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Full Paper

Personalised learning object based on multi-agent model and learners' learning styles

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Abstract: A multi-agent model is proposed in which learning styles and a word analysis technique to create a learning object recommendation system are used. On the basis of a learning style-based design, a concept map combination model is proposed to filter out unsuitable learning concepts from a given course. Our learner model classifies learners into eight styles and implements compatible computational methods consisting of three recommendations: i) non-personalised, ii) preferred feature-based, and iii) neighbour-based collaborative filtering. The analysis of preference error (PE) was performed by comparing the actual preferred learning object with the predicted one. In our experiments, the feature-based recommendation algorithm has the fewest PE.

Keywords: collaborative filtering, content-based recommendation, learning object, learning style, multi-agent model

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INTRODUCTION

The e-learning community commonly refers to online digital learning resources as learning objects. They offer a new way of thinking about learning content. Learning objects can be educational components presented in any format. Learning objects are commonly stored in learning object repositories that facilitate various functions such as learning object creation, submission, search, comment, review and so on. Rapidly evolving internet and web technologies have facilitated the use of learning objects in learning management systems (LMS), but the LMS does not offer personalised services. All learners are given access to the same set of learning objects and tools

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without considering the difference in interest, prior knowledge, experience, motivation and goals. This causes a 'one-size-fits-all' problem owing to a lack of individual learner information that can be used to perform accurate predictions of the most suitable learning object for a particular learner.

Our focus is to build a recommendation method for providing personalised learning for learners. Learning style is used as the adaptation criterion since it is one of the individual differences that plays an important role in learning according to experts.

BACKGROUND AND RELATED WORK

Learning Object

Learning objects are a new way of thinking about learning content design, development, and delivery. Instead of providing all of the material for an entire course or lecture, a learning object seeks to provide material only for a single lesson or lesson-topic within a course. Examples of learning objects include simulations, interactive data sets, quizzes, surveys, annotated texts, and adaptive learning modules. In general, learning objects have the following characteristics [1-4]:

Self-contained—each learning object can be used independently;
Reusable—a single learning object has the potential to be used in multiple contexts for multiple purposes on multiple campuses;
Aggregable—learning objects can be grouped into larger collections, allowing for their inclusion within a traditional course structure;
Tagged with metadata—every learning object has descriptive information that allows it to be found easily by a search, which facilitates the object's use;
Just enough—if a learner needs only a part of a course, he/she can use only the learning objects needed;
Just in time—learning objects are searchable; a learner can quickly find and use the content needed;
Customisable—learning objects allow for easy customisation of courses for a whole organisation or even for each individual.

A learning object does not have a predetermined size. Granularity of a learning object can extend from sub-topics to topics to lessons and to their associated media elements. A collection of learning object topics are aggregated to form lessons, modules, courses and curriculum libraries.

Learning Object Metadata (LOM)

There have been international efforts to develop learning object standards and specifications since the late 1990s. The IEEE Learning Technology Standards Committee, the IMS Global Learning Consortium Inc. and the CanCore Initiative [5] are organisations active in this area.

The IEEE learning object metadata (LOM) [6] standard is a multipart standard composed of the standard for LOM data model, the standard for extensible markup language (XML) binding, and the standard for resource description language (RDF) binding. The first part of the standard, namely IEEE 1484.12.1 LOM data model standard, has been approved and published. The LOM data model is the core of existing metadata specifications and it defines a hierarchical structure for describing a learning object. In the LOM instance, relevant characteristics of learning objects are represented by data elements that are grouped into nine top-level categories, each of which is described in Table 1.

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Table 1. Top-level LOM categories [6]

Category	Description
General	The general category groups the general information that describes the resource as a whole.
Lifecycle	The lifecycle category groups the features related to the history and current state of this resource and those that have affected this resource during its evolution.
Meta-metadata	The meta-metadata category groups information about the meta-data record itself (rather than the resource that the record describes).
Technical	The technical category groups the technical requirements and characteristics of the resource.
Educational	The educational category groups the educational and pedagogic characteristics of the resource.
Rights	The rights category groups the intellectual property rights and conditions of use for the resource.
Relation	The relation category groups features that define the relationship between this resource and other targeted resources.
Annotation	The annotation category provides comments on the educational use of the resource and information on when and by whom the comments were created.
Classification	The classification category describes where this resource falls within a particular classification system.

Learning Style

Learning style is an important criterion used in providing personalisation since it has a significant influence on the learning process. Attempts to represent the learning styles of learner and to adapt the learning object to best suit these learning styles are challenging research goals. Learning style includes every type of learning that is characteristic of an individual, i.e. a specific manner of approaching a learning activity, or the learning strategies used in order to fulfill the task.

The Felder-Silverman's learning style model [7] is one of the most widely used learning style in adaptive hypermedia systems. A model for finding the learning style of learners, according to Brown et al.[8], should be suitable for use with multimedia and adaptive web-based education system. The model should display a good degree of validity and reliability/internal consistency and thus provide accurate evaluations of the learning style. The model should also be easily administered to university students.

Another important remark by Sangineto et al. [9] was that the Felder-Silverman learning style model is widely used and validated on an engineering and science student population. Furthermore, this model contains useful pragmatic recommendations for customising teaching according to student profiles.

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Related Work

The TANGOW (task-based adaptation learner guidance on the WWW) system [10] is based on an adaptation approach similar to that used by Felder and Silverman but employs only two of the Felder-Silverman learning style dimensions, i.e. sensing/intuitive and sequential/global, and only two types of modules, i.e. 'example' and 'exposition'. For instance, in the case of sensing learners, the students are first presented with an example and only after that they are presented with an exposition regarding that concept.

