

A Fuzzy Ontology Framework Based on User Profile

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Abstract: Aimed at the problem of the classical ontology cannot represent the imprecision and uncertainty information, firstly, the ambiguity and uncertainty of fuzzy information was analyzed, and the fuzzy concept relationship was expressed by using fuzzy membership function. And then, the user interest estimation based on behavior was studied in term of user's learning preferences, and user profile was described by the learning object. Furthermore, fuzzy ontology under different granularity was built, the fuzzy concept lattice was clustered, and the concept similarity of fuzzy formal concepts was calculated. Finally, a fuzzy ontology framework based on user profile was proposed. As verified by experiment, the results have shown that the framework can reduce efficiently the uncertainty information of fuzzy ontology, and enhance the precision of ontology.

Keywords: Ontology Framework, User Profile, Similarity Degree, Fuzzy Ontology

1. Introduction

In general, the ontology is made up of lexical vocabularies, basic terms and their relationships, and the rules of the lexical extensions, which were defined in conjunction with the basic terms and relationships. The ontology as a clear conceptualized term, which was given by *Gruber* in 1993 [1], and then it was explicitly described by *Borst* [2].

In the process of ontology research and application, we always meet the problems of ontology change and evolution. For example, *Kang* and et al. [3] proposed the computational model of ontology similarity with multi-granularity by using concept lattice, and then he combined with the help of domain experts, the ontology construction, fusion and connection method under different granular structures were given. So to speak, this method was anew way that combined ontology and concept lattice. According to the combination of WordNet and ontology, *Atanassov* [4] proposed a method of micro-blog content topic extension, which sorted the blog according to the preference of the extended concept, and then this method provided the personalized recommendation for users. *Jiang* [5] proposed a distributed domain context correlation model by using fuzzy ontology, and this model made the relationships between context and domain ontology be expressed, and the problem of information integration in information overload be overcome. Furthermore, the formal concept analysis as an

effective tool of knowledge acquisition was proposed by *Wille* [6], which has been widely used in machine learning, data mining, information acquisition, personalized service and other fields. For example, *Formica* et al. [7] proposed a formal ontology construction method based on the fuzzy form concept analysis theory, and its aim was to solve the problem of the uncertain information in the personalized service semantic search process, and the idea of integrating rough set was used to discover the uncertain information in the semantic web search process. Subsequently, *Hu* et al. [8] introduced the idea of particle computation into the formal concept analysis, and constructed the concept lattice structure and maximum rule acquisition scheme in fuzzy granularity background. Especially, some special knowledge can be avoided by the coarse-grained concept lattice, while some complex conceptual knowledge structure can be prevented by the fine-grained concept lattice, and the excess number of rules would be overcome by the largest rule of the reasoning. In addition, in document [9], the data analysis and processing of the concept were applied to the multi-instance holistic learning model, and the validity of the theory was verified.

To this end, the knowledge of fuzzy concept was introduced into the ontology, and the construction method of fuzzy ontology under different granularity was discussed. And then a fuzzy ontology framework was proposed. For learning objects, they can use fuzzy ontology framework to define, implement, verify and improve the performance of retrieval,

classification and management operation, and can construct fuzzy ontology process based on *user profile* [10].

2. Domain Ontology Construction

In the context of E-learning, *user profile* was described by the learning object, and the user's preference was described by two elements of *user profile*. Thus, the construction process of ontology can be believed as the relationship expression among concepts, because the ambiguity and uncertainty of information in the real world was denoted as the fuzzy knowledge of the fuzzy ontology. Correspondingly, fuzzy ontology based fuzzy knowledge has two advantages. Of which, one is to improve the concept of formal description via the ontology, and another is to describe and deal with fuzzy information in real application fields. So, the construction process of the domain ontology can be defined as follows.

Def. 1 A fuzzy set A on the domain Θ is expressed as the membership function $A: \Theta \rightarrow [0, 1]$. Where $A(x)$ indicates the degree, and exists the relationship $x \in A$.

Def. 2 Set the set $K=(G, M, I)$ to represent a formal context. Here, G is a set of all objects, M is the attribute set of the object, $I=A(G \times M)$ is a set of fuzzy relationships between objects in G and attributes in M , and meanwhile there exists the expression $\forall (g, m) \in I, \mu(g, m) \in [0, 1]$.

