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ORIGINAL RESEARCH

Building a smart campus to support ubiquitous learning

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Abstract New technological advances in user mobility and context immersion are enabling novel adaptive and pervasive learning models in ambient environments. These advances allow physical learning spaces with embedded computing capabilities to provide an augmented self-aware learning experience. In this paper, we aim at developing a novel ubiquitous learning model within a pervasive smart campus environment. The goal of our research consists of identifying the steps towards building such an environment and the involved learning processes. We define a model of a smart campus, and advocate learning practices in the light of new paradigms such as context-awareness, ubiquitous learning, pervasive environment, resource virtualization, autonomic computing and adaptive learning. We reveal a comprehensive architecture that defines the various components and their interoperations in a smart educational environment. The smart campus approach is presented as a composition of ambient learning spaces, which are environments where physical learning resources are augmented with digital and social services. We present a model of these spaces to harness future ubiquitous learning environments. One of the distinguished features of this model is the ability to unleash the instructional value of surrounding physical structures. Another one is the provision of a personalized learning agenda when moving across these ambient learning environments. To achieve these goals, we profile learners and augment physical campus structures to advocate context-aware learning processes. We suggest a social community platform for knowledge sharing which involves peer learners, domain experts as well as campus physical resources. Within this pervasive social scope, learners are continuously immersed in a pedagogically supported experiential learning loop as a persuasive approach to learning. A learning path, which responds to learners' goals and qualifications, autonomously guides learners in achieving their objectives in the proposed smart campus. We evaluated our ubiquitous learning approach to assert the performance of these building blocks in the proposed smart campus model. The results show interesting tradeoffs and promising insights.

Keywords Ubiquitous learning · Pervasive environments · Program outcomes · Smart campus · Semantic web

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1 Introduction

A smart environment is a digitally augmented physical world where pervasively and non-invasively instrumented objects and spaces are intelligently perceptive and made responsive to the state of the environment and its inhabitants. This development has been driven by recent progresses in the Internet, which has already revolutionized our culture. Indeed, children are born and raised in an environment where virtually anything can be reached at the speed of a click. In addition, Web-enabled real-world physical things are a reality today with cars that email their owners about tires that need to be changed and sports companies connecting their training shoes to the Web to compare performances (McCullagh and Augusto 2011).

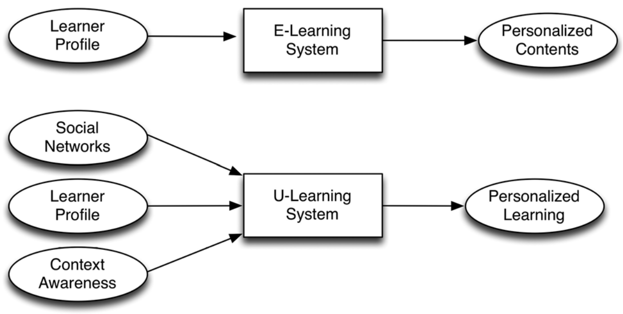

Fig. 1 E-learning and u-learning domains

The educational system is taxed to align itself to these rising profiles of learners through the deployment of technology-enhanced instruction. Learning technology has lately been driving this move where an increasing number of institutions have invested into technology-enhanced learning environments (Atif et al. 2010). Prompted by technological changes, the availability of funding initiatives, research programs and standardization initiatives [such as SCORM[1] (Huang et al. 2011)], these technology-committed institutions are increasingly aspiring at achieving new strategic goals. In the last decades, very few changes have occurred though, as universities remain conventional despite the rapid and wide proliferation of technology into our societies and the soaring enthusiasm of learners for smart gadgets , which are increasingly used productively like learning something new while on-the-go. However, these learning instances occur informally in uncontrolled environments that are remote from context and learner profile, which make it harder to find and advocate typical pedagogically-sound learning tasks (Huang et al. 2011).

Ubiquitous computing environments bring context awareness to users to enable ubiquitous learning or u-learning spaces (Hwang et al. 2010). As shown in Fig. 1 (Zhao and Okamoto 2011), learner profiles are used for adaptive contents in traditional e-learning, whereas in u-learning, adaptation of learning paths is augmented by the provision of context data (e.g. acoustics of learning environment) and social peers or tutors. A campus is a natural candidate for u-learning since it comprises all u-learning dimensions that transcend learning situations through an instructional scaffolding approach. Namely, given an e-learning system S, we say that u-learning occurs when a stimulus event E makes the probability $P(S \rightarrow S' \mid E)$ that the system changes its state, strictly greater than the probability that S changes its state, independently from E: $P(S \rightarrow S' \mid E) > P(S \rightarrow S')$ (Zhao and Okamoto 2011). Smart campuses have the capability to generate those triggers and recommend self-adaptive learning.

[1] http://www.adlnet.gov/scorm.

We adopt a user-centric approach, which aims at learning about the users' profile, to adapt services and applications according to their preferences and needs. Universities have made a substantial investment in bricks-and-mortar construction to facilitate learning, and are continually renewing the physical space in which learning occurs. Several research studies show that today's learners favor autonomy over strict guidance, to construct their own knowledge using personalized means. In these environments, the use of computing and communication services is not limited to solitary moments at an office desk, or a classroom but extended in multifaceted ways to all aspects of daily life (Fischer and Konomi 2005), and exposed through the Web for wider informational accessibility and remote operational control (Richtel 2011).

Our goal is to situate learners in a smart campus environment that provides context-based personalized learning and feedback (Chen et al. 2009). We attempt to achieve this goal by integrating real-world learning resources in a campus-wide social network. Moreover, the proposed approach is able to profile learners and record their behaviors. In addition, the provision of a smart campus environment provides support for collaborative learning (El-Bishouty et al. 2008) in a cost-effective way, using sensing technologies, tiny web servers and mobile learning devices (Hwang et al. 2009). Previous works have either focused on best practices to motivate the evolution of ubiquitous learning (Hsinyi et al. 2008), or integrated ubiquitous learning in ad-hoc contexts to explore particular learning scenarios (Zhou et al. 2012). The need for open educational resources in support of ubiquitous learning have been raised earlier (McGreal 2012), but the supply of this type of resources is not channeled in a form that could be mapped to semantic structures to facilitate interoperation.

The opportunity to transform the value of physical resources with augmented digital services is poised to boost learning experiences tremendously. Towards that perspective, we introduce Ambient Learning Spaces (ALS) as virtual spaces within an application context (Mathew et al. 2010; Mathew 2012). ALS represents one or more physical learning resources, and uses Web services to render their informational states and operational functions to interoperate with pervasive educational applications. An example of an ALS may be a Computer System lab. Each bench of the lab is equipped with a tiny Web server to enable its Web connectivity through which the bench indicates its availability, its procedure (such as assembling a PC) and its learning outcomes. Learners may adopt this ALS member in their social circle and figure out for example previous students who used that same bench for possible assistance. This integration of ALSs creates the possibility of realizing pervasive learning in our smart campus environment.

