F(g, m)), \\
 f_2: L^M &\longrightarrow L^G, \\
 f_2(B)(g) &= \bigwedge_{m \in M} (B(m) \longrightarrow F(g, m)).
 \end{aligned} \tag{4}$$

Then, for any $A \in L^G$, $B \in L^M$, (f_1, f_2) is a Galois connection based on LTV-LIA.

The proof process can be referred to [18].

Definition 8. A formal concept of $K = (G, M, L, F)$ is defined as a pair (A, B) with $A \in L^G$, $B \in L^M$, and $f_1(A) = B$ and $f_2(B) = A$, which can be called LTV-formal concept; the set A is called the extent and B the intent of the concept (A, B) .

Definition 9 (see [1]) Let $L(K)$ denote the set of all formal concepts of the context $K = (G, M, L, F)$; for any two formal concepts $C_1 = (A_1, B_1)$ and $C_2 = (A_2, B_2)$ in $L(K)$, an order relation on $L(K)$ is defined as follows:

$$(A_1, B_1) \leq (A_2, B_2) \Leftrightarrow A_1 \subseteq A_2 \text{ (or } B_2 \subseteq B_1), \tag{5}$$

the formal concept C_1 is called a subconcept of the formal concept C_2 , and C_2 is called a superconcept of the formal concept C_1 .

4. Case Database

The creation and search of case database is one of the indispensable links for any doctor to give the final diagnosis results of patients. Patients usually need to answer two kinds of questions about patients and disease attributes: the first kind of attributes, for example, the patient's age, gender, occupation, and home address, the onset time of the disease, and even a family history of disease, belong to the intrinsic attributes generally, and it is hard to be influenced by the external environment; the second kind of attribute is the symptom of the patient's current condition and the performance degree of the symptom, such as the severity and duration of cough, headache, and fever, which belongs to the variable attribute and will change with the passage of time and the change of external environment. According to the different functions of these two kinds of attributes, we call the first one as intrinsic attributes and the second one as extrinsic attributes. The construction of case database needs the following three steps: the formation of the LTV-formal context, the calculation of the LTV-formal concept with the extrinsic attribute of patients as its intent, and the construction of the LTV-CL based on the partial order relationship.

4.1. LTV-Formal Context of the Disease. The formation of LTV-formal context is inseparable from the object set and attribute set, as well as the attribute value of each object. The attribute values of extrinsic attributes can be represented by the following elements in the natural language set.

Definition 10. A descriptive adjectives set is defined as $X = \{\text{good, bad, big, little, long, short, high, } \dots\} = \{x_p | p = 1, 2, 3, \dots\}$, where $X_+ = \{\text{good, big, long, high, } \dots\} = \{x_{+p} | p = 1, 2, 3, \dots\}$ is called the positive descriptive adjectives set and $X_- = \{\text{bad, little, short, low, less, } \dots\} = \{x_{-p} | p = 1, 2, 3, \dots\}$ is called the negative descriptive adjectives set; in addition, $X = X_+ \cup X_-$.

Definition 11. Denote $R = \{r_s | s = 1, 2, 3, \dots\}$, which is called as the set of language modifiers. Define a Cartesian product between R and X , which is called the natural language set $R \times X$, recorded as $T = R \times X = \{(r_s, x_p) | r_s \in R, x_p \in X\}$. For any $r_s \in R$, they can be looked as the language modifiers, for example, slightly, somewhat, rather, almost, exactly, quite, very, highly, and absolutely.

The object set and attribute set are constructed with r patients and s extrinsic attributes of a disease in a department. According to the doctor's inquiry about each extrinsic attribute feature of a disease, the extrinsic attribute values of each patient are obtained and sorted into the disease information table, as shown in Table 1, in which

$G = \{g_1, g_2, \dots, g_r\}$ is the object set composed of patients and $M = \{m_1, m_2, \dots, m_s\}$ is the extrinsic attribute set about the relevant disease diagnosed by the doctor. a_{ij} indicates the patient's attribute value; for example, $a_{11}, a_{21}, a_{31}, \dots$ of an attribute m_1 "degree" is "very good," "somewhat good," "quite bad," and so on; $a_{12}, a_{22}, a_{32}, \dots$ of an attribute m_2 "frequency" is "very high," "a little high," "very high," and so on; $a_{13}, a_{23}, a_{33}, \dots$ of an attribute m_3 "persistence" is "very long," "a little short," "quite long," and so on. Based on this, the patient and disease information can be expressed as Table 2.