Def. 3 Set the set $K=(G, M, I=A(G \times M))$ as fuzzy formal background, and make the trusted threshold be α and $x \subseteq G, B \subseteq M$. The following definition can be obtained. That is, $X^* = \{a \mid a \in M, \forall x \in X, \mu(x, a) \geq \alpha\}$ and $B^* = \{x \mid x \in G, \forall a \in B, \mu(x, a) \geq \alpha\}$.

If a two-tuple (X, B) satisfies the relationship $X^*=B$ and $B^*=X$, then (X, B) is a fuzzy formal concept on fuzzy credibility degree α . Among them, X is the extension of fuzzy concept, and B is the connotation of fuzzy concept. Obviously, for $g \in G$, an object can be represented as $\lambda g = (g^{**}, g^*)$, and the tupe (X, B) can be denoted as $(X, B) = \bigvee_{g \in X} \lambda g$.

Def. 4 An ontology was formally represented by a two-tuple $\Theta = (C, R)$, of which C is a set of all concepts, R is a relationship set among concepts, and concepts and relationships can form a directed acyclic graph. Meanwhile, if $c_1, c_2 \in C$, $\exists \nabla \in R$, and $c_1 \nabla c_2$, then the element c_1 and c_2 exists the relationship ∇ .

Def. 5 Set an ontology field, and make the fuzzy concept set proposed by experts C . If $c_i, c_j \in C$, the similarity degree between c_i and c_j can be calculated by the formula $s_{ij} = \frac{|\{a \mid a \in c_i^* \cap c_j^*, \mu(c_j, a) \leq \beta\}|}{|\{a \mid a \in c_i^* \cup c_j^*\}|}$

Based on fuzzy reliability degree α , the above five definitions have shown the similarity possibility of two concepts in the threshold β . Here, if we take $\beta=0.1$, and then a fuzzy similarity relationship can be obtained, which was shown as follows.

$$\tilde{s} = (s_{ij})_{|C| \times |C|}$$

Furthermore, if \tilde{s} satisfies the following three prerequisites, then it is called a fuzzy equivalent relation matrix on C , which includes (1) Reflexivity: $s_{ii}=1$, (2) Symmetry: $s_{ij}=s_{ji}$, and (3) Transitivity: $\forall k=1, \dots, |C|, s_{ik} \wedge s_{kj} \leq s_{ij}$.

3. Fuzzy Ontology Framework Construction

3.1. Fuzzy User Profile

Based on the above five definitions, ontology can be formally denoted as a two-tuples, and the similarity degree of elements in a tuple can be calculated by the formula s_{ij} . For this purpose, the user's preference was expressed as a set $\Theta = (C, R)$ [11], where C was the concept set that described the user's preference, R was the fuzzy ontology of the concept set.

To describe the user's preference, the fuzzy similarity relationship was expressed as follows.

$$C^\Theta = \{(c_1^\Theta, \omega_1^\Theta), (c_2^\Theta, \omega_2^\Theta), \dots, (c_n^\Theta, \omega_n^\Theta)\} \quad (1)$$

In formula (1), C was a set of concepts c_i , ω_i was the weight of a concept. Meanwhile, the above formula also quantified the weight of each concept in learning objects, and the specify quantified process included the following two steps.

Step. 1 The weight of each concept c_i in the learning object d was a fuzzy value. According to the synonyms and frequency in the user's document, the basic weight value of each concept can be calculated, and weight values were re-adjusted.

Step. 2 In the user's documentation, if a concept was more frequent than others, then it was considered that existed the high relevant with *user profile*. To obtain this high correlation, the weight and frequency of each concept in *user profile* must be re-adjusted. Hence, the weight of the concept c_i in user profile Θ was also re-calculated.

$$\omega_i^\Theta = \sum_{j \in u} \omega_j * (1 + \frac{docs(c_i, \Theta)}{|T|}) * Ln(\frac{|\Theta|}{\Theta(c_i)} + 1) \quad (2)$$

In the above formula, ω_j was the relevance degree between the concept c_i and learning object d_j , $docs(c_i, \Theta)$ was the document number of the concept c_i in *user profile* [12], and $\Theta(c_i)$ was the number of *user profile*, which indicated the concept c_i having the determining membership. Subsequently, the weight of the concept was calculated, and the correlation distribution between the concepts was determined. Thus, the normalized weight was distributed in the interval $[0, 1]$, and the concept had an enough large weight ($\omega > 0.5$), because the normalized weight is useful for improving the learning activities in the E-learning environment [13]. Thus, the fuzzy ontology can be believed as a vector network, and this

network can also be seen as a directed graph set, of which each point expressed a concept, and an edge indicated the relation among concepts.