The proposed smart campus model harnesses ubiquitous learning using the ALS semantic construct. The enormity of potential physical structure instances, which could advertise their instructional value, is confined within ALSs to curb the complexity of dealing with redundant physical structures. For example, going back to the previous illustration, all Computer System labs have a common ALS representation.

The remaining of this paper is organized as follows: Sect. 2 states further the addressed problem and the targeted objectives. Section 3 shows some background and related works. Section 4 reveals our approach and methodology to formulate the smart campus concept. Section 5 further presents the design of and processes involved in the proposed smart campus. Section 6 discusses the experimental analysis and the performance evaluation. Section 7 concludes the paper with a work summary and some future extensions.

2 Problems and objectives

The challenge of a u-learning information-rich environment is not to provide information or learning services anytime and anywhere, but rather to push the right information at the right time in the right way to the right person (Fischer 2012). Hence, the ubiquitous environment should be personalized according to every learner's profile. Personalization tailors information and services to match the unique and specific needs of an individual learner (Adomavicius and Tuzhilin 2005). Typically, learners are immersed in ambient spaces, which compose our smart campus. This environment communicates seamlessly with its inhabitants in a persuasive way that drives learners through a continuous learning cycle such as the one shown in Fig. 2.

The learning continuum shown in Fig. 2 is actually based on Kolb's theory of experiential learning (Kolb 1984). This theory states that learners perceive and process information according to this continuum. This model dictates learning transitions from initially sensed perceptions, to observations followed by abstract conceptualizations and then concrete experiences to test implications. Depending upon the context or the ambient environment, learners may enter the learning cycle at any point. Table 1 shows brief illustrative examples of applying Kolb's experiential learning patterns in different ambient spaces of our proposed smart campus where natural actions of its inhabitants elicit appropriate responses from the embedded ambient spaces.

We already proposed and implemented digital patterns supporting Kolb's experiential learning index (Atif 2011) for classroom learning, and we aim at building ambient spaces, which specifically meet these experiential learning patterns (Atif 2010), to extend the classroom experience beyond its walls. In this research, we support the deployment of these patterns into ambient learning spaces and social connections, where actors are both people and campus-wide instructional resources. We view a smart campus as a social environment where campus students have lots of social interactions with peers, instructors and even instructional things (like lab resources). In this social ecosystem (Al Falahi et al. 2012), both learners and instructional sources are profiled and may feed their data into one another (for example, a lab tells learners about

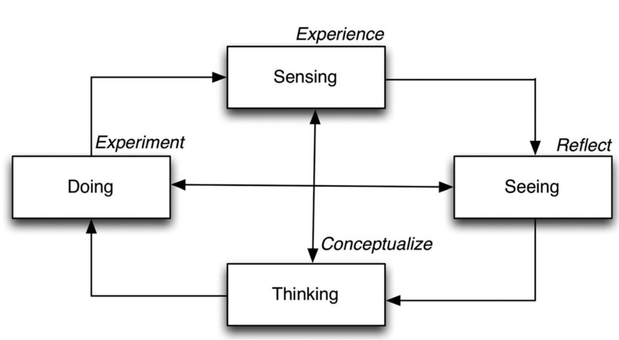

Fig. 2 Experiential learning cycle

Table 1 Experiential learning in a smart campus

Learning category	Learning model	Learning scenario
Experience (sensing)	Learn from existing experiences or examples	The learner enters an ambient space in the Engineering College of the smart campus, which proactively directs him to previous students' exhibits in Network Engineering department
Reflect (seeing)	Reflect experiences on a variety of perspectives	Some exhibits are tagged which triggers video-playbacks on the learner's mobile device to illustrate network designs for a variety of applications
Conceptualize (thinking)	Distill reflections into models	A pre-recorded classroom invites learner to view a related lecture and corresponding lecturer's office hours are indicated for further follow-up
Experiment (doing)	Experiment on actual learning situations	A networking lab in the smart campus with work benches suggests relevant networking design experiments, with self-guided tutorials, as well as access to a lab engineer for assistance

relevant workbenches). Physical objects like the Networking lab (discussed in Table 1) or related components (such as switches or routers) or even the poster exhibits (also discussed in Table 1) are Web-enabled. A learner senses the presence of these educational resources in the social network, gathers information about them, and literally "touches" the Web through them to live enriched learning experiences. We could do this by adding tiny Web servers or "touch-tags", which drive physical interactions to Web-enabled operations. These technologies augment physical real-world things with digital Web services to realize the vision of the Web of Things (Pintus et al. 2012).

The purpose of this research is to support learner-centered approaches and improve teamwork spirit across the various facilities of a university campus, in order to monitor learning needs and assess learning outcomes autonomously. A substantial part of this research is geared towards defining and developing the mechanisms and processes that allow a smart learning environment to be continuously sensitive to the learner's capabilities and responsive to his or her learning objectives. The main scope of this work relates to the following forms of learning experiences while on campus:

1. Ubiquitous Learning: which consists of building "intelligent" learning environments that are seamlessly and invisibly embedded in the campus' physical environment.
2. Context-dependent Learning: the above reference to "intelligent" learning environments refers to the capability of being able to perceive the context and to respond collectively, proactively and properly in order to maximize the learning experience utility. Context-dependency related processes under consideration in this project are:
   - Context based filtering and recommendation of instructional information and services
   - Context based Learning information and service searching
   - Context based presentation of and access to learning information and services
   - Context-based learning navigation and tasks sequencing
   - Context-based learning modification/configuration (i.e. disabling features based on learners' device)
   - Context-based learning resource allocation (digital vs. non-digital)
3. Mobile Learning which implements basic mechanisms for seamless interaction between mobile services and physical instructional objects.

Within the above scope, we aim at devising an agenda for realizing future smart campuses, as well as supporting context-awareness and learner mobility. To achieve these goals, we introduce collaborative approaches to ubiquitous learning. Our Pervasive LEARNing (PERLEARN) framework extends learning experiences beyond the classroom walls to span the campus vicinity. This environment recognizes surrounding learning objects (e.g. books, posters, and equipment) and advocate learning paths to individual learners accordingly. The proposed smart campus uses identification technologies and current developments in Internet of Things to detect and match physical instructional entities with people. A learning scenario results from this matchmaking process to meet individuals' learning goals and to enrich learning experiences, while on campus. PERLEARN also matches a learner's needs and other learners' interests or instructors' expertise and recommends the best available peer helpers or collaborators in the smart campus.