In order to describe the natural language with these different types of descriptive and restrictive words in a unified form of information, the following is a method to convert natural language into linguistic truth values.

Definition 12. Define the linguistic truth-valued set $Y = \{\text{true}(y_1), \text{false}(y_2)\} = \{y_q | q = 1, 2\}$ and the mapping t between X and Y , s.t.

$$\begin{aligned} t: X &\longrightarrow Y, \\ x_p &\longmapsto y_q, \\ t(x_p) = y_q &= \begin{cases} y_1, & x_p \in X_+, \\ y_2, & x_p \in X_-. \end{cases} \end{aligned} \quad (6)$$

Definition 13. For the set of linguistic modifiers R and the LTV set Y , define a Cartesian product between R and X ; that is, $L = R \times Y = \{(r_s, x_q) | r_s \in R, x_q \in Y\}$ and $\forall (r_s, x_p)_{ij} \in T$, $t(x_p) = y_q$.

By Definition 13, patient and disease information (Table 1) can be converted to the linguistic truth-valued formal context $K = (G, M, L, F)$, where $G = \{g_1, g_2, \dots, g_r\}$, $M = \{m_1, m_2, \dots, m_s\}$, and $F(g_i, m_j) = (r_s, t(x_p))_{ij} \in L$; that is, $(r_s, y_q)_{ij} \in L$, as shown in Table 3.

4.2. LTV-Formal Concept of Disease. By selecting the appropriate modifier set R in case of the acquired natural language, we can transform the description form of the extrinsic attribute value of each patient's general natural language to the linguistic truth values. In practice, we usually choose $R_3 = \{\text{Slightly, Rather, Absolutely}\}$. Then according to Definition 13, we can construct Cartesian product $L_3 = R_3 \times Y = \{\text{Absolutely false, Rather false, Slightly false, Slightly true, Rather true, Absolutely true}\}$, recorded as $L_6 = \{O, a, b, c, d, I\}$. By defining the corresponding operations on L_6 , we can form a six-ary linguistic truth-valued implication algebra and its Hasse diagram is shown in Figure 2. The implication operations between the linguistic truth values on L_6 are shown in Table 4.

For the LTV-LIA $L_6 = \{O, a, b, c, d, I\}$, O and I are the greatest and the smallest element of L_6 , respectively, where $O' = I$, $a' = c$, $b' = d$, $c' = a$, $d' = b$, and $I' = O$; that is to say, the attribute value "absolutely false O " inverse to "absolutely true I ," the attribute value "slightly false a " inverse to "slightly true c ," the attribute value "rather false d " inverse to "rather true b ," and the attribute value "slightly false a " and

TABLE 2: Patient and disease information.

	m_1	m_2	\dots	m_s
g_1	a_{11}	a_{12}	\dots	a_{1s}
g_2	a_{21}	a_{22}	\dots	a_{2s}
\vdots	\dots	\dots	\dots	\dots
g_r	a_{r1}	a_{r2}	\dots	a_{rs}

TABLE 3: Linguistic truth-valued formal context of patients and diseases.

	m_1	m_2	\dots	m_s
g_1	$(r_s, y_q)_{11}$	$(r_s, y_q)_{12}$	\dots	$(r_s, y_q)_{1s}$
g_2	$(r_s, y_q)_{21}$	$(r_s, y_q)_{22}$	\dots	$(r_s, y_q)_{2s}$
\vdots	\dots	\dots	\dots	\dots
g_r	$(r_s, y_q)_{r1}$	$(r_s, y_q)_{r2}$	\dots	$(r_s, y_q)_{rs}$

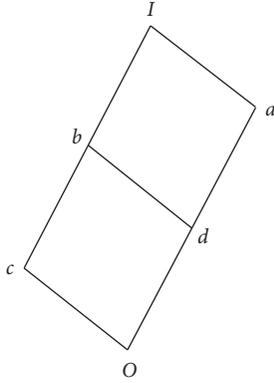
FIGURE 2: Hasse diagram of $(L, \wedge, \vee, \longrightarrow, O, I)$.

TABLE 4: Implication operation between the linguistic truth values.