3.2. Fuzzy Ontology Framework

The Ontology is the explicit formal specification for the shared conceptual models [14], and it usually contains five basic modeling languages, which are concepts, relationships, functions, axioms and examples. In contrast, fuzzy ontology represents fuzzy concepts and their fuzzy relations, and

meanwhile this relationship were represented by a four-tuples $\Theta = (C, R, P, X)$, of which C is a fuzzy concept set, R is an attribute set, P is Cartesian products between fuzzy concept set and attribute set, and X is an axiomatic set. So, according to the definition of Θ , the fuzzy concept can be represented as $C = (c_1^{r_1}, c_2^{r_2}, \dots, c_n^{r_n})$, where c_i is an object, and r_i is the property of c_i [15]. Thus, through the fuzzy concept definition, the fuzzy ontology framework was constructed as follows.

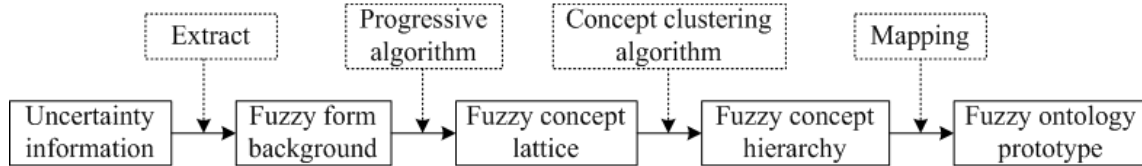


Figure 1. Fuzzy ontology construction framework.

In Figure 1, the uncertain information in the learning object was selected and formed the fuzzy formal context. To construct fuzzy concept, the fuzzy concept lattice was generated into fuzzy concept hierarchy, and a fuzzy concept clustering was formed through the concept of fuzzy clustering algorithm. Furthermore, the fuzzy concept clustering had the following properties [16].

(1) A hierarchical fuzzy concept clustering was derived from the fuzzy formal concept. In general, the formal concepts

have a father-son relationship, and the two clusters also have a father-son relationship.

(2) A fuzzy concept belongs at least to a fuzzy concept cluster. Of course, it also belongs to multiple fuzzy concept clusters. According to fuzzy concept, the clustering hierarchy and the corresponding relationship of elements in fuzzy ontology can be constructed by using mapping rules, and the specify mapping rules were shown in Figure 2.

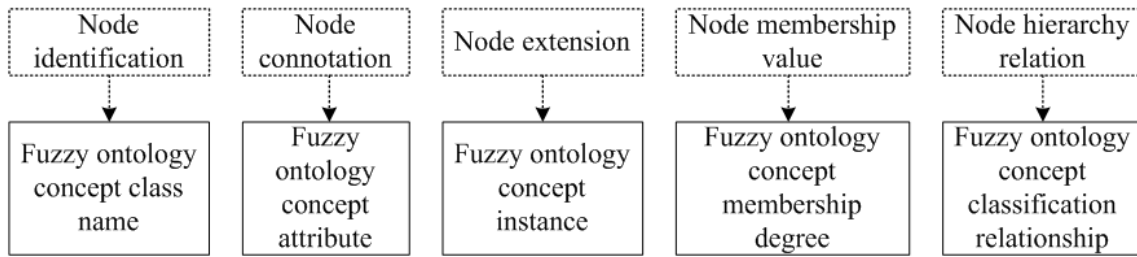


Figure 2. Fuzzy concept clustering and fuzzy ontology mapping rules.

