Arab J Sci Eng (2014) 39:1849–1861
DOI 10.1007/s13369-013-0761-4

RESEARCH ARTICLE - COMPUTER ENGINEERING AND COMPUTER SCIENCE

Adaptive Delivery of Trainings Using Ontologies and Case-Based Reasoning

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Received: 17 March 2012 / Accepted: 12 July 2013 / Published online: 11 September 2013

Abstract The delivery of trainings to diversified and constantly changing audiences is expensive and time consuming. We propose a computational approach addressing this issue by providing an adaptive training delivery framework. The approach relies on case-based reasoning (CBR) as a problem-solving method whereby cases are used rather than a prohibitive number of rules to store knowledge, i.e., experience. CBR is indeed accepted as one of the mainstream paradigms in artificial intelligence since it represents both knowledge and reasons about it. This choice is further motivated by the fact that the process of adaptation to different audiences is built on the traces left by previous learning tasks and practices that can be stored and automatically retrieved. Moreover, to address the crucial and pending issue of case indexing in CBR, we use ontologies to model and index the learning objects that represent the trainings core, thus reducing the retrieval process and improving search. Substantially, we develop an adaptation algorithm responsible for the required corrective actions in the adaptive delivery of trainings destined to diversified and heterogeneous learners.

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Keywords Case-based reasoning (CBR) · Search · Experience sharing · Learning objects · LOM · Ontologies · SCORM · Training process · Trainings adaptive delivery

الخلاصة

يُعد تقديم الدورات التدريبية لفئات متنوعة ومتغيرة باستمرار عملية مُكْلِفة ومستهلكة لوقت طويل. ونقترح - لمعالجة هذه المسألة - إطاراً حاسوبياً يتأقلم مع الفئات المختلفة لتقديم تدريبات مكيَّفة، وذلك بحسب الحالة. ولبناء هذا الإطار نستخدم التّفكير المستنبط من القضايا (CBR) كوسيلة من وسائل حلّ المشكلات حيث يتمّ استعمال القضايا، أو الحالات، بدلاً من عدد هائل من القواعد لتخزين المعرفة، أي الخبرة. ومن المعروف أنّ التّفكير المستنبط من القضايا يُعد أحد الخيارات السائدة في مجال الذكاء الاصطناعي (AI) لأنّه يقوم بتمثيل المعرفة وباستخدامها في التفكير. إنّ الدّافع الإضافي من وراء هذا الاختيار هو أن عملية التكيّف، أو التأقلم، مع مختلف الفئات التدريبية هي عملية مبنية على الآثار التي تتركها المهام والممارسات التدريبية السابقة التي يمرّ بها المتدرب والتي يُمْكِن تخزينها ثم استرجاعها تلقائيا. وعلاوة على ذلك، ولمعالجة المسألة العويصة، والمفتوحة حتى الآن، والمتعلقة بصعوبة الفهرسة التي تعيق التفكير المستنبط من القضايا (CBR) بخاصة ، فإنّنا نستخدم تبويب المعارف لنمذجة مكوّنات التعلّم وللتأشير عليها حيث تمثّل جوهر التدريبات، ممّا يُسهّل كثيراً عملية استرجاع المعرفة وتسريع الحصول على الحالات المشابهة في أثناء البحث عن حل مسألة جديدة. وبناءً على هذا، فإنّنا نطوّر خوارزمية للتكيّف، أو ألتأقلم، وهي المسؤولة عن الإجراءات التصحيحية المطلوبة في تقديم الدورات التدريبية المكيّفة التي من شأنها أن تلبّي طلبات فئات متنوّعة وغير متجانسة من المتدربين بشكل آلي.

1 Introduction

The delivery of ad hoc trainings to diversified audiences is expensive and prohibitively time consuming. Indeed, for each and every audience, there is a need for the elaboration of a specific set of fixed training modules. As a result, the delivery of trainings that adaptively address different audiences is an important and interesting task with potentially great impact on trainings delivery. In order to ease the challenging issue of the adaptation of trainings to different and diversified audiences, it is necessary to choose some basic and core configurations that are as flexible as possible to meet different environments while highlighting some local adjustments to be achieved. The knowledge-based system (KBS) framework offers a good solution.

At the outset, and in the presence of human experts, rule-based approach provides one of the easiest and straightforward solutions within KBS whenever knowledge can be expressed in IF-THEN rules. However, for the adaptive delivery of trainings, rule-based approach is simply prohibitive because of the high dimensionality of the rule space, except perhaps for trivial cases with no impact on real-life applications. Since heavily relying on experience, we show that case-based reasoning (CBR) offers an acceptable paradigm for addressing the issue of the adaptive delivery of trainings. CBR is an artificial intelligence (AI) paradigm based on analogical reasoning in which problem solving is based on the adaptation of the solutions of similar problems, already solved and stored in a case base [1]. In this respect, CBR provides a solution that is more structured than rules. Indeed, in CBR, one case might summarize a large number of rules and therefore drastically reduces the search space. Because CBR is traditionally accepted as one of the paradigms of mainstream AI, it represents both knowledge and reasons about it [2]. In CBR, a body of cases represents codified knowledge upon which the CBR operations take place such as reasoning methods for similarity assessment, case adaptation and learning of new cases. CBR is now a well-established field and the main important ways in which CBR systems were developed in the first 10 years are described in a CBR textbook [3]. One of the developments of CBR is the so-called knowledge-intensive CBR (KI-CBR) proposed by [4] that relies on a knowledge base including domain knowledge and, as well, knowledge units used during the retrieval and adaptation processes.

