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An Ontology-Supported Inquiry Learning Technique

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Abstract. *Although Inquiry-based Learning (IBL) offers compelling opportunities for the engineering education, one of the challenges to the implementation of it is that the learner always lacks of the background knowledge. To provide him with the necessary knowledge when making the inquiry, this paper proposes an Ontology Supported Inquiry Learning technique (OSIL), which works on the basis of two ontologies, i.e. curriculum ontology and the learner's ontology. The experimental results show that the constructed curriculum ontology and learner ontology is of high-quality, and the answers recommended by OSIL almost perfectly match with the true answers. From the experimental results, we can see that it is a feasible way of using the software engineering and prototype evolution method to construct the curriculum and learner ontology, and the individual inquiry based on two ontologies is able to provide the learners with high-quality personalized services.*
Keywords: Inquiry-based Learning; Curriculum Ontology; Learner Ontology; Individual Inquiry

1. **Introduction.** Recently, there has been a call for reform in the engineering education, particularly towards the Inquiry-Based Learning (IBL). Traditionally, IBL involves students developing a question, learning more about their proposed questions by performing research, developing a solution or an answer to the question and ends with an opportunity for the students to share their research and act on their solution or answer to their question [1]. The call for IBL is based on the recognition that engineering is essentially a question-driven process, and that inquiry activities are able to provide a valuable context for a learner to acquire, clarify and refine the understandings of concepts and principles in the questions that they construct [2]. Although IBL offers compelling

opportunities for engineering education, there are many challenges to the successful implementation of it. One of the challenges is the learner's background knowledge, and if a learner lacks the knowledge, he will be unable to formulate the question, develop a plan, and interpret the results. A feasible way of tackling this challenge is to provide a learner with just-in-time access to information that can provide the background knowledge necessary, and the requirement of information sources in this way yields the use of computing and networking technologies to support new forms of inquiry. To provide learners with rapidly and individual information in the inquiring procedure, in this work, we propose an Ontology-Supported Inquiry Learning technique (OSIL) for the Object-Oriented Programming (OOP) curriculum, which is a popular course in the engineering education domain. In particular, OSIL first utilizes a state-of-the-art knowledge modeling technique, i.e. ontology [3], to model the OOP curriculum's knowledge hierarchy and the learner's individual model. Then, with the help of ontologies, it automatically deals with the inquiring sentences and recommends the answers to the learner.

The terminology "ontology" was first proposed by philosophers who defined it as a systematic explanation or explanation of objective existence, and it is concerned with the abstract nature of objective reality[1]. In term of this, the ontology belongs to the branch of metaphysical theory in philosophy, as opposed to epistemology. In the area of Artificial Intelligence (AI) [4][5] and Semantic Web (SW) [3][6][7], an ontology is defined as a set of concepts and their relationships among them, which models how people understand and interpret the knowledge in a particular domain [8][9]. Neches et al. [10] first defined an ontology as "given the basic terms and relationships that constitute the vocabulary in the related field, and use these terms and relationships to define the rules for the extension of these words". Gruber [11] gave a widely accepted and adopted ontology definition, i.e. "an explicit specification of a conceptualization". Later, Borst et al. [12] made a slight modification on this basis and proposed that "An ontology is a formal specification of a shared conceptualization". Studer et al. [13] conducted in-depth research on the above two definitions and believed that an ontology is a formal, explicit specification of a shared conceptualization. Scholars generally recognize that "ontology is oriented to a specific field", which is an abstract description of the vocabulary of concepts and the relationships among concepts in a professional subject field. Domain ontology can describe the basic principles of the domain, the relationship between main entities and activities, and provide a public understanding basis for knowledge sharing and knowledge reuse within the domain. Its function is similar to the relational model, and it is the organizational framework of information resources in related fields. Domain ontology is the starting point of the entire intelligent information retrieval system. It also runs through the entire system structure, providing references and basis for its various functional modules (such as semantic coding, language inference, etc.), and plays a pivotal role in the entire system. In this work, we use the ontology to represent knowledge in OOP curriculum due to the following two reasons: (1) the ontology allows the representation of concepts and properties in order to be easily reused and extended in different contexts and applications; (2) an ontology allows the reasoning of information that is represented. For the convenience of this work, an ontology is formally defined as a 4-tuple $O = \{C, DP, I\}$ [14][15], where C is the set of concepts, such as the knowledge points, DP is the set of datatype properties, such as the features or descriptions of a concept, I is the instance set, such as the examples of a concept. Fig. 1 shows an example of ontology , where a rectangle presents a class, e.g. "Book", which has a datatype properties "author" to describe its

