A knowledge-based framework for e-learning in heterogeneous pervasive environments

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ABSTRACT

We propose a ubiquitous learning approach useful not only to acquire knowledge in the traditional educational meaning, but also to solve cross-environment everyday problems.

By formalizing user request and profile through logic-based knowledge representation languages, a lightweight but semantically meaningful matchmaking process is executed in order to retrieve the most suitable learning resources. Standard formats for distribution of learning objects is extended in a backward-compatible way to support semantic annotations in our framework.

Framework and algorithms are absolutely general purpose, nevertheless an application has been developed where the semantic-based Bluetooth/RFID discovery protocols devised in previous work, support users –equipped with an handheld device– to discover in the environment learning objects for satisfying their needs.

INTRODUCTION

Pervasive e-learning has been investigated in recent research because of its evolutionary impact on the definition of traditional e-learning: learning anytime, anyhow and anywhere. The main goal is to take full advantage from the possibility of performing the knowledge acquisition process also in case of lack of fixed infrastructures. Many studies recognize the independence of the learner's physical location and the availability of powerful learning devices as the main added value of electronic learning with respect to traditional approaches (Maurer, 1998). Hence, a full exploitation of ubiquitous computing technologies can deeply affect the most significant aspects of e-learning systems.

The main issues of the so-called mobile learning (m-learning) are identified and gathered in (Sharples, 2007). Beyond achieving benefits of electronic learning, m-learning allows a higher customization of the learning experience through adaptive techniques for content provisioning and organization. From this point of view, it is important to combine the usefulness of both e-learning approach and mobility technologies within a unified vision. Pervasive and Web-based technologies should be applied together in defining frameworks and guidelines to really allow a user to learn anywhere she is. The main challenge –or opportunity, we daresay– is to enable the knowledge acquisition across contexts and environments, rather than simply exploiting handheld devices for the fruition of learning contents. Hence, there is the need to move away from "adapting" activities and approaches designed for personal computers to mobile devices and contexts. On the contrary, a comprehensive approach should be outlined, taking into account:

- the complexity of mobile scenarios: the benefit of learning ubiquitously by using a portable device is balanced by the technological constraints of such devices (limited memory capacity, reduced computational capabilities, restricted battery power, small screen size, among others);
- the different dialectic relationship learners establish in those contexts with respect to wired ones.

Flexible and context-aware discovery techniques thus become a key element to build pervasive learning infrastructures allowing a great personalization according to individual requirements, possibilities and context, also coping with the high differentiation of current mobile devices.

In spite of the growth in the diffusion of wireless-enabled handheld devices providing the necessary connectivity for complex applications, in general they are based on short range, low power technologies like Bluetooth (Bluetooth), which grant a limited interaction among hosts. Furthermore, as ubiquitous contexts are very volatile environments, some important issues are still open. Particularly, services or resources are often unavailable because the location of mobile providers can change unpredictably (Chakraborty et al., 2001). Hence, an advanced discovery of learning resources has to be flexible and decentralized, to overcome difficulties due to the host mobility.

We borrow languages and technologies from the Semantic Web vision and adapt them to pervasive contexts in order to produce a framework fully interoperable with fixed approaches as well as with accepted standards for learning contents modeling. In this paper, a coherent knowledge-based retrieval of mobile learning resources has been devised and implemented. Resources are advertised over a mobile ad-hoc environment as *learning objects* according to the LOM –Learning Object Metadata– standard (IEEE, 2002), supported by SCORM –Sharable Content Object Reference Model– specification (SCORM, 2004) for Learning Management Systems (LMS).

The learning content needs to be redesigned to meet the requirements of a mobile exploitation (Keil-Slawik et al., 2005): in our approach learning resources have a formal characterization. Independently on the chosen syntax, learning modules are modeled as Learning Objects (LOs) according to LOM. But we propose to extend the standard to provide a semantic annotation unambiguously describing the learning object with respect to a specified ontology.

The context surrounding the learner is modeled by exploiting LIP –Learner Information Packaging– standard (LIP, 2001). Also in this case we extend LIP specification to deal with the semantic annotation of learner contextual information.

Given a learning need (user request), LOs are automatically retrieved following semantics of their descriptions. Furthermore they are ranked according to the degree of correspondence with the request. Both learning needs and resources have to be conveyed through annotations in OWL-DL (W3C, 2004). It is a formal representation language based on Description Logics (DLs) formalism (Baader et al., 2002), which allows interoperability with Semantic Web technologies and also enables a set of reasoning services. Abduction and contraction algorithms presented in (Di Noia et al., 2007) have been adapted for being performed by a mobile device.

A learner-centric perspective is adopted, providing *expertise on demand* solutions for self-training, *i.e.*, supporting a *pull* model for learning resource discovery and acquisition. Our approach is general and protocol-independent. Nevertheless it has been motivated in a cross-environment learning scenario where the semantic-enhanced Bluetooth/RFID discovery protocols presented in (Ruta et al., 2007b; Ruta et al., 2007a) are exploited as underlying interaction paradigms.

The paper is structured as follows. In the next section a motivating scenario should clarify the approach and the rationale behind it whereas in further section the proposed framework and algorithms are outlined. Finally, we comment on related work before conclusions.

MOTIVATING SCENARIO

Ubiquity, universality and efficiency are the main requirements for a knowledge-based framework aiming at supporting highly relevant and context-aware discovery and sharing of learning resources for self-training. In particular, our goal is to provide enough flexibility to support knowledge acquisition in informal and unstructured settings, in addition to more traditional and structured ones (*e.g.* real or virtual classrooms). This kind of use case can clearly show the benefits of adopting ubiquitous computing technologies in a multi-agent framework for goal-oriented knowledge acquisition and learning. The approach and algorithms are basically hardware and O.S. independent. Equipment features are taken into account when it comes to select best matching available learning resources.

Bluetooth technology is increasingly adopted in a variety of devices and appliances beyond desktop and mobile computers. This could allow exploitation of semantic-enhanced Bluetooth resource discovery protocol (Ruta et al., 2006) in many different contexts, in order to find learning modules matching with user’s interests, needs and constraints. Pervasiveness is increased by embedding semantic-enhanced RFID technology into an environment (Ruta et al., 2007a). Objects can self-describe to nearby RFID-enabled mobile devices through their attached RFID tag, so becoming knowledge resources for helping the user to perform her intended task.

The proposed approach is described and motivated referring to a scenario outlining learning needs occurring to a woman, *Janet*, in typical daily activities.

In the morning, Janet is driving her newly purchased car to her workplace. She is still unfamiliar with advanced car controls. In particular, she is currently wondering how to store a station within the memory of the car radio system. She uses her Bluetooth-enabled mobile phone to discover such an information from learning modules supplied by her car’s computer.

The car computer exposes the topics of the manual which can be discovered via the semantic-enhanced Bluetooth Service Discovery Protocol. Each topic is packaged as an atomic learning module, but dependencies and references between modules can be present. Each learning module is described by means of a semantic-based expression of its content and requirements for fruition. The mobile semantic matchmaker installed on the mobile phone could then perform a discovery process to find the learning resources best fitting the user’s request and profile. Both are expressed in a reference ontology-based formalism in order to be matched with available LOs (whose semantic characterization follows the standards-compatible format extension outlined later on).

It is important to point out the differences between user request and profile. The request expresses the learning needs and goals of a user, whereas the profile describes her current context in terms of: background knowledge and training; time and place constraints; technological restrictions imposed by software/hardware features of the user device. Hence, the request varies with each knowledge discovery process.

The envisioned framework should support applications with both explicit and implicit user interaction paradigms. In the former case, a request is directly composed by the user and submitted to the embedded mobile matchmaking engine. In the latter case, the user implicitly triggers a support request by performing a particular interaction with elements of a smart pervasive computing environment.