Historically, CBR approach can be traced back to psychology through schema-oriented memory models and the theory of remembering as developed by [5] with its direct and proven impact on Schank's theory of dynamic memory [6]. CBR approach also came under the influence of many concepts with roots outside of computer science such as the works reported in [7], establishing distinction between episodic and semantic memories in human reasoning and characterizing the exemplar view in concept definition [8].

Unfortunately, CBR suffers from the inexistence of generic knowledge representation methods; particular requirements for CBR are usually dealt with as they arise. In addition to this limitation, computationally speaking, CBR is usually confronted with the problem of case indexing especially for large knowledge bases. As a result, an additional structure has to be used to address this issue, and our contribution relies on the use of ontology [9].

Ontology is another structural way that describes dependencies between the concepts at hand and guides the search within a smaller space, limited by the concepts themselves. An ontology is used for the conceptualization of a particular domain and for knowledge exchange, and is formally described by a set of concepts represented by a graph where nodes are concepts per se and arcs are semantic relationships between concepts. The graph summarizes the basic relationships between the components of the domain, here training.

The ontology-supported CBR is further dictated by the nature of the field of e-learning itself where applications of the adaptable approach are particularly important as the e-learning process often requires such adjustments on the case-by-case basis, depending on the learners' achievements, and on a dynamic monitoring of their success in the chosen trainings [10]. A dynamic content adaptation to a successful learner profile is therefore an essential feature to be stored, monitored, indexed discovered, and retrieved. Some attempts have been directed toward the use of fuzzy logic to construct e-learner profile [11], while others concentrated on multi-agent approach [12]. In the present context, we choose the experience reuse approach to assist the users whereby the system memorizes and interprets the current tasks signatures, i.e., the traces left from experience and past practices [13].

The model allows the guidance of new learners based on the footsteps of similar peers who have achieved the same target profile starting from closely related or similar profiles [14]. To achieve the proposed objectives, at the pre-implementation level, we represent trainings in the form of ontologies. These latter are used to semantically index learning objects, on the basis of the current standards of e-learning. One of this set of standards is SCORM (sharable content object reference model) [15]. Another standard is LOM (learning object metadata) [16]. Standards are used to ensure the homogeneity of representations of the learning resources and to further facilitate interoperability [17].

On the basis of the arguments expanded above, we propose a framework for adaptive delivery of trainings that is rooted in CBR. Further, we use ontologies for indexing the cases to facilitate both search and retrieval of cases.

The paper is organized as follows. In Sect. 2, we describe the cognitive and computational processes involved in the adaptive delivery of trainings with special emphasis on CBR. Section 3 describes the standardization process and the basic structural building blocks of the proposed framework. Section 4 highlights architectural considerations, while Sect. 5 discusses the basic step of the proposed methodology with the presentation of an adaptation algorithm responsible for the corrective action when looking for the solution. Section 6 presents a working example. Finally, we conclude our study with some indication to further eventual improvements.

2 Basics of a Methodology for Adaptive Trainings Elaboration

2.1 Steps for Trainings Elaboration

The proposed methodology follows the steps summarized below.

// Methodology 1 – Trainings elaboration steps //

```
1. Training needs identification
   The learner expresses the training
   needs in the form of goals such as the
   study of a particular concept or a set
   of concepts at a given level.
2. Gap reduction
   Reduce the gap between the actual
   profile and target profile; this
   operation requires:

   2.1 Definition of the concepts already
       acquired, i.e. actual profile of the
       learner
   2.2 Definition of the concepts to be
       acquired (target profile) of the
       learner
   2.3 To take corrective actions; this
       requires some knowledge about
       learners who have achieved the same
       target profile with close initial
       profiles
3. Final gap evaluation
   Measure the final gap at the end of the
   training; this operation requires the
   repetition of Steps 1-2 above until the
   gap is acceptable, i.e. the learner
   succeeds in the training or is directed
   to another level of the training.
```

Methodology 1 – Trainings elaboration steps

As shown in Methodology 1 above, the basic adaptive delivery of trainings begins by identifying training needs. The next step is to bridge the gaps by comparing objectives and results, and finally to conduct an evaluation of that specific training. If the assessment reveals a new gap then corrective actions are undertaken, such as novel trainings solutions.

2.2 CBR as a Chosen Methodology

Historically, the foundations of CBR come from multidisciplinary areas initiated about three decades ago with the aim to determine the role of memory in human reasoning when solving past problems [6]. CBR has further come under direct influence from cognitive science, artificial intelligence (AI), machine learning and from mathematics. Clearly, these areas overlap, but they still capture the main foundational perspectives of CBR. Although some works have concentrated on CBR as applied to e-learning [10], and others on the study of multimedia learning objects [18], no works have considered the approach of blending CBR and ontologies as far as delivery of trainings is concerned. Why? Historically, CBR and ontologies have existed separately for the last three decades, or so. They have been used, separately, to solve various problems ranging from engineering and science to humanities and decision-making processes at various levels of complexity with various degrees of success. Traditionally, CBR and ontologies are considered as two separate problem-solving paradigms within the artificial intelligence (AI) field. Each one of these has its own community with its ad hoc methodologies, issues and approaches to tackle them. For instance, as far as knowledge representation is concerned, CBR uses cases while ontologies rely on dependency graphs. As a result, CBR and ontologies remained separated, at least so far. Some exceptions need to be pointed out. One of the approaches blended ontologies and CBR within the framework of Semantic Web [19] but relied on readily made implementation tool such as C-OWL. The novelty of our approach is that, although we still use cases for knowledge representation, we call upon ontologies for indexing them, thus improving the case-retrieval process and contributing to one of the most important issues in CBR.

