LORecommendNet: An Ontology-Based Representation of Learning Object Recommendation

Noppamas Pukkhem

Department of Computer and Information Technology, Faculty of Science,
Thaksin University, Thailand
noppamas@tsu.ac.th

Abstract. One of the most problems facing learners in e-learning system is to find the most suitable course materials or learning objects for their personalized learning space. The main focus of this paper is to extend our previous rule-based representation recommendation system [1] by applying an ontology-based approach for creating a semantic learning object recommendation named "LORecommendNet". The "LORecommendNet" ontology represents the knowledge about learning objects, learner model, semantic mapping rules and their relationship are proposed. In the proposed framework, we demonstrated how the "LORecommendNet" can be used to enable machines to interpret and process learning object in recommendation system. We also explain how ontological representations play a role in mapping learner to personalized learning object. The structure of "LORecommendNet" extends the semantic web technology, which the representation of each based on an OWL ontology and then on the inference layer, based on SWRL language, making a clarify separation of the program components and connected explicit modules.

Keywords: learning object, ontology, recommendation, semantic web.

1 Introduction

Online learning resources are commonly referred to as learning objects in e-learning environment. They will be a fundamental change way of thinking about digital learning resource. Actually, learning objects can be learning components presented in any format and stored in learning object repositories which facilitate various functions, such as learning object metadata, learning object creation, search, rating, review, etc. Rapidly evolving internet and web technologies have allowed a using of learning objects in Learning Management System, but the problem is that it does not offer personalized services and dues to the non-personalized problem. All learners being given access to the same set of learning objects without taking into consider the difference in learning style, prior knowledge, motivation and interest. This gives result in lack of learner information to perform accurate recommending of the most suitable learning objects. This work provides prior knowledge about learners and learning objects in semantic web approach that can be used in our semantic-based recommendation model.

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An ontology is an important tool in representing knowledge of any resources in WWW. Until now, knowledge bases are still built with little sharing or reusing in related domains. Our focus is on developing the ontology-based representation called "LORecommendNet" in order to present the knowledge about the learner, learning object and propose an effective process for enhancing learning object selection of learners through our semantic-based recommendation model. In reasoning process, we proposed a set of personalization rules that will allow reasoning on the instances of “LORecommendNet”.

The remainder of this paper is organized as follows. Section 2 gives background and previous work. An overview of the learning object concept, learning style and related works is also included. Section 3 presents the analysis and design of learning objects and the learner model ontology of LORecommendNet. Then, section 4, we propose our designing of an inference layer by using SWRL and Jess Rule. Finally, section 5 concludes this paper, giving a summary of its main contribution and pointing towards future research directions.

2 Background Knowledge and Previous Work

2.1 Learning Objects and Learning Object Metadata

Learning objects are a new way of thinking about learning content design, development and reuse. Instead of providing all of the material for an entire course or lecture, a learning object only seeks to provide material for a single lesson or lesson-topic within a larger course. Examples of learning objects include simulations, and adaptive learning component. In general, the learning objects must have the following characteristics; self-contained, can be aggregated, reusable, can be aggregated, tagged with metadata, just enough, just in time and just for you [2].

International efforts have been made on developing standards and specifications about learning objects since late 1990’s. IEEE Learning Technology Standards Committee, IMS Global Learning Consortium, Inc., and CanCore Initiative [3] are organizations active in this area. IEEE LOM Standard is composed of Standard for Learning Object Metadata Data Model, Standard for XML Binding and Standard for RDF Binding which is a multipart standard. The first part of the standard, IEEE 1484.12.1 LOM Data Model standard [4], has been accredited and released. The LOM Data Model is the core of existing metadata specifications. It defines a hierarchical structure for describing a learning resource by data elements that are grouped into nine categories; *General, Lifecycle, Technical, Meta-metadata, Educational, Relation, Rights, Classification and Annotation.*

2.2 Learning Styles and Preferences

Learning style is an important criterion towards providing personalization, since they have a significant influence on the learning process. Attempting to represent the learners’ learning styles and adapting the learning object so as the most suit them is a challenging research goal. Learning style designates everything that is characteristic for an individual when the learner is learning, i.e. a specific manner of approaching a learning activity, the learning strategies activated in order to fulfill the task.