The request is then built in a semi-automatic way, by interpreting the current user action and formalizing her intention into an information/knowledge need, while possibly leaving room for direct customization. On the contrary, the user profile changes with less frequency and generally in an automatic fashion, *e.g.* by updating the description of user location, characteristics of her device and the knowledge and experience she has gained.

User request and profile have their counterparts in the annotation of a learning module, in the form of description and requirements respectively. The description expresses the topics and contents of a learning resource in an unambiguous way, according to a reference ontology which models a broader discipline. On the other hand, requirements model necessary conditions for adequate fruition and comprehension of a learning module. They can concern (but are not limited to): (a) prerequisites on cultural or technical background knowledge; (b) time and location constraints for learning module fruition (*e.g.* a silent room is needed for an interactive pronunciation lesson); (c) constraints on hardware/software features for accessing a learning module (*e.g.* playing videos in a particular format with a certain minimum screen resolution). In a matchmaking session, both elements have to be taken into account. First of all, user profile must satisfy the prerequisites for fruition of a LO, otherwise knowledge acquisition cannot occur. Subsequently, the best matching descriptions with respect to user request are computed among available learning objects whose prerequisites are satisfied.

As a very small example, Janet's request can be stated as: user instructions on radio memory management for car sound system. At the same time, her profile can be modeled as: 5 minutes of available time for resource fruition, 240x320 pixel screen and support for Java ME and Flash Lite formats. Let us suppose that – among others – the following user manual topics are provided as learning objects:

A_1*:* user instructions on radio memory management for Acme car sound system; length of activity is 2 minutes and format is Flash Lite.

A_2: user instructions on CD player for Acme car sound system; length of activity is 4 minutes and format is Flash Lite.

A_3: user instructions on air conditioning regulation: length of activity is 7 minutes and format is Flash Lite.

The detail level of descriptions reflects the "density" of learning resources for a given domain. In the previous example, single functionalities of station memory management (add, delete, modify) could be explained either within the same learning module or in separate ones. Furthermore, a car manufacturer could provide different sets of learning objects targeted to users and car electrician respectively. They would be annotated with respect to different reference ontologies. Hence, a requester could limit her search to the desired category through a preliminary ontology agreement with a provider of learning objects.

Janet reaches her workplace at a law firm. She looks in her office library for a book on maritime law for the case she is currently working on. She does not find it, then she remembers *that her colleague Mark has taken it. Unfortunately, he is away for a meeting. Janet uses her mobile phone to search for learning resources on maritime law which are either offered by colleagues in her vicinity or available in the knowledge base (virtual library) of the firm.*

Learning objects and request are modeled in a similar way as in the previous use case, hence details are omitted for the sake of conciseness. They refer to an ontology modeling knowledge in the field of law. Differently from the previous case, the mobile device of the requester collects resources from multiple nodes. Mobile devices of co-workers are involved, as well as a Bluetooth zone server of the office, acting as a gateway toward learning material owned by the company. This use case is more similar to traditional e-learning approaches, which enable collaboration and resource sharing among learners, as well as access to a central repository of learning resources. Extensions of this use case may include semantic-based composition of learning objects to achieve an on-the-fly mobile courseware definition, given the background knowledge and the current learning needs of the user.

In the evening, after work, Janet goes to the city museum to see an exhibition of Renaissance paintings. In particular, she would like to learn more about portraits. Paintings are tagged with RFID transponders for both inventory and semantic-enhanced knowledge provisioning to visitors.

A semantically annotated learning object is directly associated to each painting via its RFID transponder. Janet's mobile phone comprises an RFID reader, which can access object descriptions. Let us suppose that the following works are currently in her radio range:

C_1: Renaissance oil painting with religious subject;

C_2: Renaissance oil self-portrait;

C_3: Renaissance tempera painting with mythological subject.

The mobile matchmaker embedded in the user's device matches her request with retrieved annotations and results are returned as a ranked list of learning objects. The user can select the ones she is interested in and access them. Otherwise, if she is not satisfied with results, she can start a Bluetooth-based discovery session by interrogating devices of other visitors in the same room. With respect to the previous use case, it can be noticed that no central repository of learning resources is present. A "virtual" knowledge base is built instead in a dynamic way, by accessing relevant content (*i.e.* referring to the same domain ontology as the request) provided through RFID. Moreover, a peer-to-peer user community is formed in an ad-hoc fashion in order to exchange learning resources. Such wireless ad-hoc network can be leveraged to satisfy further learning needs, beyond the original one. In the above example, after accessing the learning module about self-portrait C_2 (which is the best match for user request), Janet could search for further information about portrait as a genre across history. Even though that is not the subject of the exhibition, other visitors –who are supposedly interested in art as much as Janet– might possess and share learning material on such topic. User profiles and learning object requirements are involved into matchmaking, as already explained. This final use case shows the benefits of extending and integrating current smart identification technologies in an overall framework for knowledge discovery and mobile e-learning.

PROPOSED FRAMEWORK

In what follows we present a lightweight, hardware and O.S. independent framework to assist everywhere a learner equipped with a mobile device and wireless technologies like Bluetooth and RFID. The following subsections respectively outlines the discovery architecture, the modeling approach to learning needs, learner profile and learning objects and finally the algorithms featuring the matchmaking process.

Prototype architecture

The proposed approach and algorithms are fully reusable in several pervasive scenarios. In particular the wireless link toward a hotspot could be whatever. We have experienced and tested the framework on mobile devices equipped with Bluetooth and RFID connectivity. No specific requirements in terms of available memory and computational capabilities are mandatory. Bluetooth has been chosen as it is one of the most widespread wireless technologies. Common handheld devices usually integrate a Bluetooth connectivity because of its low cost and great diffusion.

Figure 1 shows the reference discovery architecture in terms of involved wireless technologies and protocols.

In a previous work (Ruta et al., 2007a), the EPCglobal standard for UHF tags and protocol was extended with semantic-based capabilities, while keeping full backward compatibility. An RFID tag could then store a rich description, expressed in DIG language (Bechhofer et al., 2003).

Tagged objects were then dipped into a mobile ad-hoc network, and could be dynamically discovered according to the degree of correspondence between their characteristics and a user request. As part of the solution, an effective compression algorithm was devised for semantically annotated object descriptions, in order to cope with the limited storage and transmission capabilities of RFID systems. To the best of our knowledge, this proposal represents the only framework devised specifically for pervasive RFID applications where item identification is not enough.