\longrightarrow	O	a	b	c	d	I
O	I	I	I	I	I	I
a	c	I	b	c	b	I
b	d	a	I	b	a	I
c	a	a	I	I	a	I
d	b	I	I	b	I	I
I	O	a	b	c	d	I

“rather true b ” and “slightly true c ” and “rather false d ” can’t be compared in its semantics, so they are called incomparable linguistic truth values, i.e., a incomparable b and d incomparable c , denoted as $a // b$, $d // c$.

According to Theorem 1 and Definition 8, the linguistic truth-valued formal concepts are generated from the formal context $K = (G, M, L, F)$ described by patients and their diseases.

According to the Algorithm 1, the set of LTV-formal concepts is $C = \{c_u | c_u = (A_u, f_1(A_u)), u \in [1, n^r]\}$.

Example 2. The LTV-formal context $K = (G, M, L, F)$ is shown in Table 5, in which the three patients form the object set $G = \{g_1, g_2, g_3\}$ and the extrinsic attributes set $M = \{m_1, m_2, m_3, m_4\}$, and L is the LTV-LIA shown in Figure 2.

According to Algorithm 1, the LTV-formal concepts generated by Table 5 are as follows:

$$\begin{aligned}
C_1 &= (\{I, I, I\}, \{O, d, O, O\}); \\
C_2 &= (\{b, I, I\}, \{O, d, d, d\}); \\
C_3 &= (\{I, b, d\}, \{d, I, c, O\}); \\
C_4 &= (\{I, I, O\}, \{O, b, c, O\}); \\
C_5 &= (\{c, b, I\}, \{O, d, a, d\}); \\
C_6 &= (\{b, I, O\}, \{O, b, b, d\}); \\
C_7 &= (\{b, c, c\}, \{a, a, d, d\}); \\
C_8 &= (\{b, b, d\}, \{d, I, b, d\}); \\
C_9 &= (\{a, b, d\}, \{b, I, c, c\}); \\
C_{10} &= (\{a, I, O\}, \{c, b, c, c\}); \\
C_{11} &= (\{c, b, d\}, \{d, I, I, a\}); \\
C_{12} &= (\{c, I, O\}, \{O, b, b, a\}); \\
C_{13} &= (\{c, c, c\}, \{a, a, a, a\}); \\
C_{14} &= (\{b, c, O\}, \{a, I, b, d\}); \\
C_{15} &= (\{d, b, O\}, \{b, I, b, b\}); \\
C_{16} &= (\{a, c, O\}, \{I, I, c, c\}); \\
C_{17} &= (\{d, I, O\}, \{c, b, b, b\}); \\
C_{18} &= (\{c, c, O\}, \{a, I, I, a\}); \\
C_{19} &= (\{d, c, O\}, \{I, I, b, b\}); \\
C_{20} &= (\{O, c, O\}, \{I, I, I, I\}).
\end{aligned} \tag{7}$$

In order to conveniently construct Hasse diagram of the LTV-CL, we follow the hierarchical relationship from top to bottom and construct it.

4.3. LTV-CL of Disease. The process of lattice building is actually the process of concept clustering. For the same batch of data, the generated lattice is also unique. The construction algorithm of concept lattice is mainly divided into batch algorithm and progressive construction algorithm. In this paper, from the point of view of batch algorithm, we construct the LTV-CL generated by patient and disease information. The generation algorithm is as follows.

Through the generation of Hasse diagram of the LTV-CL, it not only can show the relationship between the linguistic truth formal concepts more intuitively but also can provide detailed case base for doctors’ diagnosis.

Example 3. According to Algorithm 2, we can build the corresponding LTV-CL as shown in Figure 3.

Based on the constructed case base, the attribute matching is carried out from two aspects: extrinsic attribute and intrinsic attribute.

5. Attribute Matching

For the patients to be diagnosed, if we want to find similar cases in the established case database, we need to perform