[1]https://en.wikipedia.org/wiki/Ontology#cite_note-1

feature and an instance "Albert Camus: La chute", and the relationship between "Book" and "Product" is the subsumption relationship, i.e. "Book is-a Product".

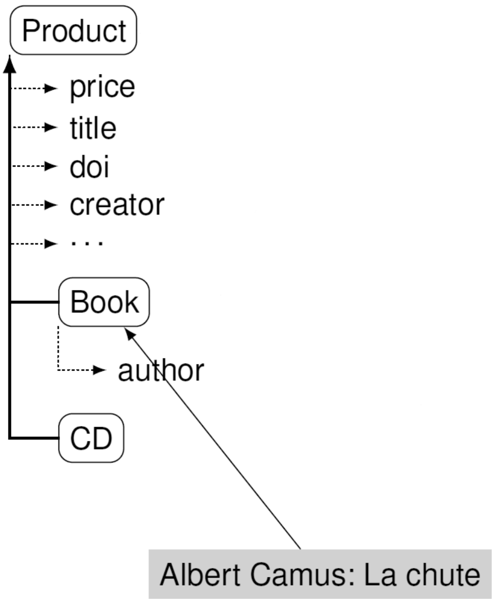

FIGURE 1. An example of an ontology.

The proposed OSIL is able to answer the learner's inquiry in time and strengthen remote communication. Current online Q&A techniques are independent of the learning process, which do not take into consideration a learner's behavioral characteristics and cognitive level. To address this problem, OSIL first uses the curriculum ontology to construct the course knowledge's hierarchy and implement their semantic representation of knowledge, which enables it understand, process and retrieve student questions at the conceptual semantic level, and then utilizes the learner ontology to depict a learner's characteristics, which is of help to provide him with decent answers. In particular, OSIL's working flow is shown in Fig. 2, which mainly consists of a curriculum ontology, a learner ontology and an individual inquiry module. The individual inquiry module is the kernel module which converts the inquiring sentences in natural language into standard words by the learner ontology, so that OSIL can effectively find the answers in the curriculum ontology, and finally, the answers are output to the learners. To implement the individual inquiring process, we need to construct the curriculum ontology and learner ontology. Comparing with other state-of-the-art ontology-based E-learning techniques [16][17][18], our approach makes use of IBL theory to design the online learning framework, which could be more effective to help the learners construct the whole course knowledge hierarchy. The contributions made in this paper are as follows: (1) an IBL-based online learning framework is proposed; (2) two ontologies, i.e. curriculum ontology and learner ontology, are proposed to support the IBL process; (3) a curriculum ontology based reasoning technique and a learner ontology based individual technique are proposed to improve the quality of the answers.

The rest of the paper is organized as follows: Section 2 describes the curriculum ontology and learner ontology; Section 3 presents the individual inquiry module in details; Section 4 shows the experiments and analyzes the results; Section 5 draws the conclusion and presents the future work.