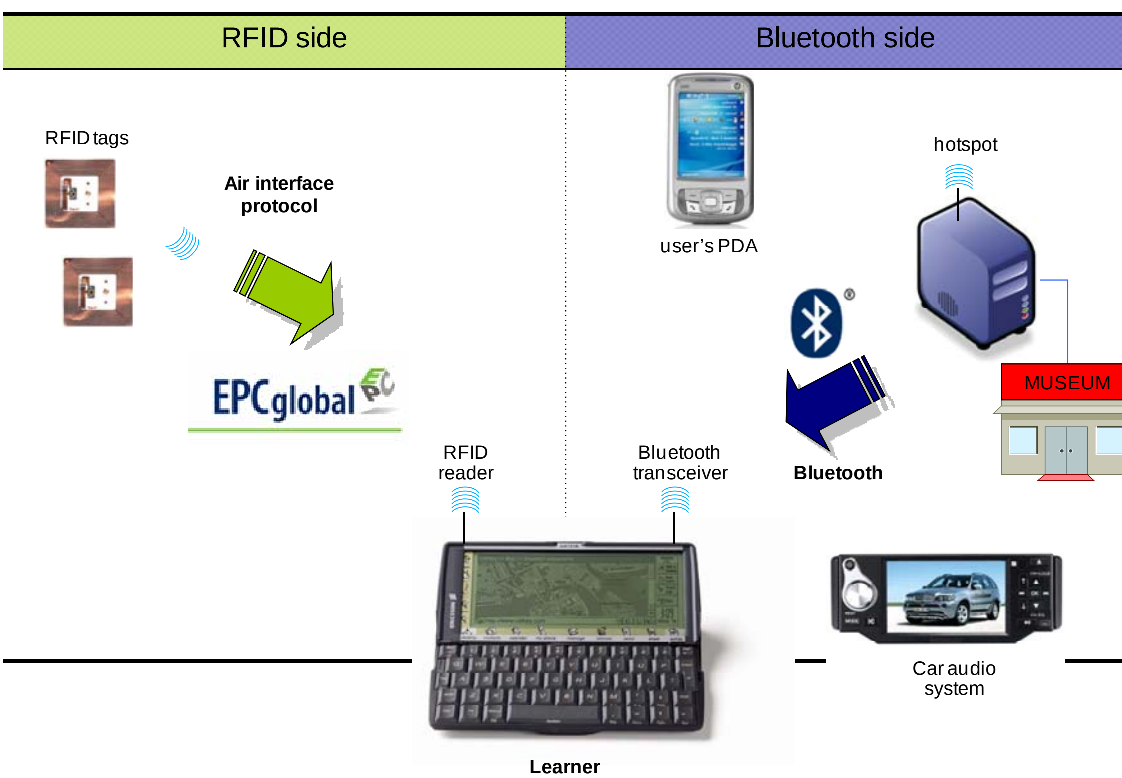

Figure1: Basic architecture

On the other hand EPCglobal RFID technology was also integrated at the application layer with a semantic-enhanced version of Bluetooth Service Discovery Protocol (SDP). It allows the management of both syntactic and semantic discovery of resources, by integrating a semantic layer within the OSI Bluetooth stack at service discovery level (Ruta et al., 2006). Hence, the standard was enriched by new functionalities which allow to maintain a backward compatibility (handheld device connectivity), but also to add the support to matchmaking of semantically annotated resources. To implement matchmaking and ontology support features, we introduced a Semantic Service Discovery functionality into the stack, slightly modifying the existing Bluetooth discovery protocol. In what follows, some basic features of both the Bluetooth and RFID side of the proposed architecture will be given.

We associated unused classes of 128 bit UUIDs in the original Bluetooth standard to mark each specific ontology calling this identifier OUUID (Ontology Universally Unique IDentifier). By means of the OUUID matching, the context was identified and a preliminary selection of resource referring to the same request's ontology was performed. Within the environment, we assume each resource is semantically annotated and a description of the resource itself is available on the hotspot as a database record labeled with a unique 32-bit identifier. Each record contains general information about a single semantic enabled resource and it entirely consists of a list of resource attributes. In addition to the OUUID attribute, there are: *ResourceName* (a human–readable name for the resource), *ResourceDescription* (the resource description expressed using DIG syntax) and a variable number of *ResourceUtilityAttr_i* attributes, *i.e.*, numerical values used according to specific applications.

In general, they are associated to context-aware attributes of a resource; in the current implementation they are not exploited.

In (Ruta et al., 2006), by adding four SDP PDUs *SDP_OntologySearch* (request and response) and *SDP_SemanticServiceSearch* (request and response) to the original standard (exploiting not used PDU ID), together with the original SDP capabilities, further semantic enabled discovery functionalities had been introduced. The overall interaction was based on the original SDP in Bluetooth. No modifications were made to the original structure of transactions. There was just a different use of the SDP framework.

Similarly to the Bluetooth SDP enhancement, we add semantic based functionalities to a RFID application infrastructure. In our framework we refer to RFID transponders agreeing the EPC standard for class I - second generation UHF tags. Memory of a EPC class I Generation-2 UHF RFID tag is divided in four logical banks: the *Reserved*, the *Electronic Product Code (EPC)*, the *Tag IDentification (TID)* and the *User* ones. EPCglobal Generation-2 UHF RFID air interface protocol is an Interrogator-Talks-First (ITF) protocol: tags only reply to reader commands.

A RFID reader can preselect a subset of the tag population currently in range, according to user-defined criteria, by means of a sequence of *Select* commands. With a *Select*, a bit string is sent to all tags in range. Each tag will compare it to a memory area specified by the reader, then it will set/reset one of its status flags according to the comparison result (match/no-match).

After this phase, the inventory loop begins. In each iteration the reader isolates one tag in range, reads its EPC code and has the opportunity to access its memory content.

Among the other available commands, only *Read* and *Write* ones are relevant for our purposes.

Read command allows to read from one of the four tag memory banks. *Write* command allows a reader to write a 16-bit word to one of the four tag memory banks.

In the proposed approach, we use two reserved bits in the EPC area within each tag memory. The first one –at 15_{hex} (101012) address– is exploited to indicate if the tag has a user memory (bit set) or not (bit reset). The second one –at 16_{hex} address– is set to mark semantic enabled tags. In this way, by means of a *Select* command, a reader can easily distinguish semantic based tags from current ones.

The EPC standard for UHF - class I tags imposes the content of TID memory up to $1F_{hex}$ bit is fixed. Optional information could be stored in the further additional TID memory. Generally these information are serial numbers or manufacturer data. Hence we use the TID memory area starting from 1000002 address. In that area we store the identifier of the ontology w.r.t. the description contained within the tag is expressed. Making the ontology support system proposed for the semantic based SDP in Bluetooth compliant with RFID systems, we set a bidirectional correspondence among OUUIDs stored in RFID transponders and those managed by Bluetooth devices. Hence we adopt a 128 bit structure for the RFID OUUIDs analogous to the one outlined before. Finally, in order to retrieve the OUUID value stored within a tag, a reader will exploit a *Read* command by adopting proper parameters.

The semantically annotated description of the good the tag is clung to is stored within the User memory bank. It is expressed in DIG formalism but, due to the strict amount of memory available, this annotation has to be compressed. For the sake of brevity, here we omit characteristics of the adopted encoding tool.

The extraction and the storing of a description carried out on a tag, can be performed by a reader by means of one or more *Read* or *Write* commands. Both commands are obviously compliant with the RFID air interface protocol.

Re-conceptualizing mobile LOs structure

Learning approaches ask for a deep re-conceptualization in order to cope with pervasive environments (Keil-Slawik et al., 2005). In particular, learning content needs to be redesigned to meet the requirements of ubiquitous computing (Chan et al., 2004; Grasso & Roselli, 2005).

Even though mobile learning is often considered more suitable to informal learning (Sharples, 2007), we propose an integrated approach supporting the fruition of learning resources with both informal and formal content, in order to fit an everyday life scenario.

Independently on the format chosen for the learning modules, they have to be modeled according to LOM standard (IEEE, 2002) as Learning Objects (*i.e.* entities, digital or not, that may be used for learning, education or training). The fact of being conform to LOM standard also ensures interoperability with SCORM specification (SCORM, 2004) for LMSs.

Together with LOM, among basic references of the proposed approach, we have to take into account also the approach of Chan et al. (Chan et al., 2004), which proposed a standard for educational metadata for m-learning called MLM. It extends LOM rights category to also cope with validation and location restrictions needed for LOs bringing formal contents. In the same paper also the LIP standard (LIP, 2001) was extended to model learner and environment contextual settings.