3 Background and related work

Ubiquitous computing extends computing capability boundaries throughout the physical environment unobtrusively (i.e. invisible to the user). Next, we introduce supporting technologies to realize this technology-augmented environment, and reveal some learning technology standards which contribute to ubiquitous learning. We also show some related works which set a similar agenda for ubiquitous learning transformation (Cope and Kalantzis 2008).

3.1 Emerging technologies in ubiquitous computing

A ubiquitous computing environment utilizes a large number of cooperative small nodes with computing and/or communication capabilities (Sakamura and Koshizuka 2005), such as handheld terminals, smart mobile phones, sensor network nodes, contactless smart cards, and Radio Frequency Identification (RFID) etc. In a ubiquitous computing environment, these technologies weave themselves into the fabric of everyday life until they are indistinguishable from it (Weiser 1991). Using current advances in Internet of Things, which is the backbone infrastructure for the Web of Things, real-world objects get digital identities and can then be integrated into a network and associated with digital information or services. These objects can facilitate access to digital resources and support their interaction. Regular mobile devices (such as tablets or smart phones) are used to physically interact with NFC[2]-tagged objects in order to facilitate interactions with their associated instructional information and operation services

[2] Near Field Communication (http://www.nfc-forum.org).

(Broll et al. 2009; Harman and Koohang 2007). Mobile devices are increasingly NFC-enabled which could unlock the gateway to information hidden in physical objects in a u-learning environment. Physical books for example, could be augmented with 3D virtual imagery via a mobile device to enrich the instructional value of the book contents (for example viewing a 3D model of a molecule discussed in the book by simply pointing a mobile camera to the molecule in the book). Another simple example may enable students to create smart posters and then attach touch-tags to allow visitors to listen to an audio description of that object or even view a video-demo related to their poster through their mobile device.

Due to its ease of use and straightforwardness, this physical interaction can make mobile interaction with “people, places, and things” an enriching and intuitive learning experience. In this environment, the user-interface is formed by the tagged objects themselves to free users from the drudgery of a mouse or a keyboard, through pointing directly to virtual information. They intuitively point to the actual physical instructional object that advertises pervasive information to facilitate their inner information and operation discovery. Several research works attempted similar efforts to exploit the social and pervasive learning context of a campus. A flexible mobile social networking architecture to support social interactions in a campus has been extensively researched (Yu et al. 2011; Thomas et al. 2012; Raad and Arabia 2007; Singla et al. 2010). RFID tags have been earlier deployed on various objects at University of Tokyo to enable people to learn while on campus (Sakamura and Koshizuka 2005). More recently, a context-aware ubiquitous learning approach has been integrated at Taiwan University of Science and Technology (Hwang et al. 2011) in the form of a collaborative mind-tool based on a concept map methodology. A related approach has also been earlier proposed for Tokushima University in Japan, which utilizes ubiquitous technologies to recommend educational materials and peer helpers according to a learner’s current task and location (El-Bishouty et al. 2008). This trend will continue and is poised to transform contemporary education venues with the emergence of current social networking services, mobile devices, cloud computing, tiny Web servers and NFC technologies. To guide and assess conformity, standardization pathways have already been made earlier in learning technology domains in order to facilitate this transformation.

3.2 Learning technology standards

Shareable Content Object Reference Model (SCORM) is a well-known standard specification of reusable and interoperable learning content (Chang et al. 2008). It facilitates the aggregation of and communication between learning contents within an LMS (Learning Management System) that is used to launch the pre-packaged shareable content objects (or SCOs). A SCORM-compliant LMS keeps learner information, and can interpret instructions that dictate which SCO comes next. This process allows further personalization of SCOs presentation such as how far the user progressed in the lesson (made up by these SCOs) during the previous session (Sie et al. 2006). An SCO might also send the status of the user’s completion of the lesson to the LMS as well as the score received on a related assessment, and the level of competency achieved thus far (Bizonova et al. 2009). This information may be sent to and stored in the electronic gradebook of the LMS, so that grades for assessments included in SCORM content might appear alongside grades generated by in-house assessments of the LMS (Barrington 2012). SCORM implements the “Learning Object Meta-data” or LOM specification.[3] It describes what its content is (title, description, relationships to other contents), who owns it, how much it costs (if it has a cost), what are the technical requirements for integrating it, and what its educational objectives are (Harman and Koohang 2007). Resources for a SCORM learning object make up actually an SCO, which materializes the dynamic process of navigating through a learning object within a SCORM-based lesson. A collection of LOM-based learning objects is maintained in Learning Object Repositories (or LORs) (Sampson et al. 2011a, b). The increasing availability of learning resources on the Web and the need to make them readily accessible to educators and learners have resulted in the dissemination of learning object repositories, which are increasingly distributed (Tolba et al. 2009) and acting as the cumulative knowledge of education communities (Kallonis and Sampson 2010).

3.3 Ubiquitous Learning

The pervasiveness of learning resources and the ubiquity of the Internet spiraling through our everyday physical structures have led to a new era of industrial revolution (Rifkin 2011). This revolution will create a demand for education, which will be strongly connected to the evolving Internet of Things (Kortuem et al. 2013). An approach to harness the Internet of Things as a teaching and research vehicle has been recently motivated in the form of a platform for computer science instruction (Chin and Callaghan 2013). This approach is part of a wider EU initiative called Living Labs (Mulvenna et al. 2011), which aims at stretching a regular “bricks and mortar”

[3] Learning Object Metadata specification is available at: http://ltsc.ieee.org.

campus into intelligent interconnection of "sensors and effectors", to support research and innovation. Later on, this movement has expanded into promoting user-driven methods and tools for improving the real-world development of products and services. It employs a Web-based infrastructure for innovation to integrate people into the entire development process as users and co-creators. This User Driven Innovation (UDI) has since then become an area for research and development and a strategically chosen area in many countries, specifically in the EU (Schaffers et al. 2011).