Felder-Silverman learning style model [5] is the one of the most widely used learning style in adaptive hypermedia system. Another important reason noted by Sangineto [6], Felder-Silverman learning styles was widely experimented and validated on an engineering and science student population. Furthermore, this model contains useful pragmatic recommendations to customize teaching according to the students' profiles.

2.3 Semantic-Based Tools

There are several semantic-based tools for information extraction and transform into meaningful which can be used through the process of building ontology-based model in our work:

- *XML Schema* is a structure of blocks of XML document formatting, similar as DTD (Document Type Definition). It can be used to store content and document's structure, but not all knowledge about content can be represented in the tree structure, and it is time consuming to maintain the order of presentation of knowledge. So, only XML Schema is not reasonable to represent documents.
- *RDF (Resource Definition Framework)* is a set of recommendations for well-formed XML documents. It is a more data aspect framework than human aspect. So, it is designed for enabling machine processing rather than for ease of human understanding.
- *OWL (Web Ontology Language)* is a language for definition of web ontologies which explicitly represents the semantics of terms in vocabularies and its relationships between these terms [7]. This is an accepted standard, language and platform independent and well- formed XML- markup language.
- *SWRL (Semantic Web Rule Language)* is a proposal in submission by the W3C, aiming at combining OWL and inference rules language [8]. SWRL rules reason about OWL individuals in terms of classes and properties. SWRL provides seven types of atoms: *Class, Individual, Data valued property, Different individual, Same individual, Built-in* and *Data range atoms.*

2.4 Previous Works

In our previous work [1,9], we developed the method for generating the course concept map called "Course Concept Map Combination Model: CMCM. The course concept map is the domain model that represents all possible sequences of learning concept for a specific course. The domain model stores the knowledge about the course preferences, instructor's characteristics and experiences. The main concept map was implemented by using the Cmaptool [10]. In recommendation model, we proposed three recommendation algorithms: i) preferred feature-based, ii) neighbor-based collaborative filtering and iii) non-personalized. The result is the preferred feature-base algorithm having more accuracy prediction than others. Previous work of recommendation system was tested and several experiments were proposed in order to show the suitability of using recommendation algorithm for recommending learning object to learners based on their learning style.

For improving the semantic recommendation in our previous work, we extended the LORecommend ontology for reasoning rules by using SWRL. The idea behind the semantic recommendation is, as the name suggests, to add a level of meaning to the Web. As this reason, it can be more easily manipulated by computer programs, and more effectively by humans. The proposed ontology-based representation model was presented in section 3. With this improvement, supported our recommendation system higher scalability and easier maintenance of the approach are expected.

3 LORecommendNet: Ontology-Based Representation Model

Ontologies in our system are written in OWL. To support the development of the ontologies and rendering in OWL, we use the open source tool Protégé 4.3[11]. Next subsection, concrete examples of the LORecomendNet within our recommendation system will be presented.

3.1 Learning Object Ontology

The main part of LORecommedNet is learning object ontology. Properties of learning objects as well as relationships to other learning objects are defined by the learning object ontology. Based on IEEE LOM standard, there are many kinds of learning object feature. The summarized results that rating from 15 experts in feature selection process is presented in Table 1. and their description is presented in Table. 2.