2. **Curriculum Ontology and Learner Ontology.**

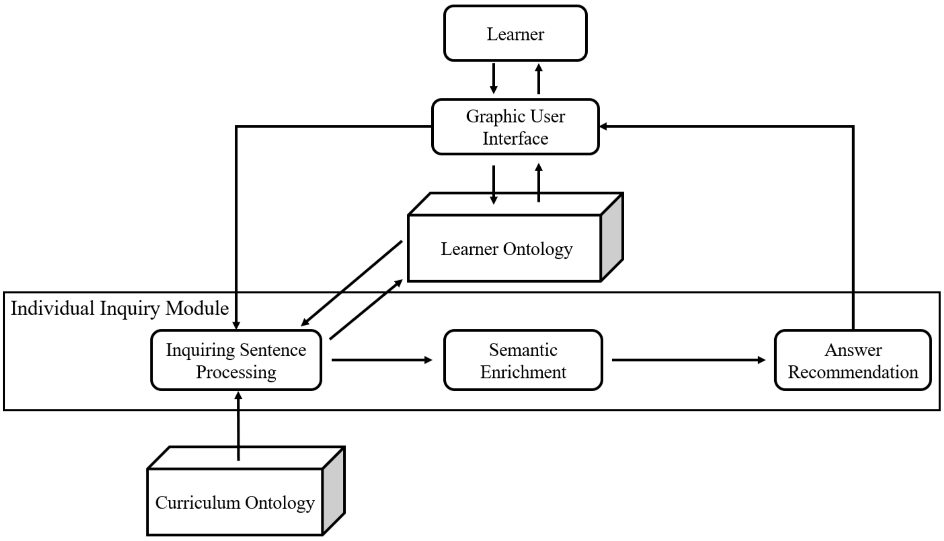

FIGURE 2. The flowchart of ontology-supported inquiry learning technique.

2.1. **Curriculum Ontology.** Curriculum ontology focuses on recording related curriculum knowledge, and the construction of a curriculum ontology that can be shared is important for the OSIL. The construction of an ontology is a complex process, which requires the participation of many domain experts and long-time investment [19]. Although various experts have proposed different ontology constructing methods in practice, but in general, the process of constructing an ontology consists of the following steps:

- sharing a general understanding of the information organization system between people or intelligent agent software;
- determining the domain knowledge that can be reused;
- clarifying the agreement in the field;
- distinguishing between domain knowledge and general operational level knowledge.

To ensure the quality of the OOP curriculum ontology, this work borrows the ideas and experience from software engineering and a prototype evolution method, which consists of two sequential procedures, i.e. standardized expression and normalization. In the domain of software engineering, the process of developing a software engineering can be divided into four steps, i.e. software requirements analysis, software development, software testing, and software evolution. Correspondingly, the process of developing a curriculum ontology on OOP course consists of the following steps:

- Requirements analysis. In this step, we need to clarify the purpose, scope and purpose of the ontology construction. The knowledge in the ontology must be constructed according to specific application requirements. Generally, the requirements can be clarified through the following questions: what domain does the ontology belong to; what the purpose of establishing the ontology; what kind of ontology description language is preferred;
- Ontology construction. This step aims at implementing an ontology, which uses a set of procedures and standards to normalize the development process, so that researchers and builders understand their goals and work to be done, and minimize the loss of off-target. At the same time, a reasonable and effective development

plan facilitates the inspection and control of the construction process, prevents possible problems, and takes effective response measures on time to place the ontology construction under a standardized, visualized, and controllable management and improve the efficiency of ontology research and construction.

- Ontology evaluation. Like software testing in the software engineering, the ontology's quality requires evaluation. However, there is no standard method for ontology evaluation, let alone a standard testing cases. At present, commonly used ontology evaluation indicators are ontology correctness, consistency, scalability, validity, and ontology scale and description ability.
- Ontology evolution. Knowledge development is an endless process, and thus, an ontology always needs to be updated since it takes a huge human and time resources to construct a universal ontology. Ontology evolution is a method of continuously enriching, perfecting, and improving the ontology structure, concepts and relationships by integrating a new ontology, defining new concepts and relationships by experts, or discovering new knowledge through methods such as machine learning.

Fig. 3 shows the hierarchy of curriculum ontology with respect to the chapter of "Graphical User Interface" in the curriculum ontology. The knowledge points of this chapter mainly include the classes "Event", "Font", "Color", "Menu", "Layout" and "Component", and the class "Component" owns several function component class and "Container" that can be further divided into classes "Window" and "Panel". The relationships between each class are the subsumption (is-a). In Fig. 4, this course hierarchy already contains all the important concepts in the chapter "Graphical User Interface" of OOP curriculum. The relationship between the classes is logically rigorous and consistent, and this ontology is in a hierarchical structure is extensible, rich and complete in semantics, and can be mapped with other related resources.