MIT has actually pioneered the above trend of self-contained environments which house both people and technology as a novel form of educational establishment.[4]This project aimed at creating and demonstrating technologies with the potential for revolutionary change throughout a university curriculum (Ehrmann et al. 2007). Part of this initiative includes the iLabs projects, where students can use Web browsers to design experiments and collect data from distant laboratory equipment (Namuganga et al. 2012). However these models lack the learning personalization dimension and do not integrate a uniform representation of ubiquitous learning resources. Indeed, personalization is paramount in ubiquitous learning because of context awareness (Li et al. 2012). A ubiquitous learning system must not only provide learning resources at any time and in any place to a learner, but also adjust the delivery of these resources to the learner context as ubiquitous learning overcomes space limitation. Furthermore, ubiquitous learning services tend also to be proactive. That is different from traditional learning services which are initiated by the learner himself or by an instructor in a classroom-like environment, where the learner profile is pre-established. Hence, adjusting the delivery of learning resources also implicates a dynamic profiling process of the learners to assert context awareness. To ensure interoperability of ubiquitous learning services with existing institution-wide instructional resource infrastructures such as Learning Management Systems (LMSs), a standard-based representation of these services should be advocated (Karavirta et al. 2013; Conde et al. 2012).

In this paper, we extend the LOM standard to pervasive environments and propose a framework, which integrates the learner profile to personalize instruction in those environments. The rise of the Internet of Things promotes M2M concept, which refers to: Man–Man, Man–Machine and Machine–Machine interactions that collectively construct ubiquitous learning sessions (Xue et al. 2011). We aim at realizing this form of social intelligence to empower learning communities in tomorrow's smart campus. The

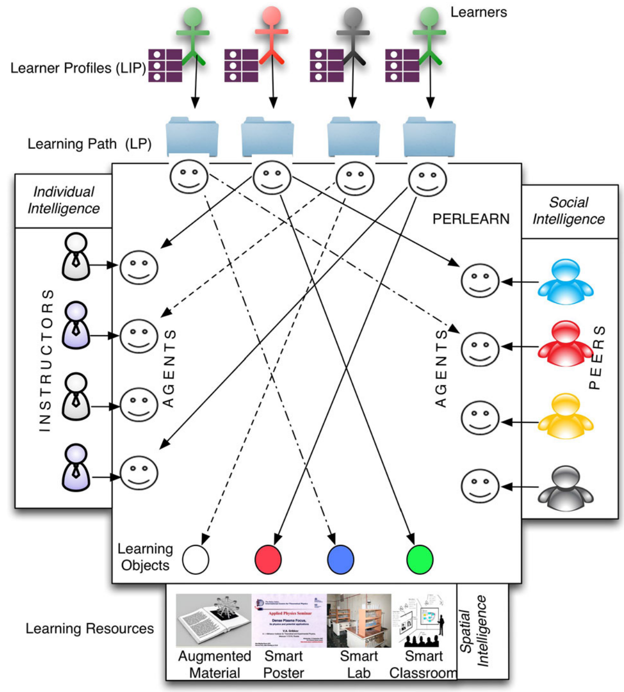

Fig. 3 Pervasive learning environment

evolution of the Web proved to facilitate a collaborative creation environment to support ubiquitous learning and social intelligence (Hwang et al. 2012).

4 Approach and methodology

Next we discuss our methodical approach to model learning processes, learners, and the learning environment to meet u-learning attributes of a smart campus.

4.1 Ubiquitous learning model

A smart campus provides connectivity between learners and their surrounding environments (Thomas et al. 2012). For students, learning-goals are inherently identified to trigger didactic models which guide their instruction around 'real-world' data, based on their unique learning contexts and delivered in the right time at the right location. For academics, this is a new enhancement of pedagogical processes through which learning is diffused Just-in-Time like a production process, when individual learners are ready to achieve a targeted level of instruction. The proposed smart campus transcends inner intelligence and becomes aware of the context in which it operates. Contextual information is central to the effective realization of the smart campus initiatives as it facilitates personalized instruction. Context is formed around a number of roles and multiple data sources, captured through Cloud-based

[4] http://icampus.mit.edu/.

services and intelligent agents as illustrated in Fig. 3. Web-based agents address a number of functions; e.g., organize, fetch and personalize learning services in the smart campus.

Our model aims at unleashing the instructional power of three prevailing sources of intelligence in a smart campus which are: individual intelligence provided by instructors or field experts, social intelligence produced by peer learners and spatial intelligence which is embedded in surrounding smart things (Atif 2013), as illustrated in Fig. 3. Learning objects encapsulate learning resources to provide a uniform semantic representation of various instructional assets. However, traditional LOM-based learning objects refer to classical digital educational resources with metadata. In this paper, we expand this description to provide PLOM objects (or Pervasive LOM objects) which representational capability is stretched to physical educational entities such as a smart classroom, poster or lab, or even augmented reality books. Further in Fig. 3, peers represent members of the smart campus who may be solicited for sharing prior experiences to deal with or going through a PLOM object. PERLEARN maintains a repository of these experiences and dynamically detect the relevant ones and establish the necessary relationships between learning seekers and learning providers. Similar sporadic relationships are enabled with instructors, but for a higher order mentorship-like relationship. Rules could be employed to dictate the level of relationship to establish.

4.2 Learner profile

Our interest is to stereotype learning situations (rather than learners) based on user interactions, and then to advocate dynamically an autonomic learning service (Atif et al. 2010). The IMS Learner Information Package or LIP,[5] is a specification of standard means for recording information about learners (Dolog and Schäfer 2005). LIP is designed to access information about learners, as well as their progress records. In doing so, LIP facilitates the transfer of Learner-related information across different learning services or applications. LIP groupings include Identification, Goal, Qualifications, Certifications or Licenses (QCL), Accessibility, Activity, Competency, Interest, Affiliation, Security Key and Relationship. Identification contains attributes and sub-concepts that enable the identification of a learner (name, contact info,...etc). Affiliation includes information on the descriptions of the organizations the learner may be associated with. QCL contains elements of the learner's formal qualifications, certifications and licenses. Competency refers to skills accumulated through formal or informal training, learning experiences or work history. Activity includes activities related to the education/training/learning sessions or work the learner has been or is currently engaged in. Accessibility contains concepts related to: user preferences, language information, disabilities etc. The concept Interest contains information on hobbies and other recreational activities. Goal contains learner's goals and sub-goals as a goal can be defined in terms of sub-goals. A different "goal" structure may be used for each entry. Goal comprises:

<typename>: defining different types of goal e.g. work, educational, personal
<priority>: to prioritize goals
<status>: active, complete, etc.
<description>: indicating the goal itself

4.3 Pervasive learning object metadata

Learning resources are packaged following IEEE LOM standard to facilitate their integration in the social learning environment of the smart campus. We extend this standard specification to Pervasive LOM or PLOM to accommodate the context-acquisition and the social immersion in a ubiquitous learning environment (as discussed earlier in Fig. 1). PLOM objects form the building blocks of the smart campus structure and a specification of a PLOM object is depicted in Fig. 4. The complexity of modeling context-aware learning scenarios using a common approach to interface with a wide range of learning sources and resources is harnessed through the proposed Pervasive Learning Object Metadata or PLOM representations. This extended definition of a learning unit standard eases the deployment of learning resources in a pervasive environment, and expose them as standard Web services. This common structure is described through a semantic Web framework using OWL and SPARQL ontological definitions (Tantatsanawong et al. 2011; Sirin and Parsia 2007) to capture and reason about the semantics of learning resources in ambient learning spaces. PLOM instances generated by this model map the capabilities, context, state and rules of learning resources to shape the behavior of ubiquitous learning resources as social entities. PLOM ontological structures enable social partners of PLOM individuals to know about a resource's availability, capability, and when and how to use it.