Table 1. The result summary of learning object feature analysis and selection

LO Feature		Feature Rating	Normalized Score
LOM category	**Element**	**Score***	**(α = 0.7)**
General	Language	140	0.9032
	Description	119	0.7677
Technical	Format	129	0.8323
Educational	Interactivity Type	111	0.7161
	Learning Resource Type	143	0.9226
	Interactivity Level	109	0.7032
	Semantic Density	112	0.7226

*Number of experts = 15

Table 2. The description of the selected features for LORecommendNet

ID	Class Name	Element Path	Instance
F1	Format	LOM/Technical/Format	Video, Image,Text, Audio, Animation
F2	Interactivity Type	LOM/Educational/ Interactivity_Type	Active, Expositive, Mixed
F3	Interactivity Level	LOM/Educational/ Interactivity_Level	Very low (0), Low (1), Medium (2), High (3), Very high (4)
F4	Semantic Density	LOM/Educational/ Semantic_Density	Very low (5), Low (6), Medium (7) High (8), Very high (9)
F5	Learning Resource Type	LOM/Educational/ Learning_Resource_Type	Exercise, Algorithm, Experiment, Example, Definition, Slide, Index

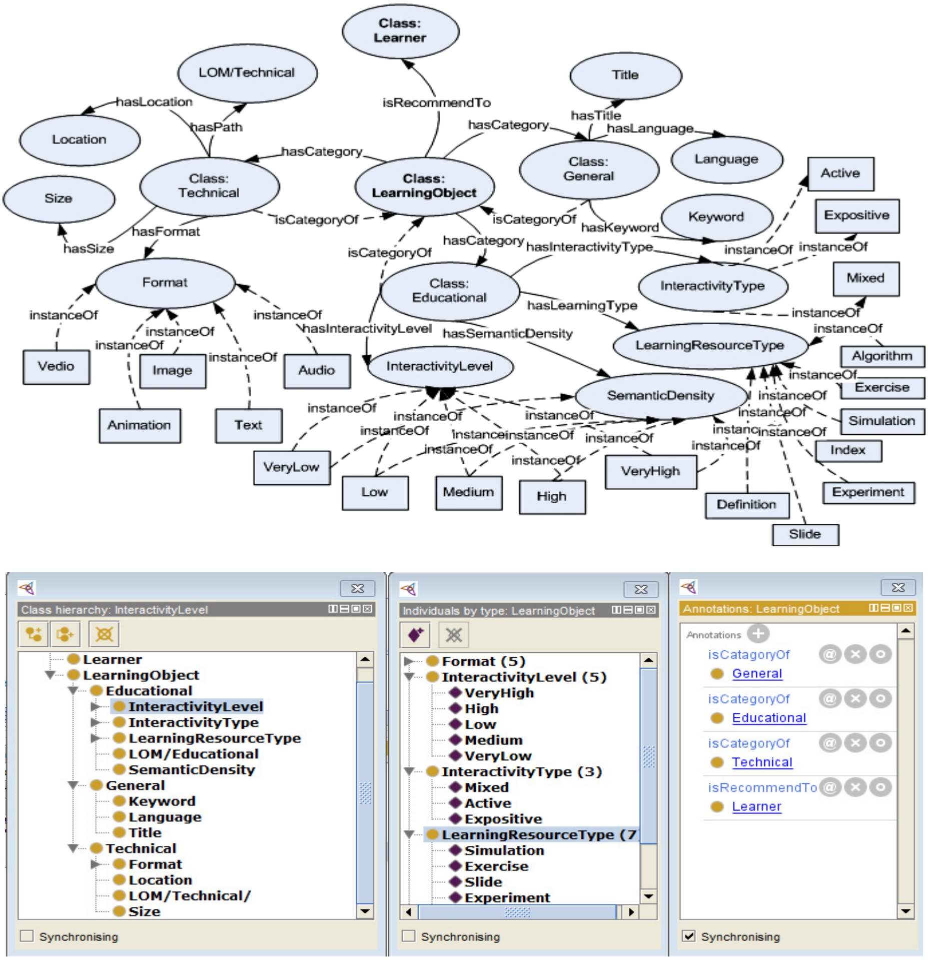

Fig. 1. A learning object ontology and the part of representation with Protégé

In our work, the learning object ontology describes about the properties of learning objects with five LOM features; format, interactivity type, interactivity level, semantic density and learning resource type. The learning object class ontology and the part of representation implementing with Protégé are presented in Fig.1. The OWL rendering format that describes about learning object class, object properties and individuals of them are shown as follows.

```
<!--The Learning Object Class-->
<owl:Class rdf:about ="#LearningObject">
<rdfs:subClassOf rdf:resource="&LO;LORecommend"/>
  <owl:Restriction >
      <owl:maxCardinality
                rdf:datatype="&xsd;nonNegativeInteger">1</owl>
```

```
       <owl:onProperty
             rdf:resource="&ls;learningObjectMetadata"/>
             ...
    </owl:Restriction>
</rdfs:subClassOf>
</owl:Class>
...
<!--Object Property-->
<owl:ObjectProperty rdf:about="
http://192.168.0.101/Learningobject.owl#hasCategory">
    <rdf:type rdf:resource="&owl;FunctionalProperty"/>
       <rdfs:range rdf:resource="&owl: http://www.owl-
ontologies.com/generations.owl#Category"/>
       <rdfs:domain rdf:resource="&owl:
http://192.168.0.101/Learningobject.owl#Learningobject"/>
</owl:ObjectProperty>
  ...
  <!--Individuals of Learning Object "LO1"-->
<owl:Thing
rdf:about="http://192.168.0.101/Learningobject.owl#LO1">
     <rdf:type rdf:resource=

"http://192.168.0.101/Learningobject.owl#LearningObject"/>
         <hasCategory rdf:resource=
         "http://192.168.0.101/Learningobject.owl#Education"/>
         <hasFormat rdf:resource=
         "http://192.168.0.101/Learningobject.owl#Audio"/>
...
</owl:Thing>
```

3.2 Learner Model Ontology