2.2.1 CBR and Cognitive Science

The major influence of cognitive science on CBR is centered on fundamental concepts such as experience, memory and analogy. These concepts have their roots outside of computer science. For instance, the distinction between the so-called episodic and semantic memories in human reasoning [7] characterized the exemplar view in concept definition [8]. Furthermore, schema-oriented memory models and the theory of remembering with their long tradition in psychology [5] have had a direct influence on Schank's theory of dynamic memory [6].

2.2.2 CBR and Analogical Reasoning

In the early phases of the field, CBR research paid attention to analogical reasoning in particular. The cognitive foundations of analogy had indeed a long history. It is commonly admitted that CBR is a special type of analogical reasoning, while general analogical reasoning typically reasons *across* multiple domains and CBR reasons inside one *unique* domain. Many researchers studied analogy with different perspectives, such as derivational analogy and analogical mappings. These mappings are related to adaptation rules but several differences exist; for example, humans usually do not often use adaptation [20]. While the study of analogical reasoning in humans has been a focal issue in cognitive science, for a long time, less work has been focused on computational or formalized aspects of analogy. Indeed, only very few computational models of human analogical reasoning have been proposed, although some of these have had significant impact on CBR. Among these, we can refer to computational models such as relational mapping developed by [21].

2.2.3 CBR and Artificial Intelligence

2.2.3.1 CBR and Knowledge Representation Like many paradigms of artificial intelligence (AI), as stressed earlier, CBR has both the capacity to represent knowledge and to reason about it. That is why CBR is fully accepted as one of the important paradigms of AI. In CBR, knowledge is represented using cases on which the reasoning methods for similarity assessment, case adaptation and learning of new cases are applied. However, CBR suffers from the inexistence of genericity in knowledge representation; specific requirements for CBR are usually processed as they come. An example is the rule knowledge that is often used in adaptation. Although rules have been extensively reported in the literature, specifically on rule-based knowledge systems, little generic work has been done on rule systems for adaptation as used in CBR [22].

2.2.3.2 CBR Indexing Issues and Data Structures In addition to the issue of genericity of knowledge representation, and as exposed earlier, indexing represents a non-trivial issue in CBR. On top of traditional data structures used in data base management system (DBMS) and other well-known structures such as decision trees and discrimination trees, an important tree structure is k-d tree as a multidimensional binary search tree. In k-d tree, each node consists of a "record" and two pointers. The pointers are either null or point to another node. Nodes have levels and each level of the tree discriminates for one attribute. The partitioning of the space with respect to various attributes alternates between the various attributes of the n-dimensional search space. Although k-d trees complexity properties and related questions for CBR have been investigated to some extent, many problems concerning k-d trees have not been solved, so far [23]. Other types of indexing trees have also been discussed but there are open issues such as context-based tree choice.

2.2.4 CBR and Machine Learning

2.2.4.1 Machine Learning Process Machine learning is an adaptive process whereby computers can improve from experience, by example, and by analogy. As a result, a machine that learns will have the ability of improving actions with respect to some task on the basis of experience. Learning capabilities are therefore essential for automatically improving the performance of a computational system over time on the basis of previous history. A basic learning model typically consists of the following four components:

- learning element, responsible for improving its performance,
- performance element, or decision support system (DSS) responsible for the choice of actions to be taken,
- critical element, a form of "moralizer" which tells the learning element whether the criteria are met within some critical boundaries, and
- problem generator, responsible for suggesting actions that could lead to new or informative experiences [24].

2.2.4.2 Machine Learning vs. CBR The traditional debate is still open as to whether CBR belongs to the machine learning paradigm. For some authors, CBR can hardly be considered a machine learning method. It is at most a sort of lazy learning since it postpones the main inductive step until problem solving while simply storing a specific instance at learning time [22]. It might well be argued that CBR can be considered as a sub-field of machine learning since it uses experience as a salient feature in addition to the calculation of a similarity measure. The debate is not yet settled.

2.3 CBR Advantages and Disadvantages

2.3.1 CBR Advantages

As for any methodology, there are some advantages of using CBR [25]. Among these are the following:

- It reduces the amount of knowledge acquisition actually needed, because the CBR system searches current cases for solutions rather than inferring solutions from a rule base which can contain a prohibitive number of rules.
- It improves over time as case base grows. The CBR system learns over time by adding new cases to the knowledge base. This avoids the need to add new rules or modify existing rules in the knowledge base.
- It can be used when only a small fraction of the domain theory is available.
- It can provide solutions from incomplete problem statement.

2.3.2 CBR Disadvantages

On the other hand, the disadvantages of using CBR are:

- All cases have to be stored in the knowledge base. As a result, care is needed to ensure that cases are referenced correctly with appropriate attributes.
- Ensuring that there is an efficient method for accessing cases, as well as identifying their important attributes for any search.
- CBR does not provide a good presentation of information to the user.
- Cases may not cover the domain well and most appropriate cases may not be retrieved. In this extreme situation, a human intervention is necessary to monitor knowledge within the case base.
- CBR needs similarity, adaptation, and verification of knowledge. Furthermore, in the absence of a good theory, the indexing, retrieval, and learning can indeed be problematic.

3 Standardization Issues

Any environment or system is supposed to interact at one stage or the other with real-life systems like operating systems and the Web, for instance. Consequently, to be widely accepted, any environment has to comply with some adopted standards, hence standardization. For example, Internet as an environment cannot exist without standards like TCP/IP, HTTP, HTML, among others.

Any scientific community needs its own standards and e-learning community is no exception to this rule. In general, the purpose of e-learning interoperability standards is to provide normalized data structures and communications protocols for e-learning objects and cross-system workflows. The IEEE Glossary defines interoperability as "the ability of two or more systems or components to exchange information and to use the information that has been exchanged" [26].