The metadata of a PLOM object comprises various ontological definitions as shown in Fig. 4. PLOM-Annotations ontology provides rich semantic-content to capture user experiences and feedback about the learning resource. For the annotations, we use Meaning of a Tag (MOAT) to represent tag details (Passant and Laublet 2008). PLOM-Location provides a record of how an object can be traced

[5] Learner Information Package (LIP) specification, available at: http://www.imsglobal.org/profiles/.

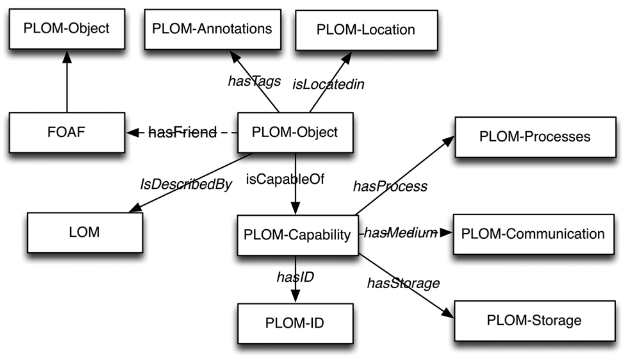

Fig. 4 Pervasive learning object metadata

from the virtual space to its physical whereabouts. PLOM-Capability ontology recognizes four capability dimensions of candidate pervasive learning resources to be Identity (Id), Processing (P), Communication (C), and Storage (S), referred to as the IPCS capability set (Mathew et al. 2010). This enables the classification of learning objects based on different combinations of IPCS capability dimensions. These dimensions provide applications hints of what capabilities a learning object has or does not have. Developers of ubiquitous learning applications are able to augment the necessary capabilities if they are required within a particular learning context. PLOM-Capability ontology mandates the minimum requirement for a physical resource to participate in an ALS to be a unique ID within the application context of ALS. This taxonomy refers to resources as "Smart Learning Resource" when it has all four IPCS capabilities and referred to as pervasive when it accumulates all PLOM specification attributes, including LOM-based profile, location, social and the extensible annotations dimensions. The *Friend of a Friend*(FOAF)[6] ontology is used to associate the PLOM-Object with other PLOM-Objects. PLOM-Profile matches the standard resource's LOM specification of the learning resources, and also integrates additional variables to enable social and ambient integration.

Pervasive learning resources in a smart campus are inherently dynamic and proprietary in nature i.e., during the lifespan of a resource (Mathew et al. 2010). They include various context values and also adapt to various ownership. Moreover, these resources also have various inherent characteristics like manufacturer/author details, date of manufacturing/authoring, version number, user experiences, and ownership history. PLOM-Profile hosts the structure and content of the semantic information that describes a learning resource. These XML descriptors and the other PLOM ontologies contribute to the semantic representation of a pervasive learning resource. PLOM-Profile has actually two sets of elements, ⟨plom : preset⟩ which is a representation of all inherent properties that are instantiated at the time when a physical resource is virtualized (as resource's capabilities, LOM instances and manufacturer/author details are initialized), and ⟨plom : dynamic⟩ which is a representation of properties that augment over time (owner history and user experiences). A hypothetical and partial example of a PLOM-Profile is illustrated through an example representing a learning poster in the smart campus and is shown next.

```
<?xml version="1.0"?>
<rdf:RDF xmlns:rdf=... xmlns:moat=...
xmlns:foaf=... xmlns:plom=... xmlns:poster=...>
<rdf:Description rdf:about=...>
<plom:profile>
<plom:preset>
       <poster:lom>Poster5AWS12</poster:lom>
       <poster:department>Biomedical</poster:department>
       <poster:author>Amina</poster:author>
       <poster:prod>01/04/2012</poster:prod>
  </plom:preset>
  <plom:dynamic>
       <plom:owner>... </plom:owner>
       <plom:venue> ... </plom:venue>
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                     <foaf:name>Amel</foaf:name>
                     <foaf:mbox rdf:resource=.../>
              </foaf:Person>
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                  <moat:Meaning>
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              </moat:hasMeaning>
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                     <moat:meaningURI rdf:resource=... />
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       </plom:tags>
  </plom:dynamic>
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</rdf:Description>
</rdf:RDF>
```

A learning object (referring to a physical resource) needs to be augmented with necessary capabilities to be a recognized entity within an ALS. The software and hardware modules that essentially enable pervasive learning objects to be represented on the Web are illustrated in Fig. 5. A PLOM object is realized by augmenting a physical resource with a tiny Web server, and *an adapter* to enable its connectivity to the Internet. Then RESTful Web

[6] http://xmlns.com/foaf/spec/.

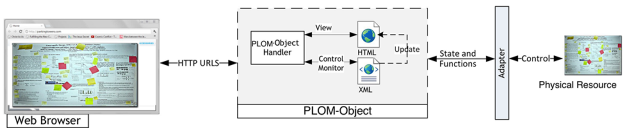

Fig. 5 Transforming learning resources into PLOM objects

services are provided to interact with the resource over the Web using HTTP URLs. PLOM-Object Handler receives the requests for resource's services. The adapter provides the necessary drivers to interact with a resource's information or operations. We represent resource's states and functions in XML, to ensure interoperability between PLOM objects. The HTML presentation enhances human perception of PLOM objects. The XML conveys the dynamic context of learning resources and then the HTML is updated in real-time based on the XML. Both XML and HTML are lightweight and provide structured constructs for resource representation. An Ambient Learning Space or ALS provides a mash-up of PLOM objects Handlers of various resources within an application context as discussed further in the next section.

4.4 Ambient learning space

As illustrated in Fig. 6, learning resources are augmented with pervasive and social capabilities and clustered into ALSs. The collaborations and compositions of ALSs create the social platform of our smart campus to share and integrate direct interactions with learning resources. Similarity criteria based on spatial, temporal or topical dimensions are used to cluster resources into ALS communities. Besides similarity criteria, communities can be sporadically formed using other types of relationships like complementary relationships or simply "friendship". The smart campus integrates people and physical resources within communities represented by ALSs. Both member types are represented through their socially-augmented LIP (for people) and PLOM profiles (for resources). These XML profiles can be parsed to determine the context and similarities with other members of the smart campus to match dynamically their participation in a pervasive learning session.