The Heritage Alive Learning System [11] provides an adaptively customised learning interface. It contains three pairs of widget placeholders (text/image, audio/video and Q&A board/bulletin board). Each pair consists of a primary and a secondary information area. The space allocated on the screen for each widget varies according to the student's Felder-Silverman learning styles. For example, for a visual learner, the image data widget is located in the primary information area, which is larger than the area of text data widget.

Bajraktarevic and Shonam [12] present the course content in a specific layout, corresponding to the Felder-Silverman learning styles (only sequential/global preference). Pages for global learners contain diagrams, table of contents, overview of information and summaries, while pages for sequential learners include only small pieces of information and forward and back buttons.

Graf et al. [13] use adaptation features such as the order of examples, exercises, self-assessment tests, content objects, number of presented examples, and exercises to adapt the course to the four Felder-Silverman learning styles.

In our previous work [14], we implemented a method for generating a course concept map called the course concept map combination model (CMCM) (see the right box in Figure 1). The course concept map is a domain model that represents all possible sequences of learning concepts for a specific course [15]. The domain model stores the knowledge about course preferences and instructor's characteristics and experiences. The main concept map was implemented using CmapTools [16], which is a suite of tools for generating and sharing concept maps in an electronic form. CmapTools supports the generation and modification of concept maps as well as the addition of navigational links from individual concepts to other concept maps and multi-media material such as images, diagrams and video clips, thereby enabling the construction of rich knowledge models. The tools facilitate storage of and access to concept maps on multiple servers, providing the network services required to support knowledge sharing across geographically distant sites. The concept map can be used as the structure of contents that support the learning object recommendation method (Figure 1) described in this paper.

LEARNER MODEL

A learner model is one constructed by observing the interaction between a learner and a learning system in an instructional environment. Building the learner model (Figure 1) starts with an analysis of the learner's learning style using an index of learning styles (ILS) questionnaire.

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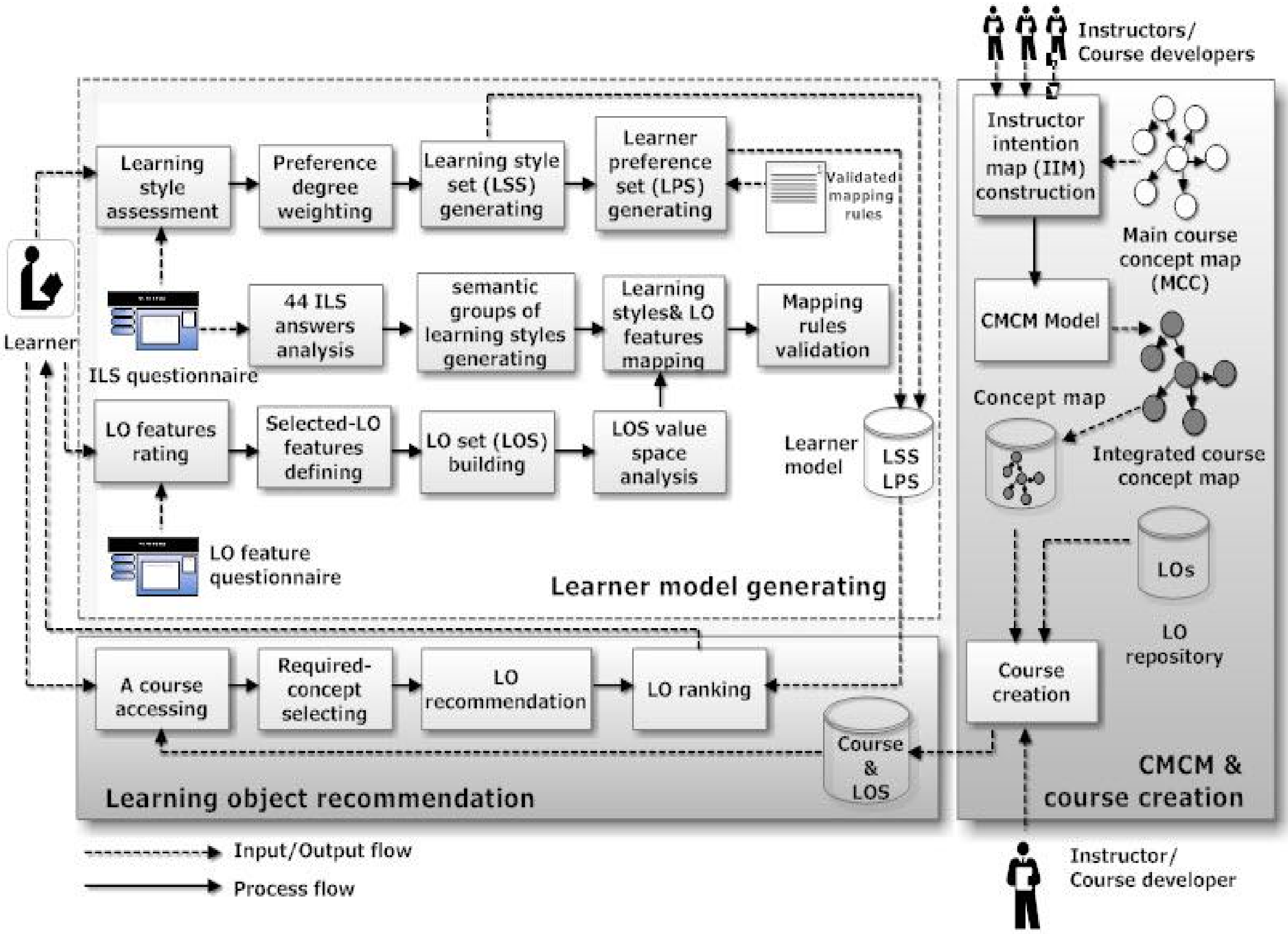

Figure 1. Abstract of recommended model for learning object based on learning styles

The ILS is a 44-question instrument designed to assess preference on the four dimensions of the Felder-Silverman learning style model [17]. The learner's responses are evaluated by the learning style indicator. Then learners are classified using a learner style set (LSS) that contains the learning styles of each learner by assigning a weight parameter (0, 0.5 and 1). In our study, preference scores (PS) are scaled into three groups:

Strong preference: learner strongly prefers to learn with this learning style. The score ranges between 8 and 11 (weight = 1);

Medium preference: learner quite prefers to learn with this learning style. The score ranges between 4 and 7 (weight=0.5);

Weak preference: learner does not prefer or does not like this learning style. The score ranges between 0 and 3 (weight = 0).