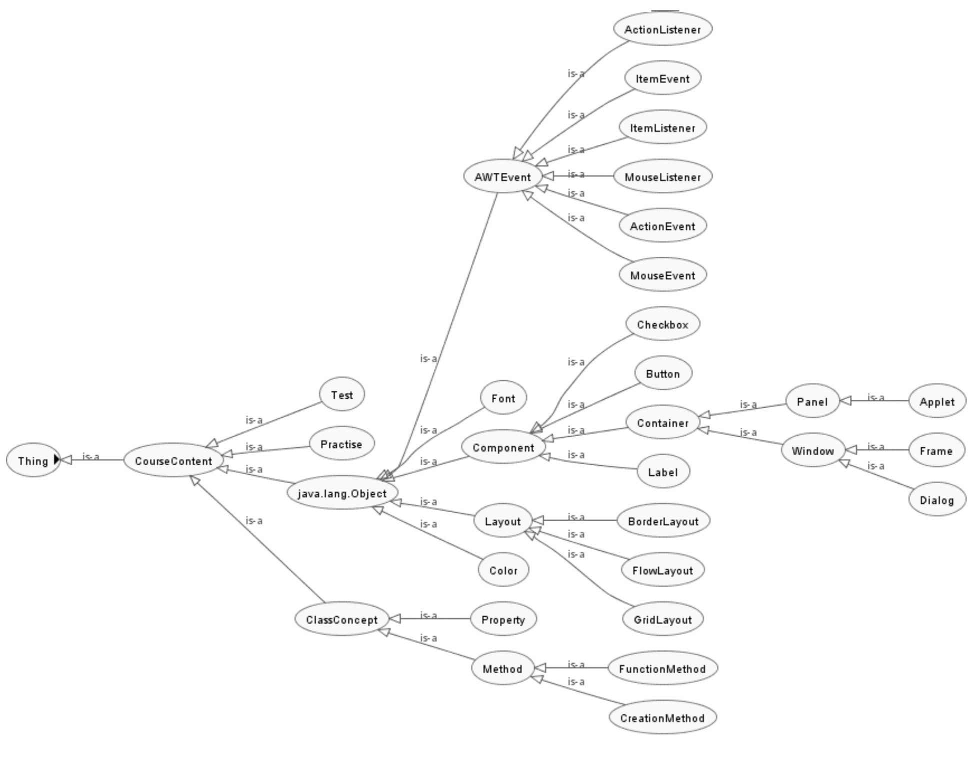

FIGURE 3. The hierarchy of curriculum ontology.

2.2. **Learner Ontology.** The construction of an effective learner ontology to track learner's learning progress and behaviors is critical to the success of the individual inquiring process. When a learner makes an inquiry, we take his background information into consideration, and search for him the answers with decent depth and breadth. In particular, the individual technique in this paper can be defined as a 2-tuple $(BaseInfo, Thesaurus)$, where $BaseInfo$ refers to a learner's basic information, such as name, password, contact information, his learning weight (reflecting a learner's learning progress), and $Thesaurus$ is a learner's preferred retrieving words. In general, there are two ways of obtaining a learner's individual information: (1) ask him to fill in an individual information form; (2) learn it from his interactions with the system. In this work, we construct a learner ontology to establish the individual model, which can record his related information, describe his habitual expression of a concept, and directly use it to match his inquiring word. Unlike the curriculum ontology, a learner ontology focuses more on recording user-related information, which can be directly used to process a learner's inquiring sentence. OSIL establishes the learner ontology through the graphic user interface and manages a learner's personal information and common synonyms. Fig.4 shows the hierarchy of learner ontology.

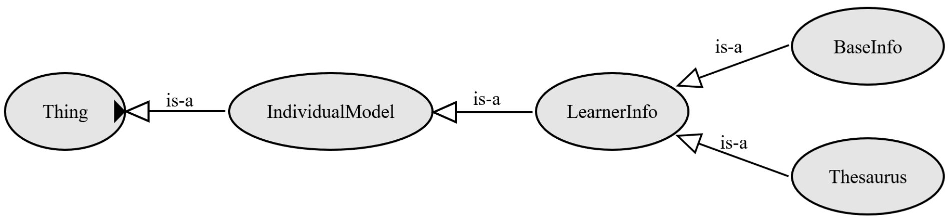

Figure 4. The hierarchy of learner ontology.