As an illustration of an ALS, consider a scenario where the ambient space within an application context is a Chemistry Lab. The lab has a number of weighing balances spread across several venues of the smart campus, which are associated with faculty members who are then aware about the availability and operational features of these balances. Some of these faculty members have defined certain schedules and restrictions for the use of these balances. When a new PLOM-enabled digital balance is ordered and arrives at one of the lab venues, it first

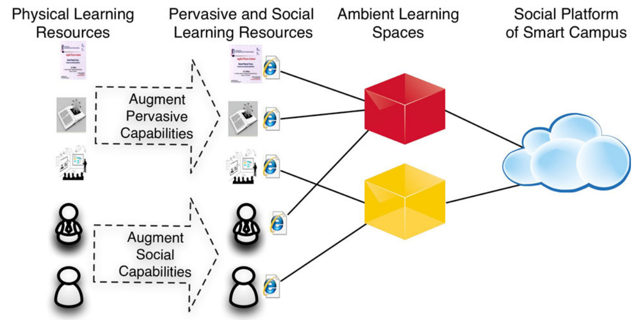

Fig. 6 Ambient learning spaces

associates itself inherently with its own kind i.e., joins a group of similar balances on campus, and then sends friendship requests to faculty members associated with the older balances in the group who may then use it to schedule experiments for students.

Similarities are examined among profiles of the smart campus members. For physical resources, these could be PLOM-Annotations, PLOM-Location, PLOM-Capability, or FOAF. We adopt a threshold-based technique for the clustering to determine the suitable cluster assignment based on a resource's similarity with any of the existing ALSs' members. We develop a scalable clustering algorithm to create and maintain the community of learning resources. Namely, given a threshold μ, a similarity function σ, and resources $d_1 \ldots d_n$ to cluster, the algorithm considers each resource d_i and calculates the corresponding similarity $\sigma(d_i, c_j)$, for each existing cluster c_j, for $j = 1, \ldots, l$. If no matching cluster is found (i.e. $(d_i, c_j) > \mu, j = 1, \ldots, l$), either d_i is considered at the next clustering cycle or we manually create a new cluster c_l for d_i. Alternatively, d_i is assigned to cluster c_j with the highest $\sigma(d_i, c_j)$.

In this first stage, we create ambient learning spaces (ALSs) like the above Chemistry Lab, which suits the context of an application, for example the group of weighing-balances. These are groups with at least one member (manually inserted) which acts as a seed or centroid to adopt future members. Similarities that exist between the preset parts ($\langle$plom : preset$\rangle$) of the resources' PLOM-Profiles are used to create clusters around the predefined seed. During a clustering process, every new resource (for example our newly procured weighing-balance) that is PLOM-enabled but not in an ALS is adopted into an ALS by comparing similarities of its PLOM-Profile ($\langle$plom : preset$\rangle$) with the available cluster seeds. If a resource is not matched into any cluster then the resource could be adopted during another periodic clustering process or manually administered as a new seed to form a new ALS. The seed in each ALS provides a common representation for similar things. The clustering process ensures the reelection of the seed i.e., the clustering process may change the centroid of the cluster. Hence, over a period of time the seed becomes a *purified* representation of a cluster.

Our approach is to drive smart campus resources to build a presence in the induced pervasive environment through joining an ALS, which bridges PLOM objects and social campus communities. This hierarchical structure facilitates the organization of the multitude PLOM objects available in the smart campus. To achieve this organization, we first integrate a resource into a topical ALS (such as Chemistry Lab), and in the second stage we use opportunistic social relationships of a member of that ALS with campus people (or other resources) to dynamically infer the integration of the other ALS members into social communities. This social propagation of PLOM objects aims at increasing the pervasiveness of learning resources across a smart campus environment.

5 Social collaboration specification

The success of a smart campus lies on its ability to populate communities based on social links that exist between its members. The social networking platform suggests possible links between members based on ties that are assumed to exist between them. Learning resources whether tangible or abstract have heterogeneous properties, but they can be inherently grouped based on profile, spatial, or social ties. These communities of a smart campus thrive in a conglomeration of ALSs as part of the campus PERLEARN model, as shown in Fig. 7. The collaborations and compositions of ALSs create the social synergies in the smart campus.

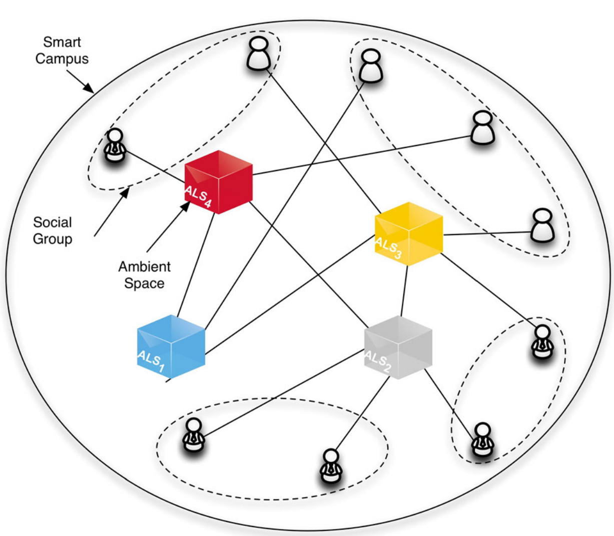

Fig. 7 Smart campus PERLEARN: a social platform for connecting resources and people through ALSs

5.1 Social platform

Campus people and resources are members of the campus-wide social network platform. The social link of ALSs uses the dynamic (⟨plom : dynamic⟩) part of the PLOM-Profiles to contain say members' feedback. ALSs are initially set up with at least one such social connection (i.e. manually assigned) which acts as a seed or centroid for inferring the social connections of future ALS members. Social connections to ALS members are iteratively suggested to members (people) of existing groups in the social network where the ALS seed is already a member. A social group can for example be a course offered in the smart campus and gathering members enrolled or interested in that course as well as ALSs' members which support that course, for example a Chemistry course as a social group and the Chemistry lab ALS members (i.e. weighing balances).

To build ALSs and advocate social inferences within PERLEARN, we measure the content and the structural similarities among PLOMs' content (i.e. LOM data) and structure (i.e. PLOM tags) separately and combine the results with different weights. This gives relative importance to the structure and content depending on the type of resources under consideration.