The LSS is a combination of each learning style and its weight. The learning object selection rules are used to identify the preferred learning object features for each learner and to create a learner preference set (LPS) that contains the preference of each learner. Both the LSS and LPS are stored in the learner model database.

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Learner Analysis Experiment

Learner analysis is the first step in developing a learner model because the learning styles of learners need to be known in order to develop an appropriate learner model in our system. We examined the learning styles of third- and fourth-year students majoring in computer science (CS) and information technology (IT) at Thaksin University (Thailand) during the academic year 2009.

The Thai-version ILS was administered to all participants. Students were asked to complete a self-administered questionnaire at the end of one lecture period during the first semester. Each dimension of the ILS has a two-pan scale, with each pan representing one of the two categories of the dimension (e.g. sensing and intuiting) and weight in a pan representing the skills associated with that category. The indications of the ILS are shown in Table 2. If a learner has a preference for sensing, for example, it means he/she has more weight in the sensing pan than the intuitive pan.

Of the learners in the 2009 cohort, 142 participated in the study by completing the ILS. In active/reflective (D1) category, the majority of learners preferred the strong active learning style (80 learners) and 16 learners preferred the strong reflective style. In visual/verbal (D3) category, many learners preferred the strong visual style (77 learners) and fewer learners preferred the strong verbal style (28 learners). There was not much difference in the strong preferences in D2 and D4 learning styles. In the former, 53 learners preferred the strong sensing style and 47 learners preferred the strong intuitive style. In the latter, 21 learners preferred the strong sequential style and 25 learners preferred the strong global style. Thus, we could define those features of learning objects that were related to both active/reflective and visual/verbal categories. This is the implicit information to be used in matching the learning style of the learner and the learning object.

Table 2. Indications of the ILS [17]

Dimension No.	Question No.	Symbol
D1	1, 5, 9, 13, 17, 21, 25, 29, 33, 37, 41	**A**-**A**ctive/**R**-**R**eflective
D2	2, 6, 10, 14, 18, 22, 26, 30, 34, 38, 42	**S**-**S**ensing/**I**-**I**ntuitive
D3	3, 7, 11, 15, 19, 23, 27, 31, 35, 39, 43	**U**-Vis**U**al/**B**-Ver**B**al
D4	4, 8, 12, 16, 20, 24, 28, 32, 36, 40, 44	**Q**-Se**Q**uential/ **G**-**G**lobal

Learner's Learning Style Set (LSS)

The result of the learner's learning style analysis from the above subsection was used to create the learner's LSS. We define the LSS of learners in Definition 1.

Definition 1: *Learner style set* $LSS(L) = \{(P_i, Pw_i)\} \mid P_i \in \{A, R, S, I, U, B, Q, G\}$, *where* Pw_i *is the weight with interval [0–1] for each* P_i *and i is the number of learning styles.* For example, for a particular learner L_1, we might have $LSS(L_1) = \{(A,1), (R,0), (S,0.5), (I,0.5), (U,1), (B,0), (Q,0), (G,1)\}$

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Learner Preference Set (LPS)

For generating the LPS that describes the preferred learning object features of the learner, we developed the learning object selection rules for matching the learner preference with suitable features of learning objects (LO-learner preference matching). The features and their value space, based on the IEEE LOM metadata in the proposed recommendation algorithm, are identified in Table 3.

Table 3. Selected features for learning object recommendation

ID	Name	Element path	Value space
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, Simulation, Experiment, Definition, Algorithm, Example, Slide, Index

This feature set was used in the feature-based recommendation algorithm. Definition 2 is the feature set used to describe a learning object.

***Definition 2**: Learning object set, LOS_{LO}, is a discrete set of all selected learning object features necessary to describe the characteristics of a specific learning object:*

$$LOS_{LO} = \{F_1, F_2, F_3, F_4, F_5 \mid \forall F_i \in LOM, F_i \neq F_j\}$$

For example, three learning objects in Table 3 were explained by Definition 2 as follows:

LOS_{LO001} = {*F1, F2, F3, F4, F5*} = {*animation, active, 4, 8, simulation*}

LOS_{LO002} = {*F1, F2, F3, F4, F5*} = {*text, expositive, 2, 7, algorithm*}

LOS_{LO003} = {*F1, F2, F3, F4, F5*} = {*video, active, 4, 7, definition*}

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Mapping Selected Learning Object Features to Learners' Learning Style

Felder and Silverman [17] defined eight learning styles: active, reflective, sensing, intuitive, visual, verbal, sequential and global. Examples of semantic group (SG) associated with the ILS answers are explained in Table 4.

Table 4. Examples of 'A-Active' learning style's SG associated with ILS answers

Learning Style	SG	ILS questionnaire indicator No.		Extracted words for validating mapping rule
		Answer 'a'	Answer 'b'	
A-**A**ctive	Trying something out (SG1)	1 17 25 29	-	Try out Start solution immediately Try out Practice
	Social oriented (SG2)	5 9 13 21 33 37 41	-	Talk Contribute idea Group Group Group Group, outgoing Group

The values of these properties constitute the input for the planner to generate a recommendation adjusted to the learner's preferences and learning styles. However, this process is only possible if there is an implicit relationship between the learners' characteristics and the different kinds of learning objects and activities associated with the learning design. If these learning objects are characterised by the metadata, rules can be applied to assign the learning objects to the learners' learning style in the LMS. In this study, the IEEE LOM was used to characterise learning objects. An appropriate learning object is one that addresses at least one characteristic of the learner.