We propose an extension of LOM and LIP standards for modeling mobile LOs content, learning context and learner features. Given the learner centric perspective we take, first of all there is the need to model all the significant contextual information about the learner. Crucial features to convey are reported in what follows:

- *Learning Need*: knowledge request originating the further process of learning resources retrieval.
- *Time*: interval the user prefers to spend in the learning activity she is asking for.
- *Equipment*: technological constraints of the learner, that is the technological features of the handheld device the learner holds.
- *Profile*: personal and cultural features of the learner.

Previous characteristics are highly depending on the context and they need to be analyzed every time a learning need arises and a learning process takes place. In particular, the learning need and the time availability have to be specified at each request, while the learner equipment and profile may be considered unchanged until the learner does not explicitly update them.

The retrieval process consists of finding resources satisfying as much as possible the learning need, among those learnable in the available time, through the mobile device at hand and compatible with the learner profile.

In the proposed approach, we model the learning request according to a subset of DLs and we exploit DLs also to model the cultural component of the learner profile as well as structural information, technological and time constraints, used to refine the discovery of learning resources in a given environment.

LIP standard makes the data structures in Table 1 available for storing learner information. In the third column we added significant information exploited in the semantic-based matchmaking.

Data Structure	**Description**	**Matchmaking information**
Identification	Biographic and demographic data	Structural Elements of the *Profile*: Age, Language, Geographical Position
Goal	Learning, career and other objectives and aspirations	*Learning Need*: DL Description of the learning objective *Time*: Preferred Time availability for Learning
Qualifications, Certifications and Licenses	Qualifications, certifications and licenses granted by recognized authorities	Structural Elements of the *Profile*: learner formal qualifications
Activity	Any learning-related activity in any state of completion	/
Transcript	A record to provide an institution-based summary of academic achievement.	/
Interest	Hobbies and recreational activities	/
Competency	Skills, knowledge and abilities acquired in the cognitive, affective, and/or psychomotor domains	Cultural Elements of the *Profile*: DL description of the background knowledge
Affiliation	Membership of professional organizations	
Accessibility	General accessibility to the learner information as defined through language capabilities, disabilities, eligibilities and learning preferences including cognitive, physical and technological preferences	*Equipment*: learner technological constraints

Security key	Set of passwords and security keys assigned to the learner for transactions with learning information systems and services	/
Relationship	The set of relationships between the core components.	/

Table 1: Reference LIP Data Structures

In the learning resources discovery, we take into account only information stored in Identification, Goal, Competency and Accessibility data structures. We model the learning need as a DL description in a *Goal* data structure, which also embeds the time availability information. The learner profile is conveyed through *Identification*, *Competency* and *Accessibility* data structures: in particular, the technological preferences are stored in the *Accessibility* component whereas the cultural profile is a DL description within the *Competency* structure. Once the learner information is conveyed through LIP standard data structures, it can be automatically exploited as input of a retrieval process of learning resources described according to the LOM standard.

The LOM base schema describes LOs following the data element categories shown in Table 2. In the third column of it we added significant information exploited in the semantic-based matchmaking.

Category	**Description**	**Matchmaking information**
General	Learning object description as a whole	*Learning Content*: DL description of the LO content Structural Elements of the *Profile of the intended learner*: Language, Geographical Position
Lifecycle	History evolution and current state of the LO	/
Meta-metadata	Information about the metadata instance itself	/
Technical	Technical requirements and characteristics of the LO	*Equipment*: Technological Requirements for LO fruition *Time*: intended duration of the learning process
Educational	Educational and pedagogic characteristics of the LO	Structural Elements of the *Profile of the intended learner*: age range and formal qualifications Cultural Elements of the *Profile*: DL description of the required background Knowledge
Rights	Intellectual property rights and usage conditions for the LO	/
Relation	Relationship between a LO and other related Los	/
Annotation	Comments on the educational usage of the LO (information about when and by whom the comments were created)	/
Classification	Description of the LO w.r.t. a	/

	particular classification system	

Table 2: Reference LOM Categories

The *General* category is exploited both for modeling the learning resource content and important information like language and geographical coverage for the fruition according to DL formalism. The *Technical* category includes all the requirements for the fruition of the learning resource –in terms of software and hardware constraints– and the learning duration. The *Educational* category carries out important information like the age range and role of the user, together with a description of competences required for the fruition.

Matchmaking algorithms

From now on we assume that learner request and profile as well as learning resources are annotated in a language whose semantics can be mapped to DL $\mathcal{ALN}(D)$, for instance (a subset of) OWL DL or the more compact XML-based DIG language. Formulas (concepts) in $\mathcal{ALN}(D)$ we use to represent user profile and learning request, are built according to the following rules:

$$\mathtt{C}, \mathtt{D} \rightarrow \mathtt{CN} | \neg \mathtt{CN} | \forall \mathtt{R.C} | \mathtt{C} \sqcap \mathtt{D} | (\geq \mathtt{nR}) \ | (\leq \mathtt{mR}) \ | \geq_k \mathtt{g} | \leq_k \mathtt{g}$$

where *CN* is a concept name. For what concerns the ontology $\mathcal{T}$ (Terminological Box in DL-words) we only allow relations between concept names in the forms:

$$\mathtt{CN}_1 \sqsubseteq \mathtt{CN}_2 \sqcap \ldots \sqcap \mathtt{CN}_n \qquad (1)$$

$$\mathtt{CN}_1 \equiv \mathtt{CN}_2 \sqcap \ldots \sqcap \mathtt{CN}_n \qquad (2)$$

$$\mathtt{CN}_1 \sqsubseteq \neg \mathtt{CN}_2 \sqcap \ldots \sqcap \neg \mathtt{CN}_n \qquad (3)$$

to represent respectively (1) subclass axioms; (2) equivalence axioms; (3) disjoint axioms. Furthermore, given a concept name *CN* we cannot have more than one equivalence axiom, with *CN* on the Left Hand Side (LHS) and if *CN* appears on the LHS of an equivalence axiom then it cannot appear on the LHS neither of a subclass axiom nor of a disjoint axiom. In order to avoid cycles within an ontology $\mathcal{T}$, we do not allow a concept name *CN* appears, directly or indirectly, both on the LHS and on the right hand side of an axiom (Baader et al, 2002). Since the above conditions allow to represent concept taxonomies in a formal way, we will call such an ontology *formal-taxonomy*.

DL-based systems usually provide two basic reasoning services for $\mathcal{T}$, namely (a) *Satisfiability* and (b) *Subsumption* in order to check (a) if a formula *C* is consistent with respect to the ontology ($\mathcal{T} \not\models C \sqsubseteq \bot$) or (b) if a formula *C* is more specific or equivalent to a formula *D* ($\mathcal{T} \models C \sqsubseteq D$). Both Subsumption and Satisfiability are adequate in all those scenarios where an exact (yes/no) retrieval is required. For example, given a LO description and a Learning Need, respectively represented by $\mathtt{LO}$ and $\mathtt{LN}$, we are able to determine whether they are compatible or not, *i.e.* whether $\mathtt{LO}$ models information which is not in conflict with the one modeled by $\mathtt{LN}$ or not. This task can be easily performed checking if $\mathcal{T} \not\models \mathtt{LO} \sqcap \mathtt{LN} \sqsubseteq \bot$ holds or not. On the other hand, using Subsumption we can verify if a $\mathtt{LO}$ satisfies a request $\mathtt{LN}$. It is easy understandable that if the relation $\mathcal{T} \models \mathtt{LO} \sqsubseteq \mathtt{LN}$ holds, then $\mathtt{LO}$ results more specific than $\mathtt{LN}$ and contains at least all the requested features.

In (Colucci et al., 2003; Di Noia et al., 2003b) Concept Contraction and Concept Abduction, non-standard inference services for DLs, were introduced and defined for matchmaking scenarios. In the following subsections we briefly recall their definitions, explaining their rationale and the need for them in the proposed m-learning framework.