Content similarity invites an ALS potential candidate to join the ALS membership based on their LOM content. For example, a chemistry balance joins the Chemistry Lab ALS. The Chemistry Lab in this case may already be represented by a current member such as a lab book which guides experiments planning and records personalized data entry, to run and record the results of some lab related experiments. This is a digital resource but represented by its PLOM profile and manually inserted into the Chemistry Lab ALS. Consider such ALS member W_x, where any future candidate W_y, to be included in that ALS needs to be "close enough" to W_x. This content similarity is measured by *ContSim* $(W_x, W_y) \times \tau$. The structural similarity between W_x and W_y is defined as StructSim((W_x, W_y) $\times$ 1 $-$ τ. The value of τ ranges between 0 and 1 and determines the weight of content vs. structural similarity. For example, if location determines ALS membership, then structural attributes should prevail but if the academic subject is the determinant factor, then content attributes are the dominant factor. The combined value of both similarities is measure as:

$$Sim(W_x, W_y) = ContSim(W_x, W_y) \times \tau + \mathrm{StructSim}(W_x, W_y) \times (1 - \tau) \qquad (1)$$

The content similarity considers the value of the various elements in PLOM-Profile. A set of distinct terms $T = \{t_1, t_2, \ldots, t_m\}$ is extracted from the set of all profiles $W = \{w_1, w_2, \ldots w_n\}$. A term matrix $S_{(m \times n)}$ is constructed where m is the number of terms in T and n is the number of profiles. Each attribute $w_{x,i}$ in $S_{(m \times n)}$ is a vector member representing the frequency of term t_i in PLOM-Profile w_x. Content similarity is then calculated using a Cosine formulation as follows:

$$ContSim(w_x, w_y) = \frac{w'_x \cdot w'_y}{|w'_x| \times |w'_y|} = \frac{\sum_{i=1}^{n} w_{x,i} \times w_{y,i}}{\sqrt{\sum_{i=1}^{n} w_{x,i}^2} \times \sqrt{\sum_{i=1}^{n} w_{y,i}^2}} \quad (2)$$

The structural similarity depends on how intrinsic PLOM profiles properties are organized and tagged. However, given the XML tree structure of each profile, the elements in the profile are naturally organized in a tree-like structure. We match the structure of PLOM-Profiles by dividing the profile into distinct paths. These paths are used to measure structural distances between different PLOM profiles. Given a dataset of PLOM-Profiles $W = \{w_1, w_2, \ldots, w_n\}$, a set of distinct XML paths $P = \{p_1, p_2, \ldots, p_f\}$ are extracted from W. A path p_i contains elements name from the root element to the leaf element, which hosts the content. The structural model of a PLOM object w_i is a vector $\{p_{i,1}, p_{i,2}, \ldots, p_{i,f}\}$, where each element of the vector represents the frequency of a path in P that occurs in w_i. Consequently, given two PLOM profiles w_x and w_y, and their corresponding vectors $\{p_{x,1}, p_{x,2,\ldots,}p_{x,f}\}$ and $\{p_{y,1}, p_{y,2,\ldots,}p_{y,f}\}$ respectively, the distance between the two profiles is computed using the Euclidean distance, as follows:

$$StructSim(w_x, w_y) = \sqrt{\sum_{i=1}^{f} (p_{x,i} - p_{y,i})^2} \quad (3)$$

Using the similarity measure in Eq. (1), a pair-wise PLOM-Profile comparison is computed following Eqs. (2) and (3) results, to generate a similarity matrix for clustering things into ALSs. K-Means algorithm is applied to determine clusters or ALSs from the similarity matrix.

5.2 Learning design and processes

Our goal is to associate each ALS with a learning pattern in the experiential continuum shown in Fig. 2 to encompass the places in which learning occurs, and advocate appropriate ALSs for each phase in the continuum. For example, the workbench of a Chemistry Lab ALS is associated with the "Experiment" stage of the continuum. On the other hand, a PLOM-enabled poster exhibit could be associated with "Experience" stage and the associated video, viewed through the embedded NFC tag could be associated with the "Reflect" stage. Finally, a classroom where related concepts are presented could represent the "Conceptualize" stage. Hence, this approach aims at pedagogically-supporting immersive learning experiences to meet LIP-specified learning objectives.

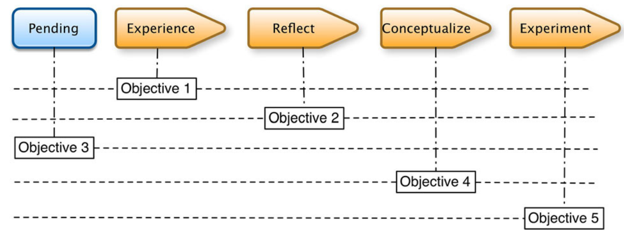

Fig. 8 Personalized learning calendar

While learners navigate throughout the smart campus premises, virtually they move across multiple ALSs, which contents and services are advocated. PLOM objects populate inherently ALSs and hence the pervasive learning space of the smart campus inherently, as discussed in the previous section. The system maintains the status of each learning objective and its associate continuum stage to notify learners whenever they navigate across appropriate ALSs. Figure 8 shows an illustration of this book-keeping process for each individual learner in the smart campus.

PERLEARN exploits the inter-relationships between LIP and the smart campus elements to define learning paths alongside the proposed experiential continuum for an individual learner, to match preset objectives and cognitive preferences, and record acquired competencies. The access to ambient learning content from multiple, distributed sources allows learning applications to transparently update learners' profile. This shift requires changing learning design focus to developing learning applications formed out of distributed learning networks that are largely self-managing, self-validated, and transparent to the learner. Learning becomes flexible, accessible, and transparent. These three benefits are traditional autonomic computing functionalities adapted to learning technology in this research. Different Autonomic Web services (*AWS*) intervene at different levels of a learner's LIP record. The autonomic activities in a learning system can broadly be categorized into four areas to match the proposed learning continuum:

- *Monitor_Context_AWS*
- *Reflect_AWS*
- *Reflect_AWS*
- *Conceptualize_AWS*
- Experiment_*AWS*

These four areas of autonomic activities as well as the synergistic correlations they provide in a closed-loop format are illustrated in Fig. 9. Each *AWS* is followed by a validation step to record acquired competency. It is possible that this process be reiterated or composed of a set of