The learner model is described by ontology-based for conceptualizing and exploited by the inference engine. For creating the learner model ontology that describes the preferred learning object features of learner, we initial with the process of the learners' learning style analysis using an index of learning styles (ILS) questionnaire. The ILS is a 44-question instrument designed to assess preference on the four dimensions of the Felder-Silverman learning style model. Each dimension of the ILS has a 2-pan scale which represents one of the two categories (eg. Visual/Verbal).

The valid rule is the rule that is the member of the intersection set of word meaning between semantic group (SG) and LO features. Table 3 shows the detail of semantic mapping, the semantic groups (SG) within the dimensions provide relevant information in order to identify learning styles. If a learner has a preference for tends to be more impersonal oriented and trying things out learner would have a balanced learning style on the active/reflective dimension. However, a learner has also a balanced learning style if they tend to be more socially oriented and prefer to think about the material. Although both learners have different preferences and therefore different behavior in an online course, both are considered according to the result of ILS.

Table 3. Example of semantic groups associated with the ILS

Dimension	Set of Questions	Symbol	Semantic Group (SG)
Dimension 1	1, 5, 9, 13,17, 21, 25, 29,33, 37,41	**A**-**A**ctive	Trying something out(SG1) Social oriented (SG2)
		R-**R**eflective	Think about material(SG3) Independent (SG4)
Dimension 2	2, 6, 10, 14, 18, 22, 30, 34, 38, 42	**S**-**S**ensing	Existing way(SG5) Concrete material(SG6) Careful with details (SG7)
		I-**I**ntuitive	New ways(SG8) Abstract material (SG9) Not careful with detail (SG4)
Dimension 3	3, 7, 11, 15, 19, 23, 31, 35, 39, 43	**U**-Vis**U**al	Picture (SG11)
		B-ver**B**al	Spoken word (SG12) Written word (SG13) Difficulty visual style (SG14)
Dimension 4	4, 8, 12, 16, 20, 24, 32, 36, 40, 44	**Q**-Se**Q**uential	Detail oriented (SG15) Sequential progress (SG16) From part to the whole (SG17)
		G-**G**lobal	Overall picture (SG18) Non-sequential (SG19) Relation (SG20)

We adopt OWL (Web Ontology Language) to express ontology enabling expressive knowledge description and information interoperability of knowledge. According to the learner model ontology, the following OWL based markup segment describes the user contexts (learner) about “Learner1”. The learner ontology show in Fig. 2 depicts contexts about a learner that corresponds to Table 3. We are collecting learning style scores of a learner in four learning style dimensions (A/R, S/I, U/B and Q/G) which are their weight have an interval 0-1. The relation between a learner and their learning styles certifies by hasDimension, hasSemanticGroup and hasLearning Style.