3.1 Compliance with Standards

3.1.1 Standardization in Information Technologies

Interoperability and reusability of resources and tools are the basic objectives of standardization in the field of information technologies, destined to learning, education, and training. Standardization is meant to support individuals, groups, or organizations and to enable reusing their contents transparently, i.e., without any manual intervention when migrating from one platform to another. However, standardization excludes technical reports that define educational standards per se, cultural conventions, learning objectives, or specific learning content. One of the standardization bodies is the ISO/IEC JTC1/SC36[1], responsible for educational technologies standards [27].

3.1.2 Why E-Learning Standards?

In addition to what is stressed above, standards further help the community achieve key goals for all parties involved such as tool designers, content producers, consumers, and tool vendors. These standards can be organized into general categories like metadata (data about data), content packaging, learner profile, learner prospects and content communication [28]. In our proposed method, it is required to follow specifications set out by a set of standards such as LOM [16] and SCORM [15].

3.1.3 Origins of E-Learning Standards

E-learning standard bodies like the advanced distributed learning (ADL: www.adlnet.org/), a body working under the auspices of the American Department Of Defense (DoD), the Aviation Industry CBT Committee (AICC: www.aicc.org) and IMS Global Learning Consortium (www.imsglobal.org) have accomplished noticeable work over the years. These groups' policies and standards have made it possible for end-users to run, for instance, a variety of content on any number of learning management systems (LMSs). However, two shortcomings have diminished the value of this work. First, the development of specifications, as well as the number of groups creating them, grew at a great pace. Second, many groups created standards that were engineering interoperability specifications best suited for developers and not for end-users. We will concentrate only on the issues addressed by the so-called learning object metadata (LOM) and the sharable content object reference model (SCORM).

3.2 LOM

3.2.1 LOM as an IEEE Standard

3.2.1.1 Learning Object Metadata (LOM) [http://ltsc.ieee.org/wg12/index.html] Learning objects are defined as

[1] ISO/IEC JTC 1 is Joint Technical Committee 1 of the International Organization for Standardization (ISO) and the International Electrotechnical Commission (IEC). It deals with all matters of information technology.

any entity, digital or non-digital, which can be used, re-used or referenced during technology-supported learning. Examples of learning objects include multimedia content, instructional content, learning objectives, instructional software and software tools, and persons, organizations, or events referenced during technology-supported learning. Examples of technology-supported learning include computer-based training systems, interactive learning environments, intelligent computer-aided instruction systems, distance learning systems, and collaborative learning environments.

3.2.2 Advantages of Using LOM

Reuse and interoperability are the basic advantages of standardization in general and of LOM in particular. Since the LOM solution is to store objects (data) and their descriptions (metadata), one approach is to include as metadata information about the author, version, number, creation date, technical requirements, educational context and intent, among others. Once this structure is established, it can be re-used across platforms, which represent in itself a non-negligible accomplishment.

3.2.3 Disadvantages of Using LOM

This standard is set out to specify the syntax and semantics of LOM, defined as the attributes required to fully/adequately describe a learning object. This entails the learning of a new syntax and semantics. Moreover, for learning objects to be used, they must be found. This might be a truly challenging task if we consider a large distributed environment like the World Wide Web or a large intranet. In our delivery framework, we propose to apply ontology in the use of metadata to support search, discovery, and retrieval of learning objects.

3.3 SCORM [www.adlnet.org/]

3.3.1 SCORM as an ADL Reference Model

The sharable content object reference model (SCORM), devised by the ADL, aims to foster creation of reusable learning content as "instructional objects" principally destined to Web-based learning. First released in January 2000, SCORM continues to update and expand the scope of the specifications through cooperation with industry, government and academic participants. SCORM describes a technical framework by providing a harmonized set of guidelines, specification and standards for deploying e-learning. SCORM went through a set of improvements, the last one being SCORM 2004 in its 4th Edition, published in March 2009, [15]. The first three specification books were adopted as technical reports by the ISO/IEC JTC1/SC36, standard number ISO/IEC TR 29163. Furthermore, two SCORM Users Guides are now available from ADLnet.gov; one for instructional designers [29] and the other for programmers [30] [http://www.adlnet.gov/capabilities/scorm/scorm-2004-4th].

3.3.2 Advantages of Using SCORM

At its simplest, SCORM is a model that references a set of interrelated technical specifications and guidelines which are designed to meet high-level requirements for learning content and systems. By building upon the existing Web standards and infrastructures, SCORM frees developers to focus on effective learning strategies. SCORM makes sure that all e-learning content and learning management systems (LMSs) can work properly with each other, irrespective of the platform used, just like the DVD standard makes sure that all DVDs will play properly in all DVD players. If an LMS is SCORM compliant, then it can use any content that is SCORM compliant, and conversely any SCORM-compliant content can work properly in any SCORM-compliant LMS.

3.3.3 Disadvantages of Using SCORM

SCORM 2004 introduced a complex idea called sequencing, which is a set of rules that specifies the order in which a learner may experience content objects. In simple terms, they constrain a learner to a fixed set of paths through the training material, permit the learner to "bookmark" their progress when taking breaks, and assure the acceptability of test scores achieved by the learner [http://www.adlnet.gov/capabilities/scorm/scorm-2004-4th].

4 Architectural Considerations

4.1 Basic Approach

Figure 1 describes the basic approach used in the proposed adaptive delivery of trainings framework. The knowledge base contains cases obtained from experience and are used for gap reduction. The cases are stored in the knowledge base represented at the bottom of the figure.