Concept Contraction and Concept Abduction

Starting with a LO description and a learning need LN, if their conjunction LO $\sqcap$ LN is unsatisfiable with respect to the ontology $\mathcal{T}$, *i.e.*, they are not compatible with each other, our aim is to explain which part of the request LN is conflicting with the resource LO. If we retract conflicting requirements in LN, *G* (for Give up), we obtain a concept *K* (for Keep), representing a contracted version of the original request, such that $K \sqcap$ LO is satisfiable with respect to $\mathcal{T}$. In other words, G represents "why" LN $\sqcap$ LO are not compatible.

Definition 1. *Let $\mathcal{L}$ be a DL, LO, LN be two concepts in $\mathcal{L}$, and $\mathcal{T}$ be a set of axioms in $\mathcal{L}$, where both LO and LN are satisfiable in $\mathcal{T}$. A Concept Contraction Problem (CCP) is finding a pair of concepts $\langle G, K\rangle \in \mathcal{L} \times \mathcal{L}$ such that $\mathcal{T} \models LN \equiv G \sqcap K$, and $\mathcal{T} \not\models K \sqcap LO \sqsubseteq \bot$. We call K a contraction of LN according to LO and $\mathcal{T}$.*

We note that there is always the trivial solution $\langle G, K\rangle = \langle$LN, $\top\rangle$ to a CCP (with $\top$ we refer to the most generic concept in an ontology. We have instead used $\bot$ to denote the most specific concept, the unsatisfiable concept). This solution corresponds to the most drastic contraction, that gives up everything of LN. In our m-learning framework, it models the (infrequent) situation where, in front of some very interesting resource LO, incompatible with the requested one, a user just gives up completely his/her requirements LN in order to meet LO. On the other hand, when LO $\sqcap$ LN is satisfiable in $\mathcal{T}$, the "best" possible solution is $\langle\top$, LN$\rangle$, that is, give up nothing –if possible.

Since usually one wants to give up as few things as possible, some minimality in the contraction must be defined (Gäardenfors,1988; Colucci et al., 2003; Di Noia et al.,2004). Whenever the LO description and the request LN are compatible with each other, the partial specifications problem might still hold. That is, it could be the case that LO does not imply LN – though compatible with it.

Using DL syntax we write: $\mathcal{T} \not\models$ LN $\sqcap$ LO $\sqsubseteq \bot$ and $\mathcal{T} \not\models$ LO $\sqsubseteq$ LN. Then, it is necessary to assess what should be hypothesized (*H*) in LO in order to completely satisfy LN.

Definition 2. *Let $\mathcal{L}$ be a DL, LO, LN, be two concepts in $\mathcal{L}$, and $\mathcal{T}$ be a set of axioms in $\mathcal{L}$, where both LO and LN are satisfiable in $\mathcal{T}$. A Concept Abduction Problem (CAP) is finding a concept $H \in \mathcal{L}$ such that $\mathcal{T} \models LO \sqcap H \sqsubseteq LN$, and moreover LO $\sqcap$H is satisfiable in $\mathcal{T}$. We call H a hypothesis about LO according to LN and $\mathcal{T}$.*

Note that if $\mathcal{T} \models$ LO $\sqsubseteq$ LN then we have *H* = $\top$ as a solution to the related CAP. Given LN and LO such that $\mathcal{T} \not\models$ LO $\sqsubseteq$ LN, *H* represents "why" the subsumption relation does not hold. *H* can be interpreted as what is requested in LN and not specified in LO. Hence, both Concept Abduction and Concept Contraction can be used for respectively subsumption and satisfiability explanation.

Performing the Concept Contraction in $\mathcal{ALN}$(D)

An algorithm to solve CAPs for $\mathcal{ALN}$ has been proposed in (Di Noia et al., 2007) and it can be easily extended to deal with $\mathcal{ALN}$(D). In this section we outline a novel algorithm to compute a possible solution to CCPs in $\mathcal{ALN}$(D) given two concepts $\mathtt{LO}$, $\mathtt{LN}$ and an ontology $\mathcal{T}$ built according to previous guidelines. Before computing solutions to a CCP, it is more convenient, from a computational perspective, to reduce both $\mathtt{LO}$ and $\mathtt{LN}$ to a common normal form. We use here a well know technique called *unfolding* (Baader et al, 2002) to syntactically transform two concept and preserve their formal semantics with respect to the ontology $\mathcal{T}$. Given a concept C the normalization process is performed applying recursively the following rewriting rules to each occurrence of the element appearing in the LHS of the rule.

$\mathtt{CN_1} \mapsto \mathtt{CN_1} \sqcap \mathtt{CN_2} \sqcap \ldots \sqcap \mathtt{CN_n}$ if $\mathtt{CN_1} \sqsubseteq \mathtt{CN_2} \sqcap \ldots \sqcap \mathtt{CN_n} \in \mathcal{T}$

$\mathtt{CN_1} \mapsto \mathtt{CN_2} \sqcap \mathtt{CN_3} \sqcap \ldots \sqcap \mathtt{CN_n}$ if $\mathtt{CN_1} \equiv \mathtt{CN_2} \sqcap \ldots \sqcap \mathtt{CN_n} \in \mathcal{T}$

$\mathtt{CN_1} \mapsto \mathtt{CN_1} \sqcap \neg\mathtt{CN_2} \sqcap \ldots \sqcap \neg\mathtt{CN_n}$ if $\mathtt{CN_1} \sqsubseteq \neg\mathtt{CN_2} \sqcap \ldots \neg\mathtt{CN_n} \in \mathcal{T}$

$\mathtt{C} \sqcap \bot \mapsto \bot$

$(\geq \mathtt{nR}) \sqcap (\leq \mathtt{mR}) \mapsto \bot$ if $\mathtt{n} > \mathtt{m}$

$\mathtt{A} \sqcap \neg\mathtt{A} \mapsto \bot$

$(\geq \mathtt{nR}) \sqcap (\geq \mathtt{mR}) \mapsto (\geq \mathtt{nR})$ if $\mathtt{n} > \mathtt{m}$

$(\leq \mathtt{nR}) \sqcap (\leq \mathtt{mR}) \mapsto (\leq \mathtt{nR})$ if $\mathtt{n} < \mathtt{m}$

$\forall \mathtt{R.D_1} \sqcap \forall \mathtt{R.D_2} \mapsto \forall \mathtt{R.(D_1} \sqcap \mathtt{D_2)}$

$\forall \mathtt{R.}\bot \mapsto \forall \mathtt{R.}\bot \sqcap (\leq \mathtt{0R})$

Given a concept C and an ontology $\mathcal{T}$, we call *norm*(C, $\mathcal{T}$) the rewriting of C according to the above rules.