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Input: the linguistic truth-valued formal context  $K = (G, M, L, F)$ 
Output: the linguistic truth-valued formal concept
Begin
  while  $(K \neq \emptyset)$  do
     $\forall A_l = (A_l(g_1), A_l(g_2), \dots, A_l(g_r)) \in G(O, O, \dots, O) \leq A_l \leq (I, I, \dots, I), 1 \leq l \leq n^r$ 
    for  $l \leftarrow 1$  to  $n^r$  do
      for  $t \leftarrow 1$  to  $s$  do
        for  $i \leftarrow 1$  to  $r$  do
           $f_1(g_i, m_t) := A_l(g_i) \longrightarrow F(g_i, m_t)$ 
           $B(m_t) := \bigwedge_i f(g_i, m_t)$ 
        endfor;
      endfor;
      for  $i \leftarrow 1$  to  $r$  do
        for  $t \leftarrow 1$  to  $s$  do
           $f_2(B(m_t)) := B(m_t) \longrightarrow F(g_i, m_t)$ 
           $A(g_i) := \bigwedge_t f_2(B(m_t))$ 
        endfor;
        if  $A(g_i) = A_{l_s}(g_i)$  then
          endif;
        endfor;
      endfor;
    endfor;
  end;

```

ALGORITHM 1: Linguistic truth-valued formal concepts generation algorithm.

TABLE 5: The LTV-formal context $K_{3 \times 4}$ of a hospital department.

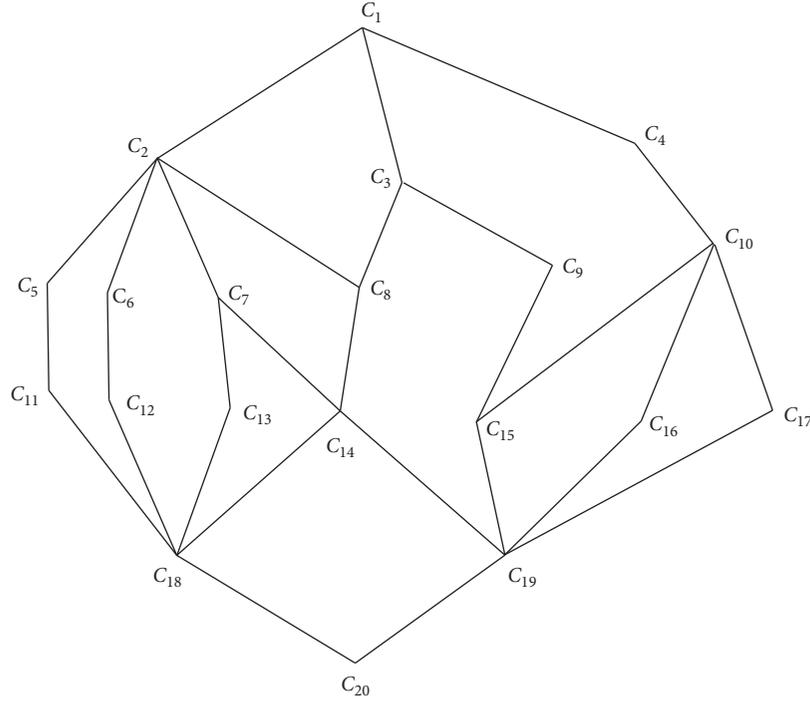
	m_1	m_2	m_3	m_4
g_1	a	I	c	O
g_2	c	b	b	I
g_3	O	d	a	d