A learner ontology consists of a learner's basic information (BaseInfo) and his preferred thesaurus (Thesaurus). When a learner makes an inquiry, OSIL takes into consideration his individual information to analyze his inquiring intention. In particular, a learner's learning weight is stored in his BaseInfo, which is pre-determined by the facilitator or teacher, which can be used in the answer recommendation.

3. **Individual Inquiry Module.** There are three main functions of individual inquiry module, i.e. inquiring sentence processing, semantic enrichment and answer recommendation. Inquiring sentence processing is responsible for processing the inquiring sentence to figure out the learner's inquiring intention; semantic enrichment expands the content from the learner's inquiring sentence to obtain similar results; answer recommendation shows the inquiring results to the learner.

3.1. **Inquiring Sentence Processing.** When the learner starts the inquiring procedure, it is critical to process the inquiring sentence and correctly understand his inquiring intention. It could be difficult for a learner to precisely express his inquiring intention, to ensure the quality of the answers, this work uses both curriculum ontology and learner ontology to process his inquiring sentence in natural language. When a learner inquires the OSIL in natural language, it uses the knowledge in the curriculum ontology to perform semantic analysis on the his inquiring sentence to figure out his inquiring intention, where we first uses a word extraction algorithm to extract the inquiring words from the inquiring sentence, and then perform a syntactic analysis.

With respect to the word extracting algorithm, it suffers from two ambiguous problems, i.e. the inclusive ambiguity and intersection ambiguity. In particular, the inclusive ambiguity means that a part of a word is also a complete word, while the intersection ambiguity is that there is an overlap between two adjacent words, which accounts for the majority of all ambiguities. The common word extracting methods are divided into three categories, i.e. those based on the dictionary and thesaurus matching, those based on word frequency statistics, and those methods based on knowledge understanding. Among them, the most popular ones are based on dictionary and thesaurus matching, the so-called Mechanical Word Extracting algorithm (MWE) [20]. It first scans the string to be analyzed with the entries in a sufficiently large dictionary, and if it is found, the word inside will be recognized. In terms of different matching directions, MWE can be further divided into the forward matching technique and reverse matching technique. In terms of the different lengths of the strings, MWE can be divided into maximum matching and minimum matching. Currently, the most popular MWEs are the Maximum Matching algorithm (MM) and Reverse Maximum Matching algorithm (RMM) [21]. MM and RMM share the basic matching principle, and their main differences are the scanning directions during the extracting process. The statistical results show that the error rate of MM method is 1/169, and that of RMM is 1/245. Since the RMM performs better than the MM in terms of the accuracy, in this paper, we utilize a right-to-left RMM as the word extracting algorithm that uses the dictionary consists of the thesaurus in two ontologies, which is shown in Algorithm 1:

Algorithm 1 Word Extraction Algorithm

if $dictionary == null$ **then**
  $dictionary = loadThesaurusFromOntologies(learnerID)$;
end if
input the sentence S, and set the number of words in the sentence as n;
set a maximum word length max, which is the maximum length of the word we want to extract;
while $n! = 0$ **do**
  take a string $subword$ with the length from $n - max$ to n from the sentence;
  if $subword \in dictionary$ **then**
    store $subword$, set $n = n - max$;
  else
    set $max = max - 1$.
  end if
end while

Since different learners have different preference on the inquiring words, the learner ontology plays a very important role when standardizing these inquiring words to figure out his inquiring intention. Given a learner ontology, the inquiring word set K, the process of using a learner ontology to standardize his inquiring words is shown in Algorithm 2.