Grouping of Learning Style Preferences

The SGs within the dimensions provide relevant information used to identify learning styles. For example, if a learner has a preference for trying things out and tends to be more impersonal oriented, the learner would have a balanced learning style on the active/reflective dimension. However, a learner also has a balanced learning style if he/she prefers to think about the material and tends to be more socially oriented. Although both learners have different preferences and therefore different behaviour in an online course, both are viewed according to the result of the ILS. Therefore, considering the proposed SGs leads to providing more accurate information about learners' preferences and thereby developing a more accurate model for identifying their learning styles based on their behaviour in an online course.

In this analysis, we define the learner characteristics required to generate recommendations according to learning styles and related competence. Furthermore, we describe the mechanism to link those features with the learning objects and resources used to create the learning object selection rules.

Table 5 presents the domain knowledge of the learning object set (LOS). We may infer from LOS definition 2 that $LOS_{LO} = \{F_1, F_2, F_3, F_4, F_5 \mid \forall F_i \in LOM, F_i \neq F_j\}$. Since LOS $\subseteq$ LOM, where LOM always describes every learning object, LO_i, the result implies that LOS always describes every learning object, LO_i. If we define the mapping rules that cover all LOS features, every LO_i can be accessed. Table 5 presents the LOM value space analysis in the LOS domain. Vi is defined as the LOM value space, where i is value space (V) number. This knowledge is used in mapping rule construction and validation.

Table 5. Examples of LOM value space analysis in the LOS domain [5–6]

Feature of LOS	LOM value space	LOS domain
Format (F1)	Video (V1)	"I see," "moving eye picture," "a recording of both the visual and audible components"
	Image (V2)	"two-dimensional figure," "map," "graph," "pie chart," "abstract painting," "computer graphic," "drawing," "painting," "photograph," "visual media," "picture," "idea"
	Text (V3)	"set of writing," "message"
	Audio (V4)	"hear," "listen," "sound"
	Animation (V5)	"motion picture," "the act of animating," "spirit," "liveliness," "airiness," "sequence of image"

The valid mapping rule is the one that is a member of the intersection set of word meaning or semantic between SGs and LOS features. Figure 2 presents the mapping process between learning style and LOS.

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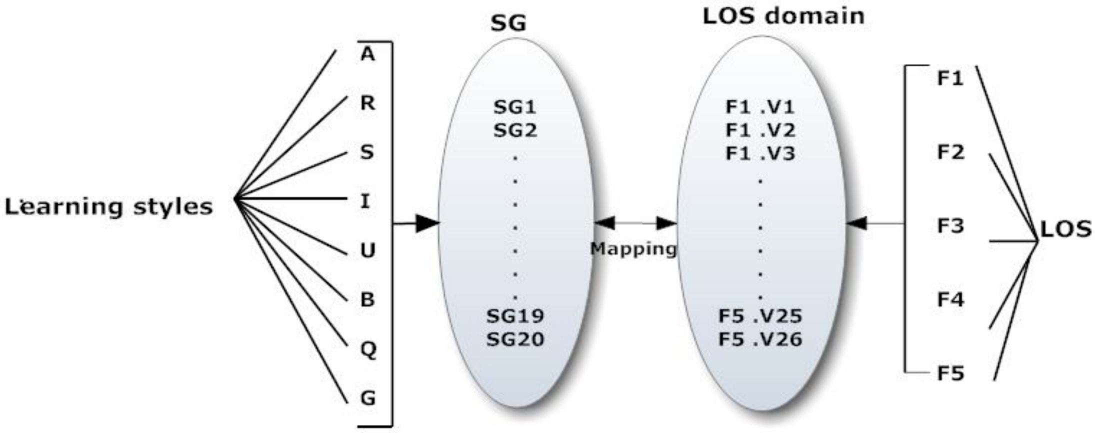

Figure 2. Semantic mapping between learning style and LOS features

Mapping Rules with Word Analysis Construction and Validation

A common way to perform the analysis of mapping is to allow the domain knowledge of learning styles and learning object features to perform this task with word analysis support. Figure 3 shows the mapping rules for this building process.