In any ontology, a set of concepts is represented by a graph with nodes representing the concepts themselves and the arcs describing semantic relationships between these concepts. The graph is a summary of the basic relationships between the components of the domain, in our case, training. Therefore, the ontology serves as a repository for semantically indexing resources. The components of the gap, i.e., the initial and target profiles are complementary views of the domain model.

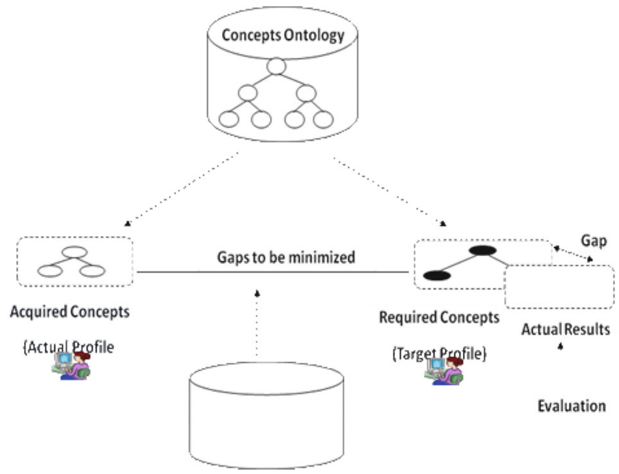


Fig. 1 Approach used in trainings elaboration

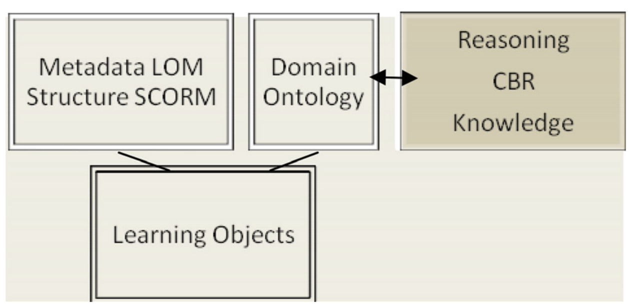


Fig. 2 Basic building blocks

4.2 Basic Structure

Figure 2 shows the basic structural building blocks of the proposed framework. There are basically two main building blocks:

- Learning block incorporating LOM-compliant metadata and SCORM-compliant structures in addition to Learning Objects; further described in Fig. 3.
- Reasoning block supported by CBR and embodying knowledge.

4.3 Indexing Issues

As stressed above, one of the major issues in CBR is the indexing of a set of cases in a meaningful and efficient memory structure. This has both cognitive and computational efficiency connotations. While cognitive issues were focused on the so-called dynamic memory issues, computational researches have concentrated on fundamental computational science, i.e., algorithms, complexity and data structures. The main data structures used in CBR remain the traditional ones as implemented in database technology, for instance [31]. Ontologies have been used to address some issues in e-learning such as knowledge management systems, but, as explained above, they have not been used in conjunction with CBR as applied to trainings delivery. Once the ontology is constructed, and from the practical point of view, the problem of indexing will be taken in charge by the data structure chosen, e.g., k-d tree, dynamic hash table, or similar ordering data structure.

4.4 E-Learning Block

4.4.1 Domain Ontology

The domain ontology is described in Fig. 3. The model represents all the knowledge concepts relevant to the domain. The aim of the diagram is to ease the semantic indexing of the learning objects on a standard basis in relation with LOM and SCORM, as motivated above.

4.4.2 Benefits of Domain Ontology Representation

The domain ontology representation allows the access to all the learning objects by the author/instructor with a possibility of either reusing these objects or designing them from scratch. This representation bears some advantages for the modeling of the author as well as the learner requests.

First, from the author standpoint, the requested concepts are directly specified in the ontology of the topic to be studied. The learning objects related to the domain are indexed by this ontology.

Finally, from the learner standpoint, it is possible to have access to different concepts relevant to a specific training. Moreover, the follow-up allows the learner to define the acquired and required knowledge necessary to the definition of a case required by CBR.

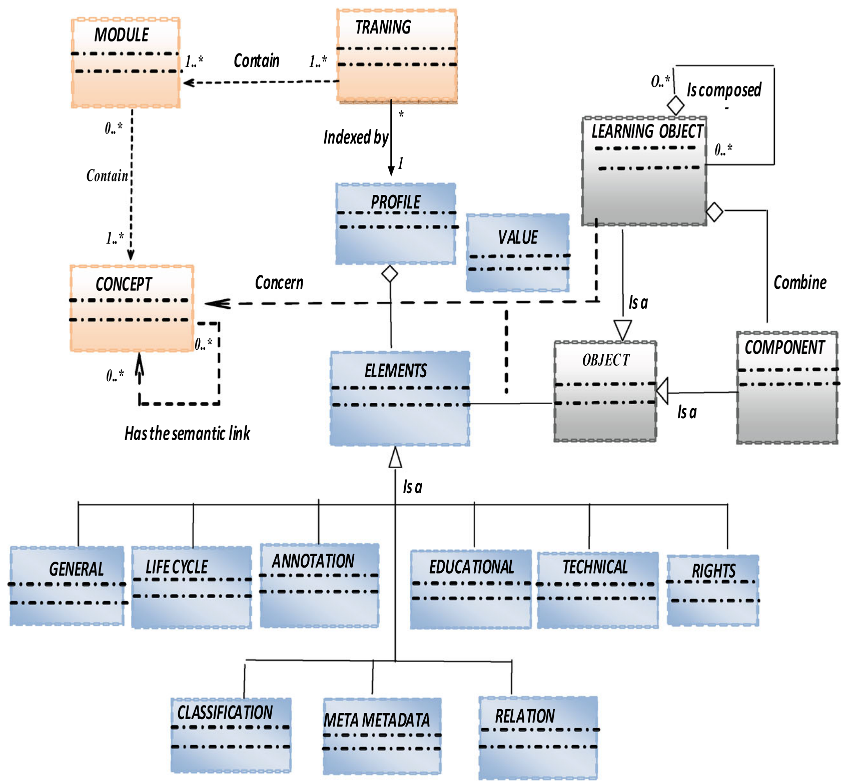
5 CBR Applied Methodological Steps

CBR is before else a comparison method since it produces results that are supposed to move constantly toward a given target based on experience. We therefore consider CBR as an approximation method, in that it reduces the error between the actual results and the target to be attained.