For example, the class Learner is described by the class learning style. The class learning style is built from four components: dimension1, 2, 3 and 4. Each dimension explains about learner learning styles. Moreover, we can describe the relationship between learning style and learner preference (TryingSometingOut, SocialOriented, ThinkAboutMaterial etc.).

4 SWRL as an Inference Layer

SWRL as an inference Layer, is used to establish individual relationships and adaptation rule. In this paper, we extend the mapping rule in our previous work into reasoning rules. Various relationships are captured in the body of SWRL rules that described about the relation among learning object, learner model and its environment.

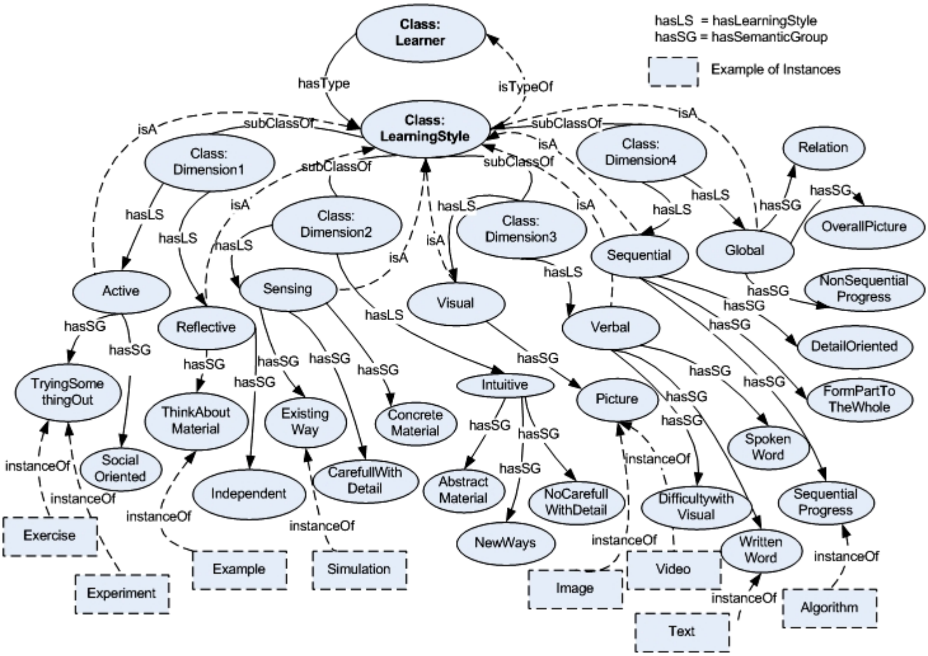

Fig. 2. Learner model ontology

The association between each learning style and the learning object features is represented by a rule-based representation. We demonstrate the example of validated mapping rule selection from all possible mapping rules as follows.

Example of Mapping Rules

```
Mapping Rule:  Reflective Learner
Propose:  Recommend Learning Object for  "R-Reflective" Learner
Rule-based Representation:
If "R" ∈ Learner(L) Then  LOM.educational.interactivity_type =
"expositive" and LOM.educational.LearningResourceType =
"definition" or  "algorithm" or "example"
Reflective := {think about it, try to understand, listen}
Map to: Interactivity Type:= "expositive" := {audio}
    Semantic density := "medium":={audio}
    Semantic density := "high":= {video}
    Learning resource type:="definition":={explanation,give
meaning }
    Learning resource type := "algorithm"= { step for action}
    Learning resource type := "example"= { show how to act}
```