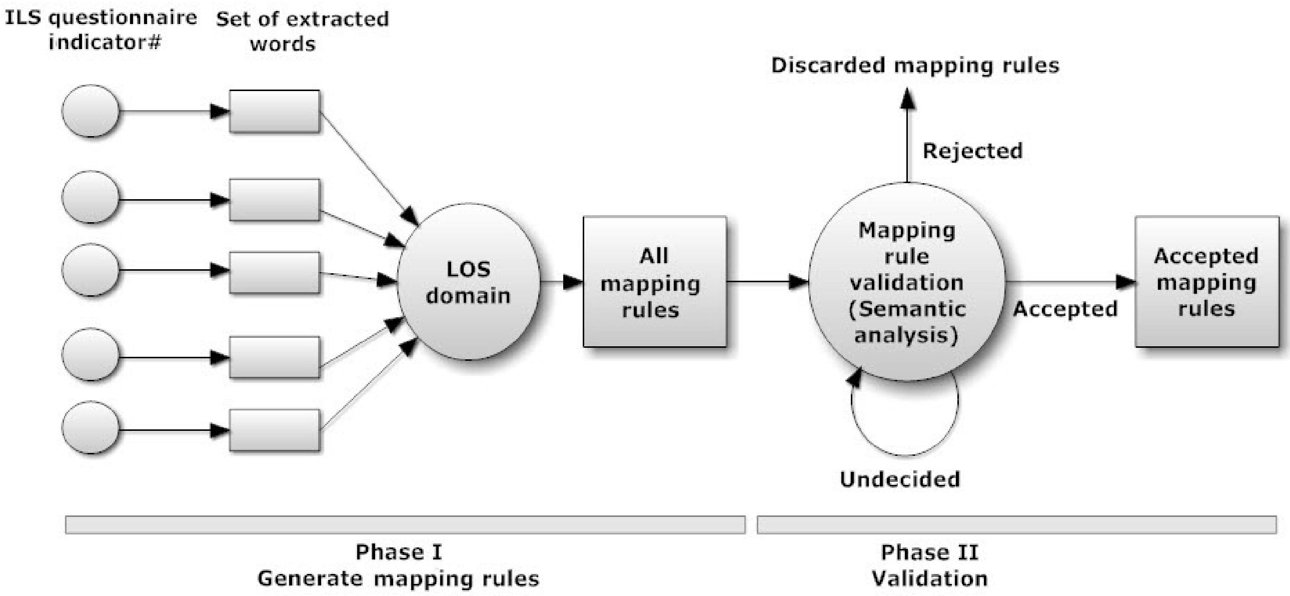

Figure 3. Learning object mapping rules for the building process

In the proposed approach, learning styles and learning object feature mapping rules are discovered and the LOS domain validated by an expert. Depending on how well the rules represent the actual behaviour of the learner, some rules are ‘accepted’ and some are ‘rejected’ by the expert.

In Phase I, mapping rule generation constitutes mapping rules describing the learning object preferences of individual learners that are generated from the learners’ ILS answer as described in

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the subsection below. Phase II constitutes the mapping rule validation process. Mapping rule validation, unlike rule discovery (Phase I), is not performed separately for each learner, but rather performed for all learners at once. The reason we perform mapping rule validation collectively (rather than individually) is that there are usually many similar or even identical rules across different learners.

All mapping rules are collected into one set. The mapping rule validation process is performed as the second part of Phase II as described in Figure 3. At this stage, all the mapping rules are considered invalid. We analyse the meaning of extracted words from 44 ILS answers and compare them with the learning object features in the LOS. Then the validation mapping as O is defined and successively applied to the set of invalid mapping rules. The validation mapping results in the validation of some of the rules. In particular, some mapping rules are accepted and some are rejected (sets O_{accept} and O_{reject} according to Algorithm 1).

Algorithm 1: Mapping rules validation process

INPUT: Set of all discovered mapping rules MR_{all}
OUTPUT: Set of mapping rules MR_{accept}, MR_{reject}, $MR_{invalid}$ such that
$MR_{all} = MR_{accept} \cup MR_{reject} \cup MR_{invalid}$
METHODS:
$MR_{invalid} = MR_{all}$, $MR_{accept} = \phi$, $MR_{reject} = \phi$
WHILE (not TerminateValidationProcess())
BEGIN Expert selects a validation operator (called O) from the set of available validation mapping. O is applied to $MR_{invalid}$, Result: disjoint sets O_{accept} and O_{reject}
$MR_{invalid} = MR_{invalid} - O_{accept} - O_{reject}$,
$MR_{accept} = MR_{accept} \cup O_{accept}$,
$MR_{reject} = MR_{reject} \cup O_{reject}$
END

Next, the validation mapping is applied to the remaining set of invalid rules (set $MR_{invalid}$). This validation process stops when the terminate validation process condition is met. In this study, this condition is that the set of validated mapping rules are covered by the LOS domain (all learning object features are referred). After the validation process is stopped, the set of all the discovered rules (MR_{all}) is split into three sets: accepted rules (MR_{accept}), rejected rules (MR_{reject}), and possibly some remaining rules that have not been invalidated ($MR_{invalid}$). At the end of Phase II, all the accepted mapping rules are used to transform the LSS to the LPS.

Based on the Felder-Silverman learning style model, the association between each learning style and learning object features is analysed. Examples of validated mapping rule selection from all possible mapping rules are presented as follows:

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Mapping rule 1. *Recommend learning object for "**A-A**ctive" learner*

If "A" ∈ LSS(L)

Then LOM.educational.interactivity_type = "active" or "mixed"

And LOM.educational.LearningResourceType = "exercise" or "simulations" or "experiment"

Mapping rule 2. *Recommend learning object for "**R-R**eflective" learner*

If "R" ∈ LSS(L)

Then LOM.educational.interactivity_type = "expositive"

And LOM.educational.ResourceType = "definition" or "algorithm" or "example"

Mapping rule 3. *Recommend learning object for "**S-S**ensing" learner*

If "S" ∈ LSS(L)

Then LOM.educational.semanticDensity = "high" or very "high"

And LOM.educational.learningResourceType = simulation or experiment

Mapping rule 4. *Recommend learning object for "**I-I**ntuitive" learner*

If "I" ∈ LSS(L)

Then LOM.educational.semanticDensity = "very low" or "low or medium"

And LOM.educational.learningResourceType = "definition" or "exercise"

Mapping rule 5. *Recommend learning object for "**U-**vis**U**al" learner*

If "U" ∈ LSS(L)

Then LOM.technical.format = "video" or "image" or "animation"

And LOM.educational.interactivity_level= "high" or "very high"

And LOM.educational.learningResourceType = "simulation"

Mapping rule 6. *Recommend learning object for "**B-**ver**B**al" learner*

If "B" ∈ LSS(L)

Then LOM.technical.format = "text" or "audio"

And LOM.educational.interactivity_level= "medium" or "low" or" very low"

And LOM.educational.learningResourceType = "definition" or "exercise"

Mapping rule 7. *Recommend learning object for "**S-**se**Q**uential" learner*

If "Q" ∈ LSS(L)

Then LOM.technical.format = "text" or "audio"

And LOM.educational.learningResourceType = "exercise" or "algorithm" or "slide"

Mapping rule 8. *Recommend learning object for "**G-G**lobal" learner*

If "G" ∈ LSS(L)

Then LOM.technical.format = "image"