In Figure 2, we can know that fuzzy ontology mapping rules was built from fuzzy concept to fuzzy ontology. First of all, the concept node identifier in fuzzy concept hierarchy is the concept class name of fuzzy ontology, the connotation of concept node is the property of the corresponding concept in fuzzy ontology, the extension of concept node is an example of the corresponding concept in fuzzy ontology, the membership value of node attributes is the corresponding attribute value of fuzzy ontology [17], and the hierarchical relationship among concepts in fuzzy concept hierarchy is the relationship between the corresponding concepts of fuzzy ontology. So, the concept of fuzzy hierarchy can be mapped into fuzzy ontology, which includes the concept of fuzzy ontology and fuzzy attribute ontology, the value of membership, fuzzy ontology and fuzzy classification, and the relationship between the concepts.

Based on the above mapping rules [18], the fuzzy ontology prototype was obtained. Of course, to add concept, non-classification relationship, attribute, axiom, instance, and

to expand the fuzzy ontology prototype, the participation of domain experts was welcomed, and a perfect fuzzy ontology was obtained. Thus, through fuzzy concept similarity, the whole process for mapping rules can be expressed by the following concept clustering algorithm.

Table 1. The concept clustering algorithm.

| Input: fuzzy concept c , the similarity threshold β | |
|---|--|
| Output: fuzzy concept clustering c' | |
| 1 | Read the edge set $c_a c_b$ in c (c_a is the parent node of c_b , the edge includes the father-son node and the similarity parameters between nodes). |
| 2 | Search the edge $c_i c_j$ ($c_i c_j \in c_a c_b$) in sequence, and calculate the concept similarity degrees $s_{ij}(c_i, c_j)$. |
| 3 | If $s_{ij}(c_i, c_j) > \beta$, the cluster $c_i c_j$ becomes a new node c_{ij} . Otherwise, return Step. 5. |
| 4 | Update the node c_{ij} , replace the parent node c_i and update the edge set. The parent node of c_i is connected to c_{ij} , c_{ij} is connected to the child node of c_j , and then the child node c_j is deleted. |
| 5 | Return Step. 2. If the edge $c_i c_j$ doesn't existed, then the condition $s_{ij}(c_i, c_j) > \beta$ cannot be satisfied. |
| 6 | The edge set is stored in c' . |

4. Experiment and Analysis

The experiment was carried out in the Metadata for E-Learning, which supported open access in the form of domain ontology to obtain learning resources, and especially for teaching resources. The basic components of Metadata were to share and reuse objects, which included the storage for resource indexes and knowledge database for metadata, and the heterogeneous repository network for the transparent retrieving.

Through metadata, we mainly integrate data resources, obtain data information of network users and restore the visualization detector. And then, based on fuzzy concept similarity degree, we used Java language to achieve incremental fuzzy concept lattice construction algorithm and clustering algorithm. For example, 18 users used simple query interface (SQI) to collect about 3,600 learning objects, of

which SQI provided the standardized communication for users, and realized the joint queries.

For a webpage, the user usually had three visiting behaviors, which included saving page, printing page and *bookmark*. No matter what kind of behaviors, it can express that the user had a high interest degree in the page. Thus, the selected learning object can extract the text content, and the learning object can generate a set of user documents.

Now, let $\Theta(C, R)$ represent user's preference, and then the user's interest degree for a web page can be described by five operations, which included saving page, printing page, *Bookmark*, visiting frequency and residence time. Here, we set the threshold value $\beta = 0.5$, a five-element operation set = {saving page, printing page, *Bookmark*, visiting frequency and residence time}, and then fuzzy similarity relationship C^Θ can be obtained by user's interest degree, as shown in Table 1.

Table 2. Fuzzy similarity relationship.