5.1 CBR as Approximation Method

CBR works in a similar way as humans when selecting a course of actions from previous similar experience. As a result, CBR is used for solving problems based on past experiences called source cases to solve new problems known as target cases.

Fig. 3 Representation of learning objects



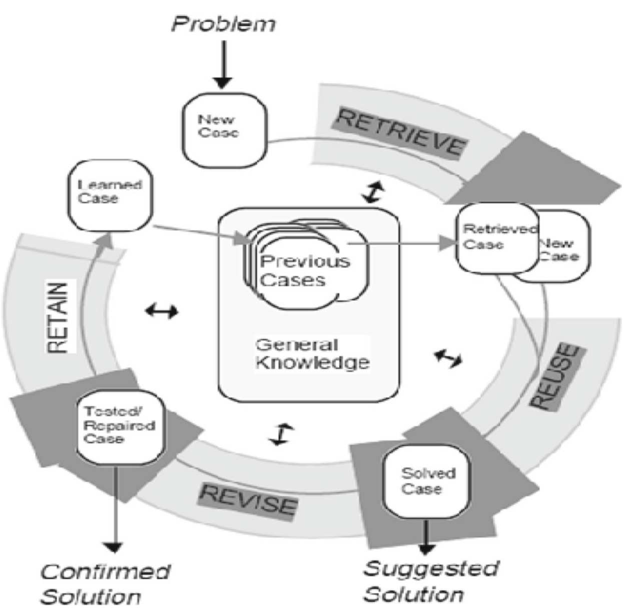


Fig. 4 CBR methodological steps

5.2 Typical CBR Cycle

The main steps involved in CBR are depicted in Fig. 4 [25]. The so-called CBR cycle is captured in a simple and uniform process model despite the many different guises that CBR systems might have [2]. However, this is only a basic model that is usually refined to fit more specific considerations. Several refinements have been proposed; they either add elements to the cycle or split it into sub-cycles, for example adding a maintenance step [32]. For our concern, the CBR cycle is broken down into four major phases in addition to a preliminary elaboration phase [33].

5.3 CBR Formalism

In CBR terminology, a case is a problem-solving component usually represented by a *problem* `pb` and a *solution* `Sol(pb)` of `pb`. A case base is (usually) a structured set of cases, called *source cases*. A source case is denoted by "`srce, Sol(srce)`". CBR consists in solving a *target problem*, denoted by `tgt`, to be compared with elements of the case base. The classical CBR process relies on two steps, namely, retrieval and adaptation. *Retrieval* aims at finding a source problem `srce` in the case base that is considered to be similar to `tgt`. The role of the *adaptation* task is to adapt the solution of "`srce, Sol(srce)`" to build `Sol(tgt)`, a solution of `tgt`. Then, the solution `Sol(tgt)` is tested, repaired, and, if necessary, memorized for future reuse [19].

5.4 Elaboration and Acquisition of a Case

The objective of the CBR elaboration phase is to prepare adequate retrieval by enriching the description of the problem, as expressed by the user. The aim is to formulate the target problem [34]; this target problem is specified in Methodology 3 below:

// Methodology 2 CBR Cycle Steps //

```
0. Elaboration phase
   This phase is used to build the
   specification of the problem which is a
   part of the target case noted Target, of
   course incomplete because it did not yet
   meet any solution.

1. Retrieval phase: Similarity
   This phase is to find the previous
   sources or cases considered most similar
   to the Target. Select indexes:
   - determine case utility/lessons

   - describe circumstances where it will
     be useful,

   - represent those circumstances
     (features), and finally

   - generalize.

2. Reuse phase: Adaptation
   This phase builds a solution to the
   problem based on source cases identified
   in the retrieval phase. Adaptation is
   done by
   - substitution,

   - parameter adjustment or heuristics,

   - local search,

   - special purpose, and

   - repair.

3. Revision phase: Observation
   This phase is to correct the solution in
   case of unsatisfactory results.

4. Retain or Learning phase
   This phase takes into account the
   experience that has just been completed
   for use in subsequent situations. This
   phase embodies the accumulation of cases.
```

Methodology 2 - CBR Cycle Steps

Figure 5 describes the process of elaborating a case. After a request is done, an identification is carried out concerning the means of evaluation, i.e., the descriptors of basic concepts that are acquired (original profile) and concepts requested (target profile). A search in the domain ontology is executed. A new case is elaborated on an iterated basis.