In this section we show rules are employed to reason over ontology-based model (learner model, learning object model). The communication between reasoning rules and the other resource information will take place by exchanging RDF annotations. Several rules is can be derived. The example of rules is presented as follows.

```
1.  Person := Learner
2.  Resource := LearningObject
3.  LearningStyle:= Active ∪ Reflective  ∪ Sensing  ∪ Intuitive
    ∪ Visual ∪ Verbal ∪ Sequential ∪ Global
4.  ActiveLearner := Person ∩ Active
5.  ReflectiveLearner := Person ∩ Reflective
6.  LOFeature:= format ∪ interactivityType ∪ interactivityLevel
    ∪ SemanticDensity ∪ LearningResourceType
7.  LOforActive :=(active ∪ mixed)∩(exercise∪ simulations ∪
    experiment)
8.  InteractivityType:= active ∪ mixed ∪ expositive
9.  InteractivityLevel:= verylow ∪ low ∪ medium ∪ high ∪
    veryhigh
10. SemanticDensity:=  verylow ∪ low ∪ medium ∪ high ∪ veryhigh
11. LearningResourceType := exercise ∪ experiment ∪ definition
    ∪ algorithm ∪ example ∪ slide ∪ index
12. LOforVisual := (video ∪ image ∪ animation) ∩ (medium ∪ high
    ∪ veryhigh)∩ simulation
```

From the ontology extracting above, the initial relations are identified to be a member of the class. Finally, adding rule mapping ontology knowledge to them, like SWRL Rule1, 2, 3 and Rule 4 etc.

Example of SWRL Reasoning Rules

```
Rule1: LearingObject(?LO) ∧ hasInteractiveType(?LO, expostive) ∧
       LearningResourceType(?LO, algorithm) → LOforReflective(?LO)
Rule2: LearingObject(?LO) ∧ hasFormat(?LO, video) ∧
       hasInteractiveLevel(?LO, high) ∧
       LearningResourceType(?LO, simulation)→ LOforVisual(?LO)
Rule3: Learner(?L) ∧ hasSemanticGroup(?L, picture) ∧
       hasLearningStyle(?L, visual) → VisualLearner(?L)
Rule4: VisualLearner(?L)  ∧ LOforVisual(?LO) → recommend(?L,?LO)
```

From the reasoning rules, we can infer the suitable learning object to the specific learner by using the relationship which presented in LOReccommendNet.

Representing SWRL Rules as Jess Rules

The SWRL rules can be represented in Jess using their facts is relatively straightforward. Once the OWL concepts and SWRL rules have been represented in Jess (using Jess Tab in Protégé 3.5), the Jess engine can perform inference process. For example, take the example SWRL Rule as:

```
LearingObject(?LO) ∧ hasInteractiveType(?LO, expostive) ∧
LearningResourceType(?LO, algorithm) → LOforReflective(?LO)

VisualLearner(?L)  ∧ LOforReflective(?LO) → recommend(?L,?LO)
```

These rules can be represented in Jess by following Jess Rule.

```
(defrule aRule (LearningObject (name ?LO))
               (hasInteractiveType ?LO expositive)
               (LearingResourceType ?LO algorithm)
=> (assert (LOforReflective (name ?LO))

(defrule aRule (VisualLearner (name ?L))
               (LOforReflective (name ?LO))
=> (assert (recommend (?L ?LO))
```

When the inference process completes, these individuals will be transformed into OWL knowledge.

5 Conclusion

This paper has described “LORecommendNet”, which is an ontology-based modeling strategy that has been employed by a personalized e-learning system, recommendation system and learning style-based adaptation. The ontology-based model constructed from the potential knowledge and competence state of the learner and the relationships between concepts in our domain. We designed the models based on an OWL ontology representation, SWRL rules and Jess Rules to infer from the ontology content. The learners can be provided with the intelligent and personalized support that recommend the most suitable learning object to them. Moreover, syntactically different but semantically similar learning objects can more easily be located. The idea behind the semantic-based representation is, as the name suggests, to add a level of meaning to the Web. As this reason, it can be more easily manipulated by computer programs, and more effectively by humans. Judging from current research directions, the future work will hold greater shareability, interoperability and reusability among existing learning management systems or e-learning application via a semantic web approach, rather than an all-encompassing knowledge model.

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