| Users | C^Θ | $(c_1^\Theta, \omega_1^\Theta)$ | $(c_2^\Theta, \omega_2^\Theta)$ | $(c_3^\Theta, \omega_3^\Theta)$ | $(c_4^\Theta, \omega_4^\Theta)$ | $(c_5^\Theta, \omega_5^\Theta)$ |
|--------|------------|---------------------------------|---------------------------------|---------------------------------|---------------------------------|---------------------------------|
| User01 | 0.17 | 0 | 0.50 | 0.17 | 0.50 | 0.20 |
| User02 | 0.20 | 0 | 0.50 | 1.00 | 0.17 | 0.15 |
| User03 | 0.33 | 0.20 | 0.25 | 1.00 | 0 | 0.31 |
| User04 | 0.67 | 0.50 | 0.67 | 0.40 | 0 | 0.32 |
| User05 | 0.50 | 0.33 | 0 | 0.33 | 0.50 | 0.25 |
| User06 | 1.00 | 0.14 | 0 | 1.00 | 0.50 | 0.14 |
| User07 | 0.50 | 0 | 0.33 | 0.20 | 0.50 | 0.23 |
| User08 | 0.33 | 0 | 0.14 | 0 | 1.00 | 0.50 |
| User09 | 0.33 | 0.33 | 0.50 | 0 | 0.33 | 0.12 |
| User10 | 1.00 | 0.25 | 0.33 | 1.00 | 0.50 | 0.22 |
| User11 | 0 | 1.00 | 0.50 | 0.17 | 0 | 0.20 |
| User12 | 0 | 0.50 | 0.50 | 0 | 0 | 0.15 |
| User13 | 0.50 | 0.20 | 0 | 0 | 0 | 0.31 |
| User14 | 0.40 | 0.50 | 0 | 0.40 | 0 | 0.32 |
| User15 | 0 | 0.23 | 0.20 | 0.33 | 0.50 | 0.25 |
| User16 | 0 | 0.14 | 0.52 | 1.00 | 0.14 | 0.50 |
| User17 | 0.50 | 0 | 0.33 | 0 | 0.50 | 0.12 |
| User18 | 0.33 | 0 | 0.14 | 0 | 1.00 | 0.50 |

In Table 2, according to Def. 4, the higher the learners' interest is, the better the concept similarity degree is, this results were also an indication that the computation process of the user interest degree met the conditions (1) and (2). As the learning object, all users were the contributor of the learning object, and users in the experiment must upload more than 18 English-based files to Metadata, because the number of documents was so much as to establish a good *user profile*. So, the text content from 3,600 learning objects was obtained, and the relationship between fuzzy similarity rate and the weight of concepts was shown in Figure 3.

According to Def. 5 the transitive closure was achieved and met the condition (3), and then a fuzzy equivalence relation matrix scan be constructed.

$$S = \begin{bmatrix} s_{11} & \dots & s_{1n} \\ \dots & \dots & \dots \\ s_{n1} & \dots & s_{nn} \end{bmatrix}$$

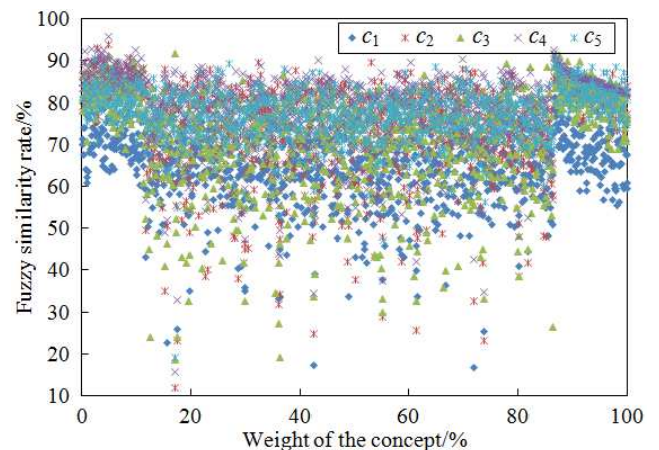


Figure 3. The relationship between fuzzy similarity and the weight of concepts.

On the basis of the matrix s , the C^Θ -based domain knowledge database was obtained, which came from the

domain expert, as shown in Table 3.

Table 3. A domain expert knowledge database based on C^Θ .

| Name | C^Θ | $(c_1^\Theta, \omega_1^\Theta)$ | $(c_2^\Theta, \omega_2^\Theta)$ | $(c_3^\Theta, \omega_3^\Theta)$ | $(c_4^\Theta, \omega_4^\Theta)$ | $(c_5^\Theta, \omega_5^\Theta)$ |
|------|------------|---------------------------------|---------------------------------|---------------------------------|---------------------------------|---------------------------------|
| 1 | 0.9 | 0.8 | 0.5 | 0.9 | 0.4 | 0.8 |
| 2 | 0.5 | 0.7 | 0.4 | 0.8 | 0.6 | 0.9 |
| 3 | 0.9 | 0.8 | 0.5 | 0.8 | 0.4 | 0.6 |
| 4 | 0.6 | 0.9 | 0.9 | 0.4 | 0.8 | 0.6 |
| 5 | 0.5 | 0.9 | 0.6 | 0.2 | 0.9 | 0.4 |
| 6 | 0.6 | 0.8 | 0.8 | 0.6 | 0.3 | 0.4 |

According to the domain knowledge database, the fuzzy concept lattice was constructed by using the concept clustering algorithm, as shown in Figure 4.