Algorithm 2 matches inquiring words with the synonym set of the related concept in the learner ontology to obtain the name of the related concept, which implements the standardizing process. If no relevant matches are found, the relevant concepts are refined or established with learner's participation. Not only have the learner's inquiring words been standardized, but the learner ontology is continuously improved in the process of standardization. In this way, we can gradually learn a learner's habits of present an inquiry, so that his inquiring intent can be better understood. The output K' is a standardized inquiring words, which is also a shared concept description. The initial value of the learner ontology is obtained through the digital form, and then it is established and

Algorithm 2 Inquiring Words' Standardization

Match K with the attribute synonym set in the concept C appearing in the learner ontology O;
if Matched **then**
  K'=the name of concept C;
else
  Prompt the learner to enter the name N of the concept C represented by K;
end if
if $C \in O$ **then**
  Add K to the synonym attribute collection of C;
  K'=the name of concept C;
else
  Create a new concept C, with N as its name;
  K'=the name of concept C;
end if
Output K';

maintained through learning online. We need to maintain the learner's weight thesaurus in the learner's ontology, which is implemented through: (1) providing a learner with an interface that allows him to directly use the personal information management function to change, and these records directly reflect changes in learners' personal information; (2) learning from previous inquiring results through validating and evaluating on the word extracting results, the inquiring results, the order of the result relevance and the output of the result record. After the word extraction and standardization, through the question identification, the inquiring sentence is assigned with a specified type according to the question library. Identifying the type of question before an inquiry can significantly improve the searching efficiency. A learner's inquiring sentence "What is the constructor of the color class?" corresponding to the answer "constructor", and therefore, this inquiring type is related with the function, and only the attribute information of its "constructor" should be returned. After identifying the type of an inquiring question, we can know exactly which attribute a learner want to know. Regarding the question "what is the constructor of the color class", we can know that he wants to know the attribute of a concept, and the answer must be the function attribute in the color entity. Finally, we extract the subject concepts according to the inquiring words by finding the words related to the subject concept, and then, expand these words semantically according to the thesaurus. The individual automatically inquiring techniques analyze the inquiring sentence, and extract inquiring words through word extraction and problem identification to prepare for the determination of the answers.

3.2. **Semantic Enrichment.** Semantic enrichment determines two types of answers: similar answers and related answers, which is implemented through the ontology reasoning techniques. In this work, we define 4 ontology reasoning functions and 2 filtering functions, which are shown as follows:

- Reasoning function.
  - *getSameInd(String indivName)* gets all the synonymous entities of an instance *indivName*;
  - *listDirectSubClassName(String indivName)* obtains the sub-entities directly belonging to the instance *indivName*;

  - *printSubClassName(String indivName)* gets all the sub-real objects of the instance *indivName*, and use this function to quickly retrieve all the concepts related to the instance *indivNam*;
  - *getSuperClassName(String indivName)* obtains the super-entity object of the instance *indivName*, and the retrieval results can be sorted in order.
- Filtering function.
  - *concept_Filter(String indiv, getDataPropValue(String userLevelInfo, String userName)* personalizes the set of instances obtained by the reasoning function according to the learner;
  - *getDataPropValue(String userName, String userLevelInfo)* obtains a learner's learning weight, and filters those unrelated concepts according to it.

These functions can be used to implement the semantic enrichment on the inquiring sentence to improve the completeness of the answers. The similar concept set is obtained from the synonym relationship of the initial retrieval concept, and all corresponding instances in the set are returned as a similar result set; the concepts obtained from the subsumption relationship between the inquiring concept belong to the related concept set, and then the concepts are sorted according to the hierarchical relationship in the relationship to ensure that the results of important relationships can be returned to the user as soon as possible. The semantic enriching procedure is shown in Fig. 5.