And LOM.educational.learningResourceType = "index"

Based on the word analysis process, an example of accepting the proposed mapping rules (validation mappings O in Algorithm 1) is shown as follows:

Example of Mapping

Active *= {try out, start solution immediately, practice, talk, contribute idea}*

Map to:

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Interactivity type

Interactivity type = "active" = {simulation, questionnaire, exercise, problem, practice}

Interactivity type = "mixed"= {video, simulation}

Interactivity type = "expositive" = {hypertext, graphics, audio, essay}

Learning resource type

Learning resource type = "exercise"= {planned sequence of actions, assignment, worksheet, tutorial}

Learning resource type = "simulation"= {behaviour of some situation, behaviour of process}

Learning resource type = "experiment"= {discover unknown, test hypothesis, establish some known truth}

Learning resource type= "definition"= {explanation, give meaning, objective}

Learning resource type= "example"= {case study, show how to act}

Learning resource type= "index"= {glossary, reference, list of contents}

…

Next, the LSS is considered with mapping rules to create the LPS. The definition of the LPS is shown in Definition 3.

Definition 3: *Learner preference set, LPS, is a set of learning object features by which the learner prefers to learn, and its preferred weight.*
$LPS = \{(\{PF_i\}, Pw_i) | PF_i \in F_i, Fw_i \in \{0, 0.5, 1\}\}$,
where PF is the preference feature and denoted by $PF = \{A, R, S, I, U, B, Q, G\}$,
Fw is the feature weight and i is the number of feature.

PROPOSED RECOMMENDATION MODEL

A learning object recommendation model provides learners with personalised learning object selection service. There are four intelligent agents in this model: learner interface, feedback, learner model and learning object recommendation.

Using XML messaging, we define a generic architecture for agent-based course brokering in order to represent the agent's roles in the recommendation process. The main agents participating (Figure 4) are described as follows:

Learner Interface Agent: This agent detects any user interaction with the learner interface and records the results, if any, of these interactions.

Learner Model Agent: This agent is for maintaining, updating, and analysing the learner profile. The learner model agent employs a learning object selection rule to create the LPS.

Learning Object Recommendation Agent: This agent uses the learner's information from the learner model agent to compute the PS of each learning object.

Feedback Agent: For system modification, the feedback agent obtains the learner's feedback and sends it to the recommended learning object. If the learner is not satisfied with the learning object, the learning object selection rule or the learner model will be updated and the process of recommendation restarted.

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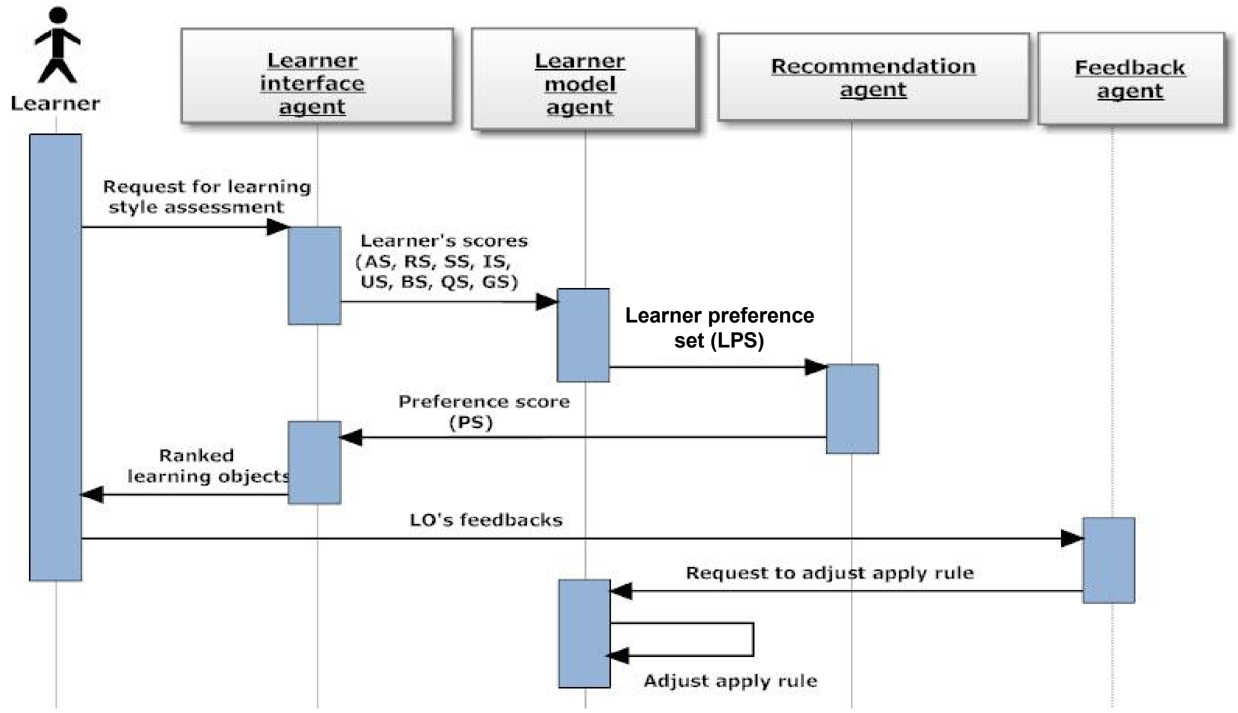

Figure 4. Sequence of personalised learning object selection

Non-personalised Recommendation Algorithms

Next, we examine the non-personalised algorithms to provide the results of learning object selection when learners do not use any of their LPS. There are two sub-algorithms. First, the random algorithm (Rand) randomly selects learning objects in the same topic, independent from the evaluation of the learner. Second, the arithmetic mean (AriMean) calculates a recommendation as the arithmetic mean of each learning object that other learners prefer, independent of how similar the other users are to the learner. The most popular learning object in the same concept will be chosen for the learner.