Algorithm: *Contract* ($\mathcal{ALN}$(D), $\mathtt{LO}$, $\mathtt{LN}$, $\mathcal{T}$)

Input: $\langle \mathtt{LO}, \mathtt{LN}, \mathcal{T} \rangle$ where $\mathcal{T}$ is a *formal-taxonomy* and $\mathtt{LO}, \mathtt{LN} \in \mathcal{ALN}$(D)

Output: $\langle G, K \rangle$ with concept $G, K \in \mathcal{ALN}$(D)

if $LN = \bot$ **then**
  return $\langle \bot, \top \rangle$;
else
  $G := \top$;
  $K := \top \sqcap \mathtt{LN}$;
  for each concept name A in K **do**
    for each concept name $A' \in norm(A, \mathcal{T})$ **do**
      if there exists B in $\mathtt{LO}$ such that $B = \neg A'$ **then**
        $G := G \sqcap A$;
        remove A from K;
      end if
    end for

end for
for each concept $(\geq xR)$ in K **do**
  if there exists $(\leq yR)$ in `LO` and $y<x$ **then**
    replace $(\geq xR)$ with $(\geq yR)$;
    $G := G \sqcap (\geq xR)$;
  end if
  for each concept $\forall R.E$ in K **do**
    if there exists $\forall R.F$ in `LO` **then**
      $\langle G', K' \rangle := Contract(\mathcal{ALN}(D), E, F, \mathcal{T})$;
      $G := G \sqcap \forall R.G'$;
      replace $\forall R.E$ in K with $\forall R.K'$;
    end if
  end for
end for
for each concept $(\leq xR)$ in K **do**
  if there exists $(\geq yR)$ in `LO` and $y>x$ **then**
    replace $(\leq xR)$ with $(\leq yR)$;
    $G := G \sqcap (\leq xR)$;
  end if
end for
for each concept $\geq_x g$ in K **do**
  if there exists $\leq_y g$ in `LO` and $y<x$ **then**
    replace $\geq_x g$ with $\geq_y g$;
    $G := G \sqcap C$;
  end if
end for
for each concept $\leq_x g$ in K **do**
  if exists $\geq_y g$ in `LO` and $y>x$ **then**
    replace $\leq_x g$ with $\leq_y g$;
    $G := G \sqcap C$;
  end if
end for
end if
return $\langle G, K \rangle$;

Algorithm1: Concept Contraction

Logic-based matchmaking

In real u-learning scenarios, it is quite rare to find exactly the resource we are looking for. Often we have to reformulate a request in order to obtain satisfactory results in an approximate search. At this point a question arises: *what* should we change? Some suggestions would be useful. Both Concept Abduction and Concept Contraction can be used to suggest guidelines on what, given an offered resource `LO`, has to be revised and/or hypothesized to obtain a full match with the preference.

We now show how the previous inferences can help in an approximate, semantic-based, resource discovery, fully exploiting their structured description. Let us suppose to have a learning need LN, a resource LO and an ontology $\mathcal{T}$ such that $\mathcal{T} \not\models \mathsf{LN} \sqcap \mathsf{LO} \sqsubseteq \bot$, *i.e.* they are incompatible. In order to gain compatibility, a Concept Contraction is needed so that giving up G in LN, the remaining K could be satisfied by LO. Now, if $\mathcal{T} \not\models \mathsf{LO} \sqsubseteq K$, the solution H_K to the CAP $\langle \mathcal{L}, K, \mathsf{LO}, \mathcal{T} \rangle$ represents what is in K and is not specified in LO.

Algorithm: *explain* ($\mathcal{L}$, LO, LN, $\mathcal{T}$)

Input: LO, LN concepts in $\mathcal{L}$ such that $\mathcal{T} \models \mathsf{LO}$ and $\mathcal{T} \models \mathsf{LN}$

Output: $\langle G, K \rangle$, H, *i.e.*, the part of LN that should be respectively retracted (G) and kept (K) and the part of LO that should be hypothesized (H) to find a full match between LO and LN.

1: **if** $\mathcal{T} \models \mathsf{LN} \sqcap \mathsf{LO} \sqsubseteq \bot$ **then**

2: $\langle G,K \rangle = contract(\mathsf{LO}, \mathsf{LN}, \mathcal{T})$;

3: $H_K = abduce(\mathsf{LO}, K, \mathcal{T})$;

4: **return** $\langle G,K \rangle$, H_K;

5: **else**

6: $H = abduce(\mathsf{LO}, \mathsf{LN}, \mathcal{T})$;

7: **return** $\langle \top, \mathsf{LN} \rangle$, H;

Algorithm2: Results explanation algorithm

[lines 1-4]. Having a request LN and an offered service LO, if their descriptions conjunction is not satisfiable with respect to the ontology they refer to (*i.e.*, they are not compatible with each other for some concepts in their descriptions), first a contraction on LN is performed in order to regain compatibility **[line 2]** and then what has to be hypothesized in LO in order to completely satisfy LN (its contraction) is computed **[line 3]**. The returned values represent:

- $\langle G, K \rangle$: the first item is what has to be given up in the request –G– in order to continue the process, or, in other words, why LN is not compatible with LO. The second item is the contracted request K that is no more in conflict with the request.
- H_K : after the contraction of LN, the request is represented by K, *i.e.*, the portion of LN that is compatible with LO. H_K represents what has to be hypothesized in LO in order to completely satisfy K, or, in other words, why LO does not completely satisfy K.

[lines 5-7]. If the conjunction of LN's and LO's description is satisfiable with respect to the ontology they refer to, then no contraction is needed and only an abductive process is carried out. Notice that H = *abduce*(LO, LN, $\mathcal{T}$) **[lines 3,6]** determines a solution H for the CAP $\langle \mathcal{L}, \mathsf{LN}, \mathsf{LO}, \mathcal{T} \rangle$, while $\langle G, K \rangle$ = *contract*(LO, LN, $\mathcal{T}$) **[line 2]** determines a solution $\langle G, K \rangle$ for the CCP $\langle \mathcal{L}, \mathsf{LN}, \mathsf{LO}, \mathcal{T} \rangle$.

As the obtained LO is an approximated match of LN, then evaluating how good is the approximation would be extremely useful. Given more than one resource, which is the best approximation? How it can be assigned a numerical score, based on K, H and G, to the approximation in order to rank the learning resources? The algorithm *explain* does not depend on the particular DL adopted. Based on the minimality criteria proposed in (Colucci et al., 2003), the length H of the solution to a CAP for $\mathcal{ALN}$(D) can be computed in a similar way as the one proposed in (Di Noia et al., 2003a). Hence, a relevance ranking score can be computed by a utility function defined as $U(G, K, H_K)$.

Dealing with user preferences

In a matchmaking process, a user request can be often split into two separate parts: **strict** requirements and **preferences**. *Strict* requirements represent what, in the request, has to be strictly matched by the retrieved resource descriptions. *Preferences* can be seen as soft user requirements. In our scenario, the user will accept even a LO whose description does not represent exactly what she prefers. Usually, a weight is associated to each preference in order to represent its worth (absolute or relative to the other preferences). Hence, for a learning need $\mathtt{LN}$ we distinguish between a concept $\mathtt{LN}_S$ representing strict requirements and a set of weighted concepts $\langle \mathtt{LN}, v\rangle$ where $\mathtt{LN}$ is a DL concept and v is a numerical value representing preference worth. It should be clear that a matchmaking process has not to be performed with respect to $\mathtt{LN}_S$. It represents what the user is not willing to risk on at all. He does not want to hypothesize nothing on it. An approximate solution would not be significant for $\mathtt{LN}_S$. Actually, performing a matchmaking process between preferences and a $\mathtt{LO}$ description makes more sense. After all, preferences represent what the user *would like* to be satisfied by $\mathtt{LO}$. Hence, even though a preference is satisfied *with a certain degree* (not necessarily completely) the user will be satisfied *with a certain degree* as well.

Given an ontology $\mathcal{T}'$, a $\mathtt{LO}$ description, a strict requirement $\mathtt{LN}_S$ and a set of preferences $\mathcal{P} = \{\langle \mathtt{LN}_i, v_i\rangle\}$ we compute a global ranking score using the following Algorithm 3. Here we retrieve, *i.e.* assign *score* greater than zero, only LOs whose description fully satisfies user strict requirements. Once we have a resource such that $\mathcal{T}' \models \mathtt{LO} \sqsubseteq \mathtt{LN}_S$, then we compute how much it satisfies user preferences. For each preference we take into account both U(*explain* ($\mathtt{LO}$, $\mathtt{LN}_i$ $\mathcal{T}'$, $\mathcal{L}$)) *i.e.*, the similarity degree computed using non-standard reasoning, and the value expressed by the user to represent preference worth.