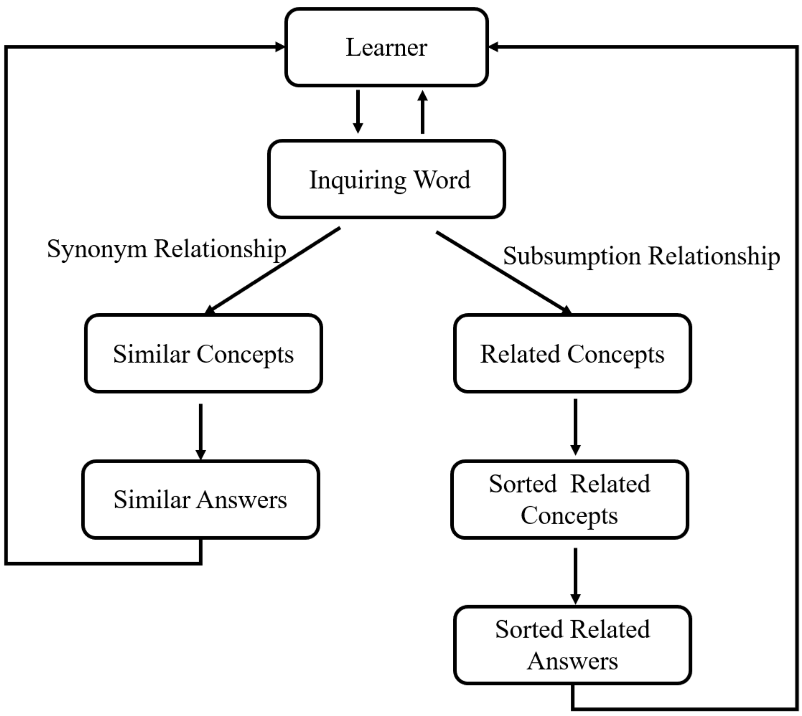

Figure 5. The semantic enriching procedure.

To obtain similar answers, before retrieving the curriculum ontology, the extracted words should be synonymously expanded based on the shared thesaurus in the curriculum ontology and the learner's thesaurus in the learner ontology. To obtain the related answers, we first analyze whether the knowledge points inquired by the learner contain sub-knowledge points. If so, a Forest Traversing Algorithm (FTA) is used to find the relevant knowledge points, which uses a depth-first search algorithm to traverse each node of the forest. The root node is the knowledge point that the learner inquires searches. During the recursion, the layer depth of each sub-node relative to the root node is recorded, and finally, the structure of sub-knowledge points is returned according to the layer depths.

3.3. **Answer Recommendation.** OSIL displays all similar answers and related answers to the learner and recommends the knowledge points for the learner in the next step according to his learning weight. With respect to the individual recommending techniques, they can be divided into two categories, i.e. concept distance based recommendation and concept information capacity based recommendation. The former mainly focuses on the hypernym and hyponym relations, which makes it unable to fully consider a concept's semantic. The latter quantifies the relation between two concepts through the appearance probability or weight of the concept and its instance, which can effectively overcome the shortcomings of the concept distance based recommending technique. Since an ontology owns not only the a subsumption relationship but also various other relationships between concepts, and thus, the hierarchy of an ontology is not a tree but a network [22]. In terms of this, we utilize the conceptual information capacity based recommending technique.

Before the recommendation, each knowledge point is assigned a weight in advance according to the recommended learning order, and we can get the correlation between two knowledge points through the calculation of the difference between the weights. The weight distribution should take into account the learning steps of each knowledge point, which consists of three steps, i.e. "understand the content", "complete the exercises" and "pass the test". They are respectively assigned with the weight of 1, 3, and 5, where the weight of "passing the test" is greater than the sum of "understanding the content" and "complete exercise" to ensure that the weight difference of different knowledge points is at least 5. After that, the threshold of the related degree can be set to 20. The learner's learning weight is compared with the weight of knowledge points in the course ontology, and the knowledge points whose difference is greater than the related threshold are filtered out, and the remaining knowledge points are arranged in ascending order of weight. The learning weight of different learners varies, and the related threshold can also be adjusted according to specific circumstances. Finally, the result of personalized recommendation is determined by the learner's learning weight and related threshold.

4. **Experiment.** In the experiment, the quality of ontology is evaluated by the Ontology Pitfall Scanner (OOPS) [23], which mainly focus on the fault diagnosis and fixation of revealed gaps (or pitfalls). OOPS diagnoses and categorizes the faults by referring to their criticality fully aligned with quality standards, i.e. "normal", "minor", "important" and "critical". OOPS findings for curriculum ontology and learner ontology are given in Tables 1 and 2. As can be seen from the tables, there is no critical pitfall.