Preferred Feature-Based Recommendation Algorithm

The preferred feature-based (PFB) algorithm is to bias learning objects towards a learner's preferences. Learning objects tending to suit a learner's preference will get a higher priority when it is matched to the learner. Two variations of the PFB recommendation algorithm, namely non-weighting feature PFB (NWF-PFB) and weighted feature PFB (WF-PFB), are proposed.

NWF-PFB recommendation

In NWF-PFB recommendation, the PS is calculated by the NWF-PFB algorithm. The results show the suitability of each learning object for the learner, independent of the feature weighting. In this algorithm, we define a feature frequency weight of the learning object's features as 1 ($\omega = 1$) for every learning object feature.

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WF-PFB recommendation

In WF-PFB recommendation, the learning object feature is weighted by using the frequency that the target feature is given by the learning object selection rule. We note that the frequencies of learning object features, which are referred to in learning object selection rules, are different. In the WF-PFB, ω is computed by $\omega = \dfrac{1}{\sum F_i \text{ appearing in each Rule}}$ and the results for ω of the learning object features are shown in Algorithm 2. Both the NFW-PFB and the FW-PFB algorithms are described using the PFB algorithm, but they are different in variations of ω. The information of learner model used in our experiment is used as an input for the learning object recommendation. An example of learner id 001 (LSS_{L001}) is described as follows:

LSS_{L001}= *{(A,1), (R,0), (S,0.5), (I,0.5), (U,1,), (B, 0), (Q,0), (G,1)}*

From the rules presented in Definition 3, the LSS of learner 001 (LSS_{L001}) can be converted to the LPS of learner 001 (LPSL001) as follows:

LPS_{L001} = *{({exercise, simulations, experiment, active, mixed},1), ({simulation, experiment, 8, 9}, 0.5), {definition, exercise, 5, 6, 7}, 0.5), ({video, image, animation, simulation, 3, 4, 5},1), ({image, index},1)}*

Both the LSS and LPS is used as input values in the PFB algorithm.

Algorithm 2: The PFB algorithm

<u>INPUT</u>: LPS, LOS,
Two choices of variation of feature frequency weight (ω)
- NWF-PFB, ω = 1 for each learning object feature i, or
- WF-PFB, ω = $\frac{1}{\#of\ RF_i}$, RF is the frequency of referred feature.
<u>OUTPUT</u>: PS of specific LO
FUNCTION**:** Preference_Score_Calculation () //compute PS of all learners
FOR EACH LPS // compute PS of learner with all learning objects
FOR EACH LOS of learning object i
INT PS = 0
//compute all of learner styles {A, R, S, I, B, U, Q, G} in LPS
FOR EACH $PF_i \in$ LPS (L)
IF ($PF_i = F_i$) and FWi<>0
THEN PS = PS + ω FW_i
BREAK
RETURN Preference_Score_Calculation()=PS
END FUNCTION

To demonstrate the program of PFB algorithm, the concept called "Process" in the operating systems course has five learning objects that are used to show the learning object recommendation for a learner. The example shown in Figure 5 presents PS after a recommendation program has been run.

When the PFB algorithm is used to compute the PS of each LO of learner ID 001, the results are: $PS(LO_{001}) = 1.8125$, $PS(LO_{002}) = 0.75$, $PS(LO_{003}) = 1.0625$, $PS(LO_{004}) = 1.75$, and $PS(LO_{005}) = 1.375$. Therefore, the recommendation order is LO1, LO4, LO5, LO3 and LO2.

```
run:
Learner ID >> 001
Active : Mixed : Execise : Simulation : Experiment : 1.0
8 : 9 : Simulation : Experiment : 0.5
5 : 6 : 7 : Definition : Example : 0.5
Video : Image : Animation : 2 : 3 : 4 : Simulation : 1.0
Image : Index : 1.0
======================
Learner ID >> 002
Active : Mixed : Execise : Simulation : Experiment : 0.5
Expositive : Definition : Algorithm : Example : 0.5
8 : 9 : Simulation : Experiment : 0.5
5 : 6 : 7 : Definition : Example : 0.5
Video : Image : Animation : 2 : 3 : 4 : Simulation : 0.5
Text : Audio : 0 : 1 : Definition : Exercise : 0.5
Text : Audio : 5 : 6 : Exercise : Algorithm : Slide : 0.5
Image : Index : 0.5
======================
Learner ID >> 003
Active : Mixed : Execise : Simulation : Experiment : 0.5
Expositive : Definition : Algorithm : Example : 0.5
8 : 9 : Simulation : Experiment : 1.0
Video : Image : Animation : 2 : 3 : 4 : Simulation : 1.0
Text : Audio : 5 : 6 : Exercise : Algorithm : Slide : 0.5
Image : Index : 0.5
======================
...
======================
Learner ID >> 001
LO_id = 001 >> 1.8125
LO_id = 002 >> 0.75
LO_id = 003 >> 1.0625
LO_id = 004 >> 1.75
LO_id = 005 >> 1.375

Learner ID >> 002
LO_id = 001 >> 1.0625
LO_id = 002 >> 1.125
LO_id = 003 >> 0.8125
LO_id = 004 >> 1.0625
LO_id = 005 >> 1.3125

Learner ID >> 003
LO_id = 001 >> 1.8125
LO_id = 002 >> 1.0
LO_id = 003 >> 0.8125
LO_id = 004 >> 1.1875
LO_id = 005 >> 0.9375
...
```

Figure 5. Output examples of PS calculated by PFB algorithm

Neighbour-based Collaborative Filtering Recommendation Algorithm (NBCF)

The neighbour-based collaborative filtering (NBCF) recommendation algorithm predicts how helpful a learning object will be for a learner by analysing feedback from similar learners. A similar learner group is defined as a group of learners who have used the same learning objects in the past and returned similar feedback.