```

Input: the linguistic truth-valued formal concepts  $C = \{c_u | c_u = (A_u, f_1(A_u)), u \in [1, n^r]\}$ 
Output: Hasse diagram of LTV-CL
Begin
  Calculate the topmost formal concept  $c_1$ , the extent set of  $c_1$  is  $\{I, I, \dots, I\}$  and the intent set of  $c_1$  is
   $\{\bigwedge_r^{i=1} F(g_i, m_1), \bigwedge_r^{i=1} F(g_i, m_2), \dots, \bigwedge_r^{i=1} F(g_i, m_s)\}$ .
   $L_v = \{c_1\}$ ; //  $L_v$  is used to save lattices
   $Q = \{c_1\}$ ; // initialize Q
  while  $Q \neq \emptyset$ 
     $c_1 = \text{out of } Q$ 
    for  $v \leftarrow 2r$  to  $n^r$ 
       $C_q := \text{Get Children}(c_1)$ ; // find out all the subconcepts
      for every node  $c \in C$ 
        If  $c$  does not exist, then
           $L_q = L_q \cup c$ ;  $c$  enter into Q;
          Add the edge from  $c_1$  to  $c$ 
        endif
      endfor
    endfor
  end;

```

ALGORITHM 2: Hasse diagram of LTV-CL generation algorithm.

FIGURE 3: LTV-CLL($K_{3 \times 4}$) based on Table 5.

two matching operations on their attributes. First, find the relevant matching formal concepts through the matching of extrinsic attributes, then find the formal concept with the highest matching degree through the matching of intrinsic attributes and the calculation of matching degree, and then calculate the treatment plan of the patient to be diagnosed.

5.1. Extrinsic Attribute Matching

Definition 14. Let $K = (G, M, L, F)$ be a linguistic truth-valued formal context and $L(K)$ a linguistic truth-valued concept lattice on K , where $G = \{g_1, g_2, \dots, g_r\}$, $M = \{m_1, m_2, \dots, m_s\}$, $L = \{a_1, a_2, \dots, a_w\}$, $F: G \times M \rightarrow L, L^G$ and L^M are the sets of all the L -fuzzy subsets on G and M , $\forall B_k = \{a_{k_1}, a_{k_2}, \dots, a_{k_s}\} \in L^M$, $a_{k_j} \in L$, $j = 1, 2, \dots, s$, and if there exists an uncertainty linguistic truth value \bar{a}_{k_j} of a_{k_j} , that is, $\bar{a}_{k_j} // a_{k_j}$, then $\bar{B}_{k^{(j)}}$ is called an incomparable set of B_k containing j incomparable linguistic truth values, denoted as $\bar{B}_{k^{(j)}} // B_k$, $\bar{\mathcal{B}}_{k^{(j)}} = \{\bar{B}_{k^{(j)}}\}$ is called a set of incomparable set, and $\bar{\mathcal{B}}_k = \cup_{j=1}^s \bar{\mathcal{B}}_{k^{(j)}}$ is an incomparable set family of B_k .

For example, $\forall B_k = \{a_{k_1}, a_{k_2}, \dots, a_{k_s}\} \in L^M$, $a_{k_j} \in L$, $j = 1, 2, \dots, s$; if $\bar{a}_{k_j} // a_{k_j}$, then there exist the following incomparable set families: the set with 1 incomparable linguistic truth value $\bar{\mathcal{B}}_{k^{(1)}} = \{\{\bar{a}_{k_1}, a_{k_2}, \dots, a_{k_s}\}, \dots, \{a_{k_1}, a_{k_2}, \dots, \bar{a}_{k_s}\}\}$ and the set with 2 incomparable linguistic truth values $\bar{\mathcal{B}}_{k^{(2)}} = \{\{\bar{a}_{k_1}, \bar{a}_{k_2}, \dots, a_{k_s}\}, \dots, \{a_{k_1}, \dots, \bar{a}_{k_{s-1}}, \bar{a}_{k_s}\}\}$;

similarly, we can get the set with n incomparable linguistic truth values $\bar{\mathcal{B}}_{k^{(s)}} = \{\{\bar{a}_{k_1}, \bar{a}_{k_2}, \dots, \bar{a}_{k_s}\}\}$.

Definition 15. Let $K = (G, M, L, F)$ be a LTV-formal context and $L(K)$ a LTV-CL based on K , where $G = \{g_1, g_2, \dots, g_r\}$, $M = \{m_1, m_2, \dots, m_s\}$, $L = \{a_1, a_2, \dots, a_w\}$, $F: G \times M \rightarrow L, L^G$ and L^M are the sets of all the L -fuzzy subsets on G and M , $\forall B_0 \in L^M$, $\exists (A, B) \in L(K)$, s.t. $B = B_0$ or $B // B_0$, and then (A, B) is called the matching formal concept of extrinsic attribute B_0 .

For the patients to be diagnosed, if there is a matching formal concept of extrinsic attribute in the LTV-formal concept established from the case database, the extrinsic attribute matching of the patients to be diagnosed is successful; otherwise, the matching is not successful.

Let $K = (G, M, L, F)$ be a LTV-formal context and $L(K)$ a LTV-CL based on K ; in case database, $G = \{g_1, g_2, \dots, g_r\}$ is the objects set, $M = \{m_1, m_2, \dots, m_s\}$ is the extrinsic attributes set, and $L = \{O, a, b, c, d, I\}$ is the LTV-LIA; for patient g_x to be diagnosed, the attribute value set of the extrinsic attribute is $B_x = \{a_{x_1}, a_{x_2}, \dots, a_{x_s}\}$, $a_{x_j} \in L$, $j = 1, 2, \dots, s$; for the convenience of the following description, $\forall a_{x_j} \in L$, denote $\bar{a}_{x_j} \in L$ as the incomparable linguistic truth value of a_{x_j} in L , that is, $\bar{a}_{x_j} // a_{x_j}$. In order to calculate the matching linguistic truth-valued formal concept of the patient g_x about the extrinsic attribute set B_x , the key step is to calculate the incomparable attribute set of B_x . The algorithm is as follows.

Based on the set $\bar{\mathcal{B}}$, which is generated by the above algorithm, the linguistic truth-valued formal concept (A, B)