Algorithm: *preference retrieve* ($\mathtt{LO}$, $\mathtt{LN}_S$, $\mathcal{P}$, $\mathcal{T}'$, $\mathcal{L}$)

Input: $\mathtt{LO}$, $\mathtt{LN}$ concepts in $\mathcal{L}$ such that $\mathcal{T}' \models \mathtt{LO}$ and $\mathcal{T}' \models \mathtt{LN}$

Output: score

1: score $= 0$;

2: **if** $\mathcal{T}' \models \mathtt{LO} \sqsubseteq \mathtt{LN}_S$ **then**

3: **for** each $\langle \mathtt{D}_i, v_i\rangle \in \mathcal{P}$ **do**

4: score $=$ score $+ v_i \cdot U$ (*explain* ($\mathtt{LO}$, $\mathtt{LN}_i$ $\mathcal{T}'$, $\mathcal{L}$));

5: **end for**

6: **end if**

7: **return** score;

Algorithm 3: Preference retrieval

Illustrative example

A very small example can further clarify the approach and the rationale behind it. A request for car radio instructions with diagrams may be modeled as:

$\mathtt{UserInstructions} \sqcap \geq 1\ \mathtt{hasDiagrams} \sqcap \exists \mathtt{hasReferenceFunction} \sqcap \forall \mathtt{hasReferenceFunction.CarRadio} \sqcap \exists \mathtt{hasTopic} \sqcap \forall \mathtt{hasTopic.Memory}$

At the same time, user profile can be modeled as:

$\leq_{\mathtt{minutes}} 5 \sqcap \leq_{\mathtt{h\_display\_px}} 240 \sqcap \leq_{\mathtt{v\_display\_px}} 320 \sqcap \forall \mathtt{hasFormat}\ (\mathtt{FlashLite} \sqcap \mathtt{JavaME})$

This expresses a maximum duration of 5 minutes for resource fruition, as well as restrictions on screen resolution and content format. Let us suppose that – among others – the following user manual topics are provided as learning objects:

A_1	*Radio station memory management, illustrated in Flash Lite format*
Description	$\mathtt{UserInstructions} \sqcap \exists\mathtt{hasReferenceFunction} \sqcap \forall\mathtt{hasReferenceFunction.(CarRadio} \sqcap \exists\mathtt{hasMaker} \sqcap \forall\mathtt{hasMaker.Acme)} \sqcap \exists\mathtt{hasTopic} \sqcap \forall\mathtt{hasTopic.Memory}$
Requirements	$\geq_{\mathtt{minutes}}\ 2 \sqcap \forall\mathtt{hasFormat.FlashLite}$

A_2	*Car CD player, illustrated in Flash Lite format*
Description	$\mathtt{UserInstructions} \sqcap \exists\mathtt{hasReferenceFunction} \sqcap \forall\mathtt{hasReferenceFunction.(CarRadio} \sqcap \exists\mathtt{hasMaker} \sqcap \forall\mathtt{hasMaker.Acme)} \sqcap \exists\mathtt{hasTopic} \sqcap \forall\mathtt{hasTopic.CdPlayer}$
Requirements	$\geq_{\mathtt{minutes}}\ 4 \sqcap \forall\mathtt{hasFormat.FlashLite}$

A_3	*Car air conditioning regulation with diagrams, illustrated in Flash Lite format*
Description	$\mathtt{UserInstructions} \sqcap =3\ \mathtt{hasDiagrams} \sqcap \exists\mathtt{hasReferenceFunction} \sqcap \forall\mathtt{hasReferenceFunction.AirConditioning} \sqcap \exists\mathtt{hasTopic} \sqcap \forall\mathtt{hasTopic.Regulation}$
Requirements	$\geq_{\mathtt{minutes}}\ 7 \sqcap \forall\mathtt{hasFormat.FlashLite}$

A_4	*Radio station memory management, illustrated in old Flash format and incompatible with Flash Lite*
Description	$\mathtt{UserInstructions} \sqcap \exists\mathtt{hasReferenceFunction} \sqcap \forall\mathtt{hasReferenceFunction.(CarRadio} \sqcap \exists\mathtt{hasMaker} \sqcap \forall\mathtt{hasMaker.Acme)} \sqcap \exists\mathtt{hasTopic} \sqcap \forall\mathtt{hasTopic.Memory}$
Requirements	$\geq_{\mathtt{minutes}}\ 2 \sqcap \forall\mathtt{hasFormat.(Flash} \sqcap \neg\mathtt{FlashLite)}$

The list of results is arranged according to an overall match score from 0 to 100. It is computed by means of the formula:

$$s = 100\% \begin{cases} 1 - p & p > T \\ 0 & otherwise \end{cases}$$

where the semantic penalty function p is computed as:

$$p = W \cdot contract + (1 - W) \cdot abduce$$

where *contract* is the penalty calculated by the contraction procedure between the local user's request and the learning object description, while *abduce* is the penalty value of the abduction procedure between the consistent part *K* of the request and description. The scoring mechanism is regulated by two user-adjustable parameters, the threshold value *T* and the weight *W*, both between 0 and 1. *T* influences the sensitivity of the discovery while *W* determines the relative weight of explicitly conflicting elements in the description of the learning object with respect to the demand.

After matchmaking the user is presented with the ranked list. In our example, with *W*=0.7 and *T*=0.6 outcomes are as reported in Table 3. A_4 is immediately discarded because it is incompatible with the learner's technical requirements; it will not be shown among available LOs. On the contrary, A3 will be shown among results, but its high penalty (due to distance in content from the request) makes it fall below the threshold and take a zero score. A_2 is close in content but not a full match (learner has to give up some of her requirements), whereas A_1 is a nearly exact match.

Supply	**A_1**	**A_2**	**A_3**	**A_4**
Requirement Give Up (G_R)	⊤	⊤	⊤	`∀hasFormat.(FlashLite ⊓ JavaME)`
Preference Give Up (G_P)	⊤	`∀hasTopic.Memory`	`∀hasReferenceFunction.CarRadio ⊓ ∀hasTopic.Memory`	n.a.
Preference Keep (K)	`UserInstructions ⊓ ∃hasReferenceFunction ⊓ ∀hasReferenceFunction.CarRadio ⊓ ∃hasTopic ⊓ ∀hasTopic.Memory`	`UserInstructions ⊓ ∃hasReferenceFunction ⊓ ∀hasReferenceFunction.CarRadio ⊓ ∃hasTopic`	`UserInstructions`	n.a.
Preference Hypothesis (H)	`≥1 hasDiagrams`	`≥1 hasDiagrams`	⊤	n.a.
contract	0	0.3	0.6	n.a.
abduce	0.1	0.1	0	n.a.
p	0.03	0.25	0.42	n.a.
s	97%	75%	0	n.a.

Table 3. Outcomes of semantic matchmaking and utility function

RELATED WORK

In the literature there are several approaches trying to exploit mobile technologies to assist learners in the real world and in everyday life.

(Yang, 2006) proposed a ubiquitous learning environment which uses semantics to model both learner and resource profiles. It aims at identifying – in a real world context – the right contents, collaborators and services that can help or interest the occasional learner. In that approach every learner becomes a peer, so every user can barter resources, information and help with whoever has the same interest in the same moment and in the same place. This is an interesting P2P collaborative approach, but learners can retrieve or share only non-standard resource types. A major requirement of our proposal is to preserve compatibility with standard e-learning technologies as much as possible.