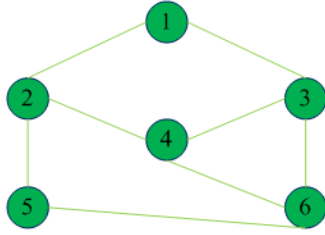


Figure 4. Fuzzy concept lattice.

The composition of each fuzzy concept and the fuzzy parameter values are shown in Table 4. To facilitate the description, six attributes in the fuzzy similarity relationship were denoted by symbols $c_i, i=1,2,\dots,6$.

Table 4. Fuzzy formal concept construction.

| Properties | Fuzzy formal concept construction | δ |
|------------|---|----------|
| 1 | $(\{1, 2, 3, 4, 5\}, \{\emptyset\})$ | 0 |
| 2 | $(\{1, 2, 3\}, \{c_1(0.6), c_5(0.5)\})$ | 0.50 |
| 3 | $(\{1, 2, 4, 5\}, \{c_3(0.6)\})$ | 0.60 |
| 4 | $(\{1, 2\}, \{c_1(0.2), c_3(0.6), c_5(0.3)\})$ | 0.35 |
| 5 | $(\{3\}, \{c_1(0.6), c_4(0.3), c_5(0.5)\})$ | 0.42 |
| 6 | $(\{4, 5\}, \{c_2(0.3), c_5(0.6), c_6(0.6)\})$ | 0.27 |
| 7 | $(\{\emptyset\}, \{c_1(1), c_2(1), c_3(1), c_4(1), c_5(1), c_6(1)\})$ | 0 |

Here, Let $\delta \in [0, 1]$, the fuzzy equivalence relation matrix s was calculated by the cut set operation, and its calculation process was shown as follows.

$$s_\delta = (\tilde{s}_{ij}), \tilde{s}_{ij} = \begin{cases} 1 & s_{ij} \geq \delta \\ 0 & s_{ij} < \delta \end{cases}$$

A partition class $c_i / s_\delta = \{p_1, p_2, \dots, p_i\}$ of domain knowledge database was obtained. If the threshold value $\beta = 0.5$, then the formal background database was also obtained via Def. 5. As shown in Table 5.

Table 5. The formal background database.

| Name | C^Θ | c_1 | c_2 | c_3 | c_4 | c_5 |
|------|------------|-------|-------|-------|-------|-------|
| 1 | 0 | 0.3 | 0 | 0.3 | 0 | 0.3 |
| 2 | 0.3 | 0 | 0.5 | 0 | 0.3 | 0 |
| 3 | 0 | 0 | 0 | 0.3 | 0 | 0.3 |
| 4 | 0 | 0.5 | 0 | 0.3 | 0 | 0.7 |
| 5 | 0.5 | 0 | 0 | 0 | 0.5 | 0.5 |
| 6 | 0.3 | 0 | 0.3 | 0 | 0 | 0.3 |

In Table 4, if $\beta = 0.1$ and $\delta = 0.6$, the fuzzy relational matrix s was got.

$$s = \begin{bmatrix} 1.0 & 0.5 & 0.5 & 0.0 & 0.0 & 0.0 \\ 0.5 & 1.0 & 0.5 & 0.0 & 0.0 & 0.0 \\ 0.5 & 0.5 & 1.0 & 0.0 & 0.0 & 0.0 \\ 0.0 & 0.0 & 0.0 & 1.0 & 0.5 & 0.3 \\ 0.0 & 0.0 & 0.0 & 0.5 & 1.0 & 0.3 \\ 0.0 & 0.0 & 0.0 & 0.3 & 0.3 & 1.0 \end{bmatrix}$$

Therefore, a concept class partition $c_i / s_\delta = \{\{1, 2, 3\}, \{4, 5, 6\}\}$. When $\beta = 0.1$ and $\delta = 0.6$, according to a concept class division, the fuzzy concept lattice was obtained by the fuzzy relational matrix s . Furthermore, six attributes in Table 2 were replaced by the symbols a, b, c, d, e and f , and the results were shown in Figure 5.