```

Input: the extrinsic attribute set  $B_x = \{a_{x_1}, a_{x_2}, \dots, a_{x_s}\}$  of  $g_x$ ,  $a_{x_j} \in L$ ,  $j = 1, 2, \dots, s$ ;
Output: the incomparable set  $\overline{\mathcal{B}}$  of  $B_x$ 
Begin
while  $B_x \neq \emptyset$ 
  for  $t \leftarrow 1$  to  $s$  do
     $\overline{a}_{x_t} := a_{x_t}$ 
     $\overline{B}_{x_t} := \{a_{x_1}, a_{x_2}, \dots, \overline{a}_{x_t}, \dots, a_{x_s}\}$ 
     $\overline{\mathcal{B}}_t := \{\overline{B}_{x_t}\}$ 
    for  $l \leftarrow 1$  to  $s - t$  do
       $t^{(2)} := t + l$ ;
       $\overline{a}_{x_{t(2)}} := a_{x_{t(2)}}$ 
       $\overline{B}_{x_{t(2)}} := \{a_{x_1}, \dots, \overline{a}_{x_t}, \dots, \overline{a}_{x_{t(2)}}, \dots, a_{x_s}\}$ 
       $\overline{\mathcal{B}}_{t(2)} := \{\overline{B}_{x_{t(2)}}\}$ 
      for  $j \leftarrow 2$  to  $s$ ;  $h^{(t)} \leftarrow 1$  to  $s - j^{(t)}$  do
         $t^{(j+1)} := t^{(j)} + h^{(j)}$ ;
         $\overline{a}_{x_{t(j+1)}} := a_{x_{t(j+1)}}$ 
         $\overline{B}_{x_{t(j+1)}} := \{a_{x_1}, \dots, \overline{a}_{x_t}, \dots, \overline{a}_{x_{t(2)}}, \dots, \overline{a}_{x_{t(j+1)}}, \dots, a_{x_s}\}$ 
         $\overline{\mathcal{B}}_{t(j+1)} := \{\overline{B}_{x_{t(j+1)}}\}$ 
         $\overline{\mathcal{B}} := \overline{\mathcal{B}}_t \cup \overline{\mathcal{B}}_{t(2)} \cup \overline{\mathcal{B}}_{t(j+1)}$ 
      endfor
    endfor
  endfor
endfor
end

```

ALGORITHM 3: Incomparable set generation algorithm.

in case database $L(K)$ is searched. If $B \in \overline{\mathcal{B}}$, then (A, B) is the matching formal concept of extrinsic attribute set B_x about the patient g_x to be diagnosed.

Example 4. In Example 2, if the extrinsic attribute set of the patient g_x is $B_x = \{a, b, c, d\}$, according to Algorithm 3, the set of incomparable set B_x is $\overline{\mathcal{B}} = \overline{\mathcal{B}}_1 \cup \overline{\mathcal{B}}_2 \cup \overline{\mathcal{B}}_3 \cup \overline{\mathcal{B}}_4$. The matching formal concept of B_x can be calculated.

As can be seen from Figure 2, $a//b$, $a//c$, and $d//c$, we can get the sets $\overline{\mathcal{B}}_1$, $\overline{\mathcal{B}}_2$, $\overline{\mathcal{B}}_3$, and $\overline{\mathcal{B}}_4$ which, respectively, contain 1, 2, 3, and 4 incomparable linguistic truth values by calculation; the incomparable sets of all extrinsic attributes are as follows: $\{b, b, c, d\}$, $\{c, b, c, d\}$, $\{a, a, c, d\}$, $\{a, b, a, d\}$, $\{a, b, d, d\}$, $\{a, b, c, c\}$; $\{b, a, c, d\}$, $\{c, a, c, d\}$, $\{b, b, a, d\}$, $\{b, b, d, d\}$, $\{c, b, a, d\}$, $\{c, b, d, d\}$, $\{b, b, c, c\}$, $\{c, b, c, c\}$, $\{a, a, a, d\}$, $\{a, a, d, d\}$, $\{a, a, c, c\}$, $\{a, b, a, c\}$, $\{a, b, d, c\}$; $\{b, a, a, d\}$, $\{b, a, d, d\}$, $\{c, a, a, d\}$, $\{c, a, d, d\}$, $\{b, a, c, c\}$, $\{c, a, c, c\}$, $\{b, b, a, c\}$, $\{b, b, d, c\}$, $\{c, b, a, c\}$, $\{c, b, d, c\}$, $\{a, a, a, c\}$, $\{a, a, d, c\}$; $\{b, a, a, c\}$, $\{b, a, d, c\}$, $\{c, a, a, c\}$, and $\{c, a, d, c\}$; by comparing with the linguistic truth-valued formal concepts in the case database shown in Figure 3, $\{c, b, c, c\}$ and $\{a, a, d, d\}$ can be found in the case database with corresponding formal concepts; that is, $C_7 = (\{b, c, c\}, \{a, a, d, d\})$ and $C_{10} = (\{a, I, O\}, \{c, b, c, c\})$.

5.2. Intrinsic Attribute Matching. In the matching formal concept, we need to further calculate the formal concept with the largest matching degree, which is realized by matching the following intrinsic attribute matching.

Definition 16. Let $K = (G, M, L, F)$ be a linguistic truth-valued formal context, L a linguistic truth-valued lattice implication algebra, and $N = \{n_1, n_2, \dots, n_t\}$ an intrinsic attribute set of G . For any $g_i \in G$ and $n_v \in N$ ($i = 1, 2, \dots, r$; $v = 1, 2, \dots, t$), f_3 is an operator defined between G and N , which is called intrinsic attribute operator; that is,

$$f_3: G \times N \longrightarrow L, \quad (8)$$

$$f_3(g_i, n_v) = a_{iv}.$$

Note: for any $g_i \in G$, the set of intrinsic attribute values of $N = \{n_1, n_2, \dots, n_t\}$ is $\{a_{i1}, a_{i2}, \dots, a_{it}\}$, which can be abbreviated as $f_3(g_i)$.

Definition 17. For any $A_1, A_2 \in L^G$, $g \in G$, and $B_1, B_2 \in L^M$, $m \in M$, the matching degree between object subsets and attribute subsets is defined as

$$\pi(A_1 \subset A_2) = \bigwedge_{g \in G} (A_1(g) \longrightarrow A_2(g)), \quad (9)$$

$$\pi(B_1 \subset B_2) = \bigwedge_{m \in M} (B_1(m) \longrightarrow B_2(m)).$$

In the linguistic truth-valued formal context $K = (G, M, L, F)$, $N = \{n_1, n_2, \dots, n_t\}$ is the intrinsic attribute set of G , the extrinsic and intrinsic attribute values sets of patient g_x to be diagnosed can be expressed as $\{F(g_x, m_1), F(g_x, m_2), \dots, F(g_x, m_s)\}$ and $\{f_3(g_x, n_1), f_3(g_x, n_2), \dots, f_3(g_x, n_t)\}$, respectively, the matching formal concept of g_x about extrinsic attributes is