With the same intention, (Chan et al., 2004) presented Mobile Learning Metadata (MLM), an educational metadata for mobile learning system. The authors enhanced existing standards and specifications for modeling learning objects, in order to support mobile and informal learning. In particular, they amended and added fields for managing both the access rights and the history of the learner. With our approach, instead, we are able to manage Mobile Learning Objects (MLO) according to current standards also allowing to semantically annotate learning contents and learner profiles. This enables a principled matchmaking for ranking available resources.

In (Castillo & Ayala, 2008) a computational model for Mobile Learning Objects and an architecture for mobile learning environment with MLOs is outlined. They are a generalization of Mobile Interactive Learning Object (MILO) introduced by (Holzinger et al., 2005) to model knowledge for fruition in mobile environments. The authors stated that, in mobile applications, some characteristics take a particular relevance when designing learning objects: among others, the availability of an MLO, the interest of other learners (to promote collaboration), the needed experience level. Hence they proposed a three-part model: the first one adapts learning contents to learner's needs according to context and location; the second one is a collaboration model the learner can construct annotating comments and sharing them within the learning community; the third one is a personalized model where interests and capabilities of the learner are considered. Upon this model, a multimedia-based application is designed and presented. An alternative approach to the definition of learning objects is given by the same authors in (Holzinger et al., 2006).

(Hwang et al., 2008) proposed criteria and strategies to establish a context-aware ubiquitous learning environment. Exploiting parameters referred to wired scenarios and related to personal and environmental data, they proposed twelve u-learning contextual models to assess learning performance of the students based on their real-world behavior. Basically, those strategies represent specific kinds of interaction between a learner and the system, based on different possible situations. The main innovation of that proposal is in the support level offered for learning activities, but the relevance of resource discovery seems to be underestimated.

In (El-Bishouty et al., 2007) a client-server application, useful to assist learner in real-world life is presented. RFID technology is adopted to detect learner position, while so-called Environmental Objects (EO) allow the system to map the physical space. When the user is in front of an EO, the system provides learning material related to that object, and suggests where are the nearest users, so that a message can be sent to them to ask for collaboration.

A further approach targeted at supporting language learning in real-life situations is presented in (Ogata, 2008). A ubiquitous learning environment is build to support vocabulary learning through RFID and language learning through a sensor network; GPS is exploited to detect the user location. Furthermore, a solution to record and reuse knowledge in real-world problems was proposed. A problem-solving procedure or action is linked by an RFID code within a tag. Keyword-based discovery is the main drawback of that approach; it limits matches to exact code-based correspondences. RFID technology is also used as a mere link to records in a data store.

(Chen et al., 2008) proposed a ubiquitous learning system, exploiting wireless technologies to aid in text composition in a context-aware fashion. The system assists students providing relevant information. It helps to observe and perceive the environment or to collaborate either with other students or with the teacher. A three-tier architecture is adopted to allow the learner to assess learning content, by using RFID for location detection. An experimental comparison between traditional methods and the proposed one, pointed out the latter resulted efficient and pleasant for students.

A framework has been proposed in (Motiwalla, 2007) for supporting distance learning through mobile devices. The impact of the approach on learning has been evaluated through student feedback analysis, both in terms of content learned and opinions about the learning methodology. Results show the leverage effect of the integration of mobile technologies with traditional education methods.

Learning support in a pervasive environment is also the goal of the GlobalEdu architecture, proposed in (Barbosa et al., 2005). It is targeted to the definition of an agent-based framework for pervasive learning rather than to its implementation through mobile devices. Similarly, a system based on agents is outlined in (Ling et. al, 2006) which provides personalized e-learning solutions. They have been deemed to have a positive effect on Life Long Learning, which is recognized as one of the key goals of e-learning technologies.

The LOM standard allows the composition of learning content in modules called Learning Objects defined in the standard itself. Research about m-learning has then addressed the topic of redesigning LOs with the aim of making their content usable through a mobile environment. In (Loidl, 2006) the features of a free and open virtual learning environment, WeLearn.Mobile, have been presented. An application allowing to present Content Packaging Specification on mobile devices is built upon the above framework.

In (von Hessling et al., 2004) a mobile environment is presented, where semantic services are matched against semantic user profiles. Here, if there is no intersection between user interests and service offers, authors conclude the user is not interested in the service. A complete and integrated solution for matching degree determination is not available.

CONCLUSION

We have proposed a ubiquitous learning approach, allowing to satisfy learning needs of a user whenever and wherever they arise. It can be useful not only to acquire knowledge, but also to solve cross-environment everyday problems.

A novel discovery framework specifically devised for mobile ad-hoc contexts without stable and fixed network infrastructures has been adapted to assist the user in retrieval and acquisition of knowledge she requires in her daily life (at home or at work, while travelling or shopping). Abduction and contraction algorithms presented in (Di Noia et al., 2007) have been revised to be widely exploited in client-server and/or p2p wireless scenarios. Thanks to a logic-based matchmaking procedure and by means of a semantic-based Bluetooth/RFID discovery protocols, users –equipped with an handheld device– can discover in the environment learning objects (modeled according to current e-learning standards) suitable for satisfying their needs.

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KEY TERMS & DEFINITIONS

Term 1: Learning Need

- Also known as: “User Request”, ”Information/Knowledge Need”
- Similar to: “Learner Profile”, “User Profile”
- Associated in the manuscript with: “LIP standard”, “Description Logics Representation”, ”Time and Place Constraints”, “Devices Restrictions”, “Learning Resource Retrieval”
- Notable appearances of this term can be found on:
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Term 2: Matchmaking

- Also known as: n/a
- Similar to: “Semantic-based Resource Retrieval”
- Associated in the manuscript with: “Mobile learning resources”, “Semantic-enhanced Bluetooth Resource Discovery Protocol”, “User Profile”, ”Mobile Semantic Matchmaker”, ”Ranked List of Learning Object”
- Notable appearances of this term can be found on:
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Term 3: Ubiquitous Computing

- Also known as: “Pervasive Computing”
- Similar to: “Mobile Computing”
- Associated in the manuscript with: “Context-aware”, “m-learning”, “Peer to Peer” , “Pervasive Environment”
- Notable appearances of this term can be found on:
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Term 4: M-Learning

- Also known as: “Pervasive e-learning”
- Similar to: “Ubiquitous e-learning”
- Associated in the manuscript with: “ e-learning”, “Handheld Device”, “Wireless Environment”, “Learning Resource”, “Learner Profile”
- Notable appearances of this term can be found on:
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Term 5: Learning Resource

- Also known as: “Learning Module”
- Similar to: “Learning objects”
- Associated in the manuscript with: “LOM”, “Description Logics Representation”, “Learner Request”, “Matchmaking”
- Notable appearances of this term can be found on:
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Term 6: Wireless Environments

- Also known as: n/a
- Similar to: “Pervasive Environments”
- Associated in the manuscript with: “Bluetooth Technologies”, “RFID”, “ad-hoc Network”

Term 7: Knowledge Representation

- Also known as: n/a
- Similar to: “Semantic-based Formalization”,
- Associated in the manuscript with: “Description Logics”, “Semantic Web”, “Reasoning Services”, “Ontology Modeling”, “Learning Need Description”, “Learner Profile Description”

Term 8: Learning Standard

- Also known as: n/a
- Similar to: “LOM”, “SCORM”,”LIP”
- Associated in the manuscript with: “Learning resources”, ”Learning context”, “LMS”, “Mobile Learning Resources”

Term 9: Handheld Device

- Also known as: “Mobile Device”, “Mobile”
- Similar to: “PDA”, “Smart-Phone”
- Associated in the manuscript with: “Bluetooth”, “RFID reader”, “Technological Restrictions”, “m-Learning”, “ Wireless Environment”, “Context-awareness”
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