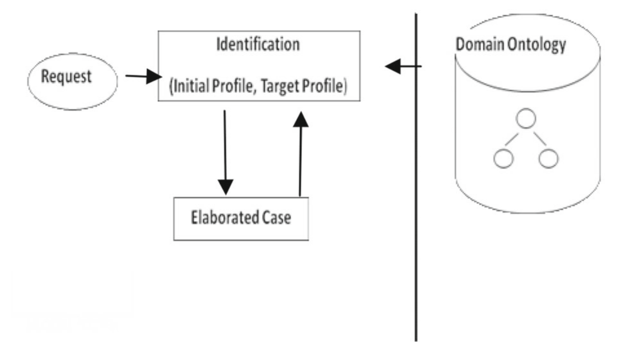


Fig. 5 Process of case elaboration

// Methodology 3 – Elaboration and acquisition of a case //

```
1.  Identify training descriptors
   // Title, objective, target audience,
   training duration…//

2.  Means for evaluation
   // Descriptors of basic concepts that
   are acquired (original profile) and
   concepts requested (target profile)//

3.  Indexing descriptors
   // Level of learners and trainings,
   percentage of learners with same gap and
   identified percentage of successes //
```

Methodology 3 – Elaboration and acquisition of a case

5.5 Retrieval

5.5.1 Similarity Measurements

The issue of the retrieval phase is to enable the identification of one or more cases useful for reasoning at a given stage, on the basis of past experiences. To measure retrieval, we can use the similarity between the indexes of the target case and the sources cases, or criteria of adaptability [34]. Indeed, the measure of similarity between the target gap and the source gap uses the hierarchical structure of concepts that are acquired (or initial) and those requested (or target), respectively. This similarity function is based on a weighted aggregation of two basic functions of similarity [35] represented by the similarity of acquired concepts and similarity of requested concepts.

5.5.2 Similarity Calculations

The similarity of acquired concepts is noted as $\mathrm{Sim}_{\mathrm{ac}}$ and similarity of requested concepts as $\mathrm{Sim}_{\mathrm{rc}}$.

We have

$$\mathrm{Sim}(\mathrm{Tg},\ \mathrm{Sg}) = \alpha\,\mathrm{Sim}_{\mathrm{ac}}(C_{\mathrm{atc}},\ C_{\mathrm{asc}}) + \beta \mathrm{Sim}_{\mathrm{rc}}(C_{\mathrm{rtc}}, C_{\mathrm{rsc}})$$

where Tg and Sg are the target gap and source gap, respectively; α and β the weights of basic similarities, such that $\alpha + \beta = 1$; C_{atc} and C_{asc} the acquired target concepts and acquired source concepts, respectively; C_{rtc} and C_{rsc} are the requested target concepts and requested source concepts, respectively.

The function of similarity of acquired concepts is a function which measures the number of concepts acquired in common between two initial profiles (target, source).

Formally,

$$\mathrm{Sim}_{\mathrm{ac}}(A,\ B) = \mid A \cap B \mid / \mid A \cup B \mid$$

The similarity between two concepts depends on the length of the path which links these two concepts and the depth of concepts in the hierarchy. A correspondence with specific nodes closer to leaf nodes drives to a more important value of similarity than nodes corresponding to higher levels in the hierarchy [36]. The function of similarity of requested concepts is given by:

$$\mathrm{Sim}_{\mathrm{rc}}(C_{\mathrm{rtc}}, C_{\mathrm{rsc}}) = 1 - \left(\frac{h(C_{\mathrm{rtc}}, M(C_{\mathrm{rtc}}, C_{\mathrm{rsc}})) + h(C_{\mathrm{rsc}}, M(C_{\mathrm{rtc}}, C_{\mathrm{rsc}}))}{h(C_{\mathrm{rtc}}, \mathrm{Root}) + h(C_{\mathrm{rsc}}, \mathrm{Root})}\right)$$

where $h(a, b)$ returns the length of the path between node a and b, $M(a, b)$ returns the most specific common abstraction (MSCA) of nodes a and b in the hierarchy of concepts and Root represents concept root.

5.6 Adaptation

5.6.1 Adaptation as Search

The process of adaptation allows the construction of a solution to the current problem by locally changing one or several solutions from those kept during the retrieval stage and whose similarity is above a given prescribed threshold. The initial state is the solution of a retrieved source case and the final state is a solution for the target case. This search is made by the application of adaptation operators, which are transformations made in the space of the solutions. Several types of adaptation operators are used in the literature to modify the solution source. Some of these are applied in our approach, such as:

- Copy operators, i.e., those accomplishing no transformation as they only copy the source solution;
- Substitution operators, i.e., those capable of changing the source solution by adding, deleting or substituting some components.

5.6.2 Representing adaptation by reformulations

5.6.2.1 Defining reformulations Reformulations are basic elements for modeling adaptation knowledge for CBR [37]. If we denote a *relation* between problems by `r` and an *adaptation function* by $\mathtt{A_r}$, then the pair $(\mathtt{r}, \mathtt{A_r})$ is called a *reformulation*. Further, if `r` relates `srce` to `tgt`, denoted by "tt srce `r` `tgt`", then any solution `Sol(srce)` of tt srce can be adapted into a solution `Sol(tgt)` of `tgt` using the adaptation function $\mathtt{A_r}$, denoted by "`Sol(srce)`A_r `Sol(tgt)`". In the reformulation model, retrieval consists of finding a similarity path relating `srce` to tt tgt, i.e., a composition of relations $\mathtt{r}_k$, introducing intermediate problems $\mathtt{pb_k}$ between the source and the target problems. Every $\mathtt{r_k}$ relation is linked by a reformulation to an adaptation function $tt A_r k$. Thus, the sequence of adaptation functions following the similarity path may be reified in an adaptation path.

5.6.2.2 Multi-cell representation When using reformulations, we can make recourse to *cells of similarity/adaptation* as shown in Fig. 6.