```

Input: the intrinsic attribute value set  $X = \{f_3(g_x, n_1), f_3(g_x, n_2), \dots, f_3(g_x, n_r)\}$  of the patient  $g_x$  to be diagnosed and the extension set  $\bar{A}_q = \{f_2(\bar{B}_q)(g_1), f_2(\bar{B}_q)(g_2), \dots, f_2(\bar{B}_q)(g_r)\}$  of formal concepts matching the extrinsic attributes of  $g_x$ 
Output:  $D$  //matching degree set
Begin
while  $X \neq \emptyset$ 
  for  $i \leftarrow 1$  to  $r$  do
    for  $p \leftarrow 1$  to  $t$  do
       $\pi_{xi} = \wedge (f_3(g_x, n_p) \longrightarrow f_3(g_i, n_p))$ 
    for  $q \leftarrow 1$  to  $\|q\|$  do
       $d_i = \wedge (\pi_{xi} \longrightarrow f_2(\bar{B}_q)(g_i))$ 
       $D = \{d_i\}$ 
    endfor
  endfor
endfor
end

```

ALGORITHM 4: Matching degree set generation algorithm.

$(\bar{A}_q, \bar{B}_q) \in L(K)$, where $\bar{B}_q \in \bar{\mathcal{B}}$, $\bar{A}_q = \{f_2(\bar{B}_q)(g_1), f_2(\bar{B}_q)(g_2), \dots, f_2(\bar{B}_q)(g_r)\}$, $q = 1, 2, \dots, \|q\|$, $\|q\|$ is the number of matching formal concepts); intrinsic attribute matching is to calculate the maximum matching degree in a series of matching formal concepts (\bar{A}_q, \bar{B}_q) ; then we find the linguistic truth-valued formal concept with the highest matching degree. The matching degree between the set of intrinsic attribute values $f_3(g_{i_1})$ and $f_3(g_{i_2})$ can be expressed as $\pi(f_3(g_{i_1}) \subset f_3(g_{i_2})) = \wedge_{n_v \in N} (f_3(g_{i_1}, n_v) \longrightarrow f_3(g_{i_2}, n_v))$. The algorithm is as follows (Algorithm 4).

From the above algorithm, we can finally calculate the matching degree between the patients to be diagnosed and the matching formal concepts obtained by extrinsic attribute matching in the case database through the intrinsic attribute matching algorithm, then find the linguistic truth-valued formal concept with the highest matching degree, and give a

more specific diagnosis according to the specific matching degree by referring to the diagnosis scheme in the case database.

Example 5. The linguistic truth-valued formal context $K_{3 \times 4} = (G, M, L, F)$ is shown in Table 4, in which, the intrinsic attributes set $N = \{n_1, n_2, n_3, n_4, n_5\}$ and $f_3(g_1) = \{a, c, b, c, d\}$, $f_3(g_2) = \{b, b, d, I, a\}$, $f_3(g_3) = \{b, a, c, c, O\}$, and $f_3(g_x) = \{c, a, b, a, O\}$. From the conclusion of Example 4, the matching linguistic truth-valued formal concepts $C_7 = (\{b, c, c\}, \{a, a, d, d\})$ and $C_{10} = (\{a, I, O\}, \{c, b, c, c\})$ of g_x can be found through the matching operation of extrinsic attributes. Denote $A_7 = \{b, c, c\}$ and $A_{10} = \{a, I, O\}$; according to Definition 17, we firstly calculate the matching degree of intrinsic attributes as follows:

$$\begin{aligned}
 \pi(f_3(g_x) \subset f_3(g_1)) &= (c \longrightarrow a) \wedge (a \longrightarrow c) \wedge (b \longrightarrow b) \wedge (a \longrightarrow c) \wedge (O \longrightarrow d) = a \wedge c \wedge I \wedge c \wedge I = O, \\
 \pi(f_3(g_x) \subset f_3(g_2)) &= (c \longrightarrow b) \wedge (a \longrightarrow b) \wedge (b \longrightarrow d) \wedge (a \longrightarrow I) \wedge (O \longrightarrow a) = I \wedge b \wedge c \wedge I \wedge I = c, \\
 \pi(f_3(g_x) \subset f_3(g_3)) &= (c \longrightarrow b) \wedge (a \longrightarrow a) \wedge (b \longrightarrow c) \wedge (a \longrightarrow c) \wedge (O \longrightarrow O) = I \wedge I \wedge b \wedge c \wedge I = c.
 \end{aligned} \tag{10}$$

The above results show that the matching degree of intrinsic attributes between patient g_x to be diagnosed and each patient in the case database is O , c , and c , respectively; then we can get $A_x = \{O, c, c\}$. According to Definition 17, it is calculated as follows:

$$\begin{aligned}
 \pi(A_x \subset A_7) &= (O \longrightarrow b) \wedge (c \longrightarrow c) \wedge (c \longrightarrow c) = I, \\
 \pi(A_x \subset A_{10}) &= (O \longrightarrow a) \wedge (c \longrightarrow I) \wedge (c \longrightarrow O) = a.
 \end{aligned} \tag{11}$$

Because $I > a$, the best matching result is the linguistic truth-valued formal concept C_7 ; at the same time, the specific treatment scheme is also given.

6. Conclusions

In order to make artificial intelligence technology play a more important role in the application of natural language, this paper continues to study the LTV-CL with the aid of the LTV-LIA based on lattice-valued logic and the classical concept lattice and gives the LTV-formal concept and the generation algorithm of concept lattice based on the application background of medical intelligent diagnosis. According to the different characteristics of patients' disease attributes obtained by doctors' consultation, two kinds of matching algorithms based on extrinsic attributes and intrinsic attributes are proposed. Combined with the calcu-

lation formula of matching degree defined in this paper and the corresponding algorithm, the matching objects in the case database are accurately matched again to achieve the best matching with the diagnosed patients, so as to give the best treatment scheme.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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