The result of this algorithm is an average ranking of the three most similar neighbours

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between the learners (SL) and the learner who prefers LO (PL). The detail of NBCF algorithm is shown in Algorithm 3.

Algorithm 3: The NBCF algorithm

INPUT: Preferred learning object ID, LSS of learner (SL)
LSS of preferred learner (PL) of preferred LO
n = number of learner style preference
k = number of nearest neighbours (k = 1, k = 3, k = 5, k = 7, k =9)
OUTPUT: Neighbour Score (NS) of preferred LO
FUNCTION: Neighbour_Score_Calculation()
FOR EACH LSS of SL
FLOAT DIS = 0, MDIS = 0
// compute distance between SP and PL by using learner style
FOR EACH LSS of PL of preferred LO
FOR EACH (P_i in LSS)
$DIS_{(SL,PL)} = DIS_{(SL,PL)} + Sqr((P_{SL}\wedge 2) - (P_{PL}\wedge 2))$
// return k learners who have the least distance of all PLs
FOR ALL $DIS_{(SL,PL)}$ between SL and PLs
Rank($DIS_{(SL,PL)}$)
RETURN Last k of $DIS_{(SL,PL)}$)
MDIS = SUM($DIS_{(SL,PL)}$)/k
RETURN Neighbour_Score_Calculation()=1-MDIS
END FUNCTION

EXPERIMENT AND RESULTS

Experimental Setting

In all experiments, learning objects were recommended to learners using different learning object recommendation algorithms based on their learning styles. Candidate learning objects were filtered by a concept map that was created by the concept map combination model (CMCM) and represented in terms of LOS. Then the actual feedback preferences from learners were evaluated according to the PS and the neighbour score (NS) that were computed by the recommendation algorithms. For the content-based approach, the PS represented the suitability of a learning object according to the learner's degree of preference for each learning object feature. Therefore, the learning object with the highest PS was recommended to the learner. For the collaborative filtering approach, the NS showed a degree of similarity between learners. The learning object that was preferred by other learners who were similar to the learner would be recommended.

Participants and Learning Object Candidates

For experiments, participants were 142 undergraduate students majoring in CS and IT at Thaksin University (Phattalung campus). We divided the undergraduate students into four groups according to their year and study major. Group 1 had 31 third-year students majoring in CS (3CS, n = 31); Group 2 had 48 third-year students majoring in IT (3IT, n = 48); Group 3 had 29 fourth-year students majoring in CS (4CS, n = 29); and Group 4 had 31 fourth-year students majoring in IT (4IT, n = 31). The default number of candidate learning objects for our experiment was 54 in the concept operating systems course. Examples of the LOS of the candidate learning objects are described as follows:

LOS_{L001} = {*animation, active, very high, high, simulation*}
LOS_{L002} = {*text, expositive, low, medium, algorithm*}
LOS_{L003} = {*video, active, very high, medium, definition*}

To understand how the recommendation results affect learners, both feedback analysis and PE between the real learner's preference and the system predictions were compared. Observing the learner's feedback directly indicated whether the proposed model recommended learning objects in accordance with the learner's preference, while calculated PE showed whether the model could accurately infer the learner's preference and interest. The prediction accuracy was good when the PE value was low. In our experiments, different algorithms showed different results. PE could be calculated by using $PE = 1 - \frac{\sum_{i=1}^{N}(LO_{ac} \cap LO_{pd})}{N}$, where LO_{ac} is an actual preferred learning object, LO_{pd} is the recommended learning object, and N is the number of learners.

As a final evaluation of the proposed algorithms, the predicted results of each algorithm were compared with the actual results. The comparison of average PE results among recommendation algorithms is shown in Table 3. It can be concluded that the WF-PFB algorithm has the highest accuracy followed by the NFW-PFB and NBCF, with Rand having the lowest performance (predicted with average PE = 0.8279).

Table 3. Comparison of evaluation results for every algorithm

Algorithm	**Variation**	**PE**				**Average PE**
		3CS	**3IT**	**4CS**	**4IT**	
Rand	-	0.8670	0.8203	0.8190	0.8051	0.8279
AriMean	-	0.3871	0.4792	0.5172	0.3824	0.4415
PFB	Non-weighting feature (NWF)	0.2903	0.2917	0.2759	0.3235	0.2954
	Weighted feature (WF)	**0.2258**	**0.2083**	**0.2414**	**0.2353**	**0.2277**
NBCF	k=1	0.6774	0.5484	0.5517	0.4138	0.5478
	k=3	0.4194	0.4516	0.5172	0.3448	0.4333
	k=5	0.4194	0.4516	0.4138	0.3103	0.3988
	k=7	0.3871	0.5806	0.4483	0.3448	0.4402
	k=9	0.3871	0.4516	0.4483	0.3448	0.4080

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CONCLUSIONS

Our model is multi-agent-based with continuous interaction among involved agents. Such an activity is facilitated by the choice of XML for both representing agent ontologies and handling data exchange. Then, based on the learning object features and the results of the learner preference analysis, the learner model that consists of LSS and LPS is created. Both the LSS and the LPS are used as criterion in the recommendation algorithms and are generated by mapping rules on the basis of a word analysis technique. When the three recommendations to learn objects and their variations were compared to determine PE, it was found that the PFB algorithm with weighted feature variation (WF-PFB) has the lowest PE result.

From a research point of view, learning style diagnosis is a prerequisite for adaptation provisioning. Because we provide both the content-based and collaborative filtering techniques, the 'one-size-fits-all' problem is solved. Finally, the efficiency of the proposed model was proved experimentally, and the accuracy of students' satisfaction was very high. In future research, we plan to apply the model on a larger scale, repeated in different domains and for longer periods of time, with a larger number of learners who have different backgrounds and knowledge levels and are in different areas of study.

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