Figure 7 describes an *n*-cell representation of similarity/adaptation process. The representation of adaptation knowledge is modeled using reformulations as a general framework. The basic transformation operations that are needed mainly concern specialization, generalization and substitution. The operations corresponding to problem relations $\mathtt{r_k}$ and adaptation functions $\mathtt{A_{rk}}$ have to be designed for a particular application. These further allow the creation of the $\mathtt{pb_k}$ problems for building the similarity path and of the solutions for the adaptation path. Relations of the form "`pb1 r pb2`" and adaptation like "`Sol(pb1)` $\mathtt{A_r}$ `Sol (pb2)`" correspond to applications of such transformations. Moreover, the reformulation framework follows the principle of adaptation-guided retrieval [38]. A CBR system using adaptation-guided retrieval retrieves the source cases whose solution is adaptable, i.e., for which adaptation knowledge is available. According to this principle, similarity paths provide a kind of symbolic reification of similarity between problems, allowing the CBR element to build understandable explanation of the results (d'Aquin et al., 2005).

5.6.3 Adaptation Algorithm

The adaptation algorithm is presented below.

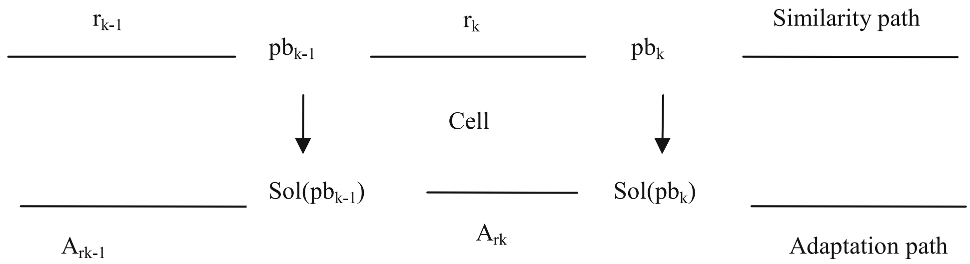


Fig. 6 One cell of similarity/adaptation paths

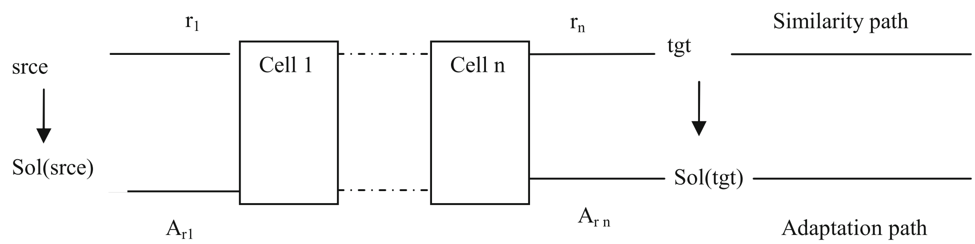


Fig. 7 Complete similarity/adaptation paths

6 Example

An individual wants to get trained in MS Windows™. A solution, i.e., an adequate training is required from the CBR system. The problem part of the case is typically expressed as follows.

The following steps are followed by our framework:

1. *Initial and target profile definitions* Once the above form is filled, it becomes a case with initial profile and target profile clearly defined but with no solution component.
2. *Similarity measurement* Using the chosen similarity measure, a case comparison is done with other cases within the knowledge base.
3. *Adaptation process* The adaptation carries out the refinement of the gap between the actual training status and the target profile.
4. *Possible scenarios*

   4.1 *Existence of a solution* If the gap is acceptable then a solution exists and the search process will provide it. Ontology-based indexing helps in retrieval.

   4.2 *No solution exits* If no solution is obtained for this type of individual training, then the new case is stored with some default solution provided by the human expert.

// Methodology 4 - Adaptation algorithm //

```
If  target case and source case are the
    same
  Then copy solution of source case in
       solution of target case
   Solution(target)←Solution(source)
Else
   Solution ←Solution(source)
If target case included in source case
Then
    For  every requested concept do
     If  the  concept  requested  by  the
         source is not requested by target
         and not a prerequisite
     Then delete it from Solution
     Endif
    Endfor
        copy Solution
        Solution(target)←Solution
Else  source case included in target case
      copy Solution(source) with addition
      of missing concept(s) taken in the
      knowledge base
      Solution(target)←Solution
 Endif
Endif
```

Methodology 4 - Adaptation algorithm

Table 1 Example of case processing

Problem part		
User needs		
Elearner a Windows™ user Version :… Elearner requests a training in Windows™ Version : Training should include basic networking		
Expected duration of training…….		
	Rate elearner actual knowledge (1-Novice,… 5, Expert)	Rate requested elearner knowledge (1-Novice, … 5, Expert)
Windows explorer		
Disk content exploration		
Copy files or folders…		
Save documents…		
Feature 1 ……………		
Feature 2 ……………		
Feature N ……………		
Printers		
Installing a printer…		
Share a printer on network		
Feature 1 ……………		
Feature 2 ……………		
Feature N ……………		
Advanced use		
Installing a local area network (LAN) Feature 1 ……………		
Feature 2 ……………		
Feature N ……………		
Miscellaneous		
Modify the start menu...		
Personalize Taskbar…		
Feature 1 ……………		
Feature 2 ……………		
Feature N ……………		
Solution part		
Elaborated by the system		

7 Conclusion

We have proposed a model for adaptive delivery of trainings using CBR. As one of the major issues that face CBR systems lies in indexing the various cases of the knowledge base, we rely on ontologies to address it. The foundational aspect of the proposal is based on an adaptation algorithm capable of reducing the gap between the source and the target profiles using previous experiences. Consequently, we showed that ontologies help in solving the CBR indexing problem as applied to the adaptive delivery of trainings. Further, algorithm complexity issues of the proposed method along with comparison with other non-CBR based methods would be a useful future research direction.

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