In addition, a class of 60 learners is invited for testing the effectiveness of individual inquiry module. In particular, we ask the learners to use 5 kinds of testing cases, which are described as follows:

- Inquiring sentence such as "color of function method" for testing the correctness of the word extraction algorithm and the standardization of inquiring words;
- Inquiring sentence such as "color function method" for testing the quality of the answer recommended by OSIL;
- Inquiring sentence such as "AWTEvent" for testing the effectiveness of the reasoning ability of OSIL;
- Inquiring sentence such as "color function method" for testing the quality of the obtained similar answers;

Table 1. Curriculum Ontology Quality Evaluation.

Pitfalls Category	Ontology Pitfall	Normal	Minor	Important	Critical
Structural Dimension	Modeling Decisions [24]		√		
	Wrong Inference [25]	√			
	No Inference [26]	√			
	Ontology Language [27]			√	
Function Dimension	Requirement Completeness [28]	√			
	Application Context [29]		√		
	Ontology Clarity [30]		√		
	Ontology Understanding [26]		√		
	Ontology Metadata [31]	√			
Consistency [32]				√	
Completeness [33]				√	
Conciseness [34]			√		

Table 2. Learner Ontology Quality Evaluation.

Pitfalls Category	Ontology Pitfall	Normal	Minor	Important	Critical
Structural Dimension	Modeling Decisions	√			
	Wrong Inference	√			
	No Inference	√			
	Ontology Language		√		
Function Dimension	Requirement Completeness		√		
	Application Context			√	
	Ontology Clarity	√			
	Ontology Understanding	√			
	Ontology Metadata	√			
Consistency		√			
Completeness		√			
Conciseness		√			

- Inquiring sentence such as "color function method" for testing the effectiveness of the learner ontology evolution.

The answers recommended by individual inquiry module are also recommended by 5 teachers in order to assert the degree of accuracy, which are shown in Table 3.

Table 3. The evaluation on the performance of individual inquiry module.

	Teacher 1	Teacher 2	Teacher 3	Teacher 4	Teacher 5
Testing Case 1	86%	80%	93%	92%	75%
Testing Case 2	97%	92%	82%	82%	83%
Testing Case 3	93%	82%	87%	95%	80%
Testing Case 4	95%	75%	90%	88%	95%
Testing Case 5	91%	78%	75%	87%	97%

According to the values in Table 3, the calculated Kappa's co-efficient [35] is 0.86, which means that OSIL's inquiring results almost perfectly match with the true answers. Particularly, in testing case 1, the ontology-based reasoning technique can effectively standardize the inquiring words and inquiring sentence; in testing case 2, the semantic annotation on the knowledge is able to help OSIL understand the learner's inquiring intention, which can improve the answers' quality; in testing case 3, the taxonomic structure of knowledge points in the curriculum ontology can be of help to supplement answer, and improve the preciseness of the answers; in testing case 4, the similar inquiring sentences obtained through reasoning technique based on two ontologies can effectively help OSIL to enrich the inquiring conditions, and improve the completeness of the answers; in testing case 5, the learner ontology established in this paper uses learner's preferred thesaurus words to update his individual model, which can effectively improve the answers' quality. To conclude, the proposed OSIL is able to rapidly provide a learner with the individual inquiring service with high-quality answers.

5. **Conclusion and Future Work.** To provide a learner with the necessary background knowledge in the IBL, this paper propose an OSIL for the OOP curriculum. OSIL first utilizes the ontology technique to model the curriculum knowledge and learner's individual information. On this basis, through the individual inquiry module, it can provide a learner with the online, just-in-time and personalized knowledge inquiring services. The experimental results show that the constructed curriculum ontology and learner ontology are of high-quality, and the answers recommended by OSIL almost perfectly match with the true answers. Although the curriculum ontology and learner ontology constructed in this work is good in terms of clarity, consistency, scalability, and compatibility, but it cannot be said to be sufficient. In the future, if more related concepts and relationships can be introduced into the ontology to expand it, it will inevitably make the ontology have stronger semantic expression capabilities and wider query scope.

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