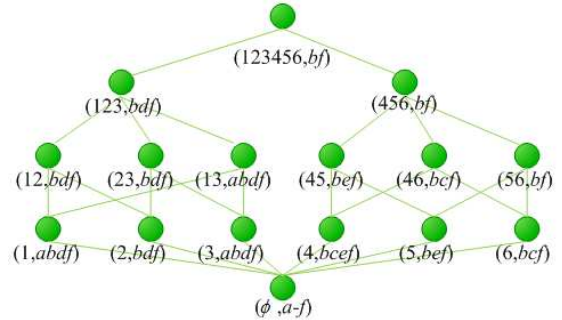


Figure 5. Fuzzy concept lattice.

The similarity degree model not only reflects the ratio of character coincides, but also reflects the ability of the superposition of characteristics values, and so it is an effective similarity measure method of fuzzy concepts. Now, we take the fuzzy concept lattice as an example, and calculate the similarity degree s_{ij} between $c_i (i=1, 2, 3, 4, 5, 6)$ and $c_j (j=4, 5, 6)$.

$$s_{ij}(c_i c_j) = \left(1 - \frac{\sum |2.3/6 - 1.6/3| + |3.4/6 - 1.3/3|}{|\{123, 456\} \cap \{456\}|} \right) * \frac{|\{123, 456\} \cap \{456\}|}{|\{123, 456\} \cup \{456\}|} = 0.38$$

According to the different similarity values, the relationship *is-a*, *part-of* was determined. If the similarity degree between concepts is greater than 0.6, and then they have *is-a* relationship. Contrarily, if the similarity degree is between 0.4 and 0.6, and then they have *part-of* relationship. Otherwise, they are abandoned.

To this end, if we selected $\beta=0.5$ and $\delta=0.5$, then its meaning is that the weight of the connotation and the extension is equal. According to fuzzy concept similarity, the fuzzy concept lattice was clustered, and the concept similarity of fuzzy formal concepts with father-son inheritance relationship was calculated, which was shown as follows.

$$s_{ij}(2,3) = 0.70, s_{ij}(2,5) = 0.60, s_{ij}(3,4) = 0.20, s_{ij}(2,4) = 0.50.$$

If the similarity threshold $\beta = 0.38$, and the fuzzy concept clustering result was shown in Figure 6.

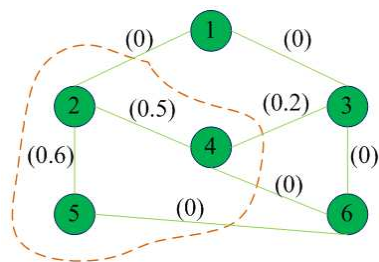


Figure 6. Fuzzy concept clustering result.

5. Conclusions

The knowledge of fuzzy concept was introduced into the ontology, the ambiguity and uncertainty of fuzzy information was analyzed, and the fuzzy concept relationship was expressed. Then, the construction method of fuzzy ontology under different granularity was discussed, the fuzzy concept cluster with the concept cluster algorithm was generated, and the fuzzy ontology mapping which was based on the fuzzy conceptual similarity was got. Finally, a fuzzy ontology framework was proposed.

Under this framework, for learning objects, they can define, implement, verify and improve the performance of retrieval, classification and management operation, and can construct fuzzy ontology process based on user profile.

The experiment was realized in the Metadata for E-Learning, which supported open access in the form of domain ontology to obtain learning resources, and especially for teaching resources, and the results have showed that the framework can reduce efficiently the uncertainty information of fuzzy ontology, and enhance the precision of ontology. Further, the future task is to improve the quality of *user profile*, the aim is to use pruning process to avoid the irrelevant concepts to disturb users, consider the feedback information from the user, and even use some hybrid screening technology to add more detailed correlation experiments.

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