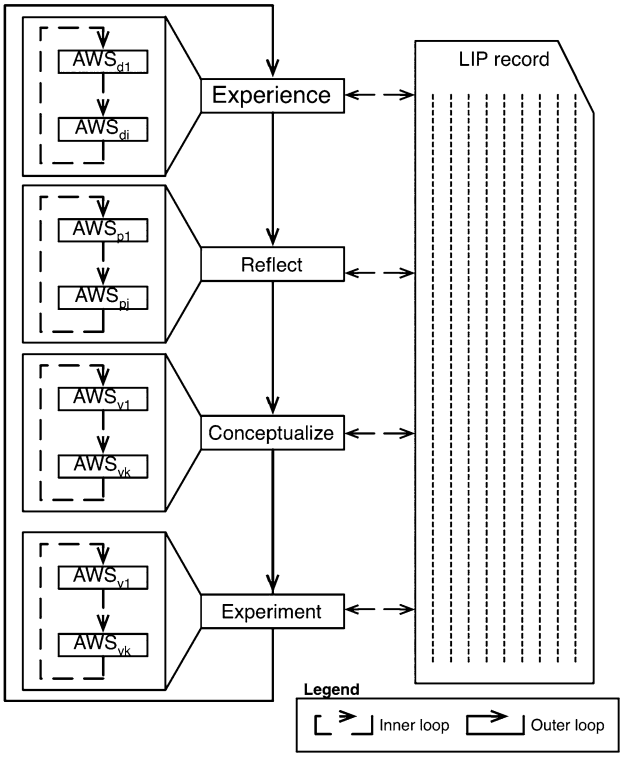

Fig. 9 Autonomic learning services

iterative sub-tasks until validation succeeds. Hence, the inner-loop in each phase shown in Fig. 9. The successful outcome of the validation process leads to an amendment in the learner's LIP profile by updating his competencies.

Similar to complex autonomic systems, which are built using intelligent agents (Joshi and Singh 1999), u-learning applications can implement their functionalities through *AWS*s. As illustrated earlier in Fig. 3, an *AWS* is a proactive entity that possesses the social ability to instruct other agents to change their behaviors (Kephart and Chess 2003). It uses fine-grained components in the development of the autonomic learning processes. *AWS* enables an autonomic behavior to sense the context and collect LIP data to compare them alongside ambient PLOM objects' related ontologies. It perceives changes and, in response to goals and ambient PLOM object settings, invokes dynamically appropriate Web services to reveal the required instructional session.

*AWS*s are geared by a six-tuple generic model (Wang et al. 2006) $\langle$K, A, G, P, I, L$\rangle$, where *K* is a set knowledge base rules, *A* is the set of behavior capabilities,*G* is the set of goals, *P* is the set of plans, *L* is the set of policies, and *I* represents the behavior preferences. *K* represents a set of rules that transcend learners into a new learning state provided certain Boolean conditions are evaluated to True. Basically, they specify the conditions under which a given learning re-configuration could be enabled to fire appropriate learning Web services. The behavior capability *A* describes the capabilities represented as a set of domain-specific learning design patterns. These are ontological learning patterns to match the continuum learning phases. The goal *G* reflects the desired state or behavior changes after executing a specified learning. *AWS* continuously fetches learning goals from the corresponding LIP record. The plan *P* determines the approaches to reach the goals. A plan connects the knowledge base rules in K, the capabilities*A*, and the goal *G* together, which illustrates what actions to take for completing the specified learners' goal based on the domain knowledge and capabilities. The plan *P* is the result of the learning-process controlled by the inner-loop of *AWS*s shown in Fig. 9. The policies *L* describe the rules to validate a learning outcome. For example, these may include assessment criteria to satisfy some competency requirements. The policy rules are specified as part of the output of the learning- validation controlled by the inner-loop of AWSs shown in Fig. 9. Finally, the behavior preferences *I* records the learner's preference indicated in LIP record (such as accessibility preferences). Based on this model, an *AWS* will repeatedly execute the following steps:

1. Monitor the environment and based on *K* rules,
2. Fetch learning objectives from LIP and add to G
3. Decompose a candidate goal into sub-goals $\delta \in G$ that match post-conditions of a capability in *A*,
4. Find a plan $(a_1, \ldots, a_n)$ in *P* where a_i is a learning action to achieve a goal δ according to the policy *L* and preferences *I*,
5. Execute the plan and feedback to LIP activity, goal, and competency fields.

6 Experiment and evaluation

Our approach to ALSs is based on the clustering process introduced in Sect. 4.4 and described in Sect. 5. We evaluate this approach in this section to assert the performance of these building blocks in the proposed smart campus model. We use *Purity* measure (Zhao and Karypis 2004) shown in Eq. (4) to evaluate the performance and accuracy of our ALS clustering approach. We simulated this approach using Matlab and C++. We performed the experiments on an Apple MacBook Pro with Mac OS X version 10.8.4, processor 2.4 GHz Intel Core i7 and 8GB memory.

It would be ideal if all ALS members are strongly connected with each other and loosely connected with other ALSs' members. We hypothesize that our clustering approach creates pure ALSs, and verify this assertion through a simulation study. Purity metric shown in Equation is commonly used in Clustering techniques to evaluate

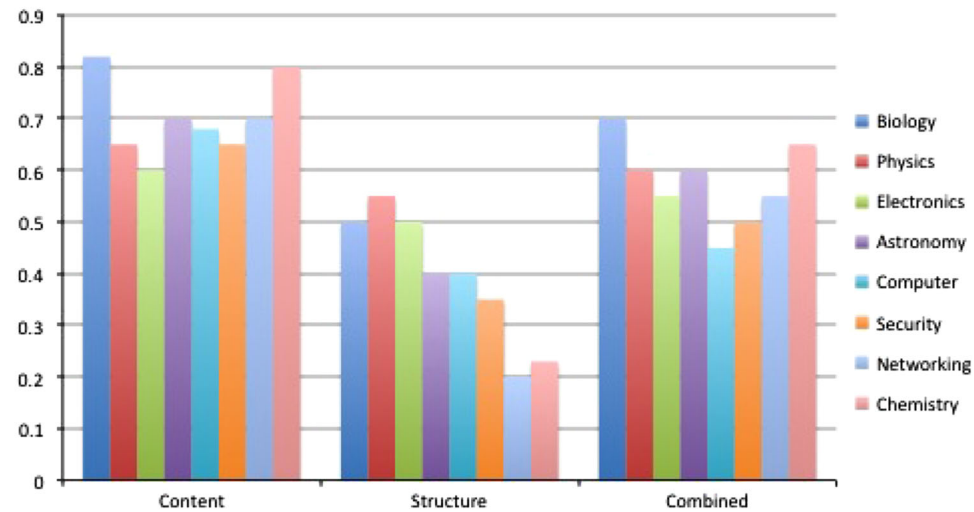

Fig. 10 Ratio of clustered PLOM objects

(a) Evaluation based on Purity **(b)** Evaluation based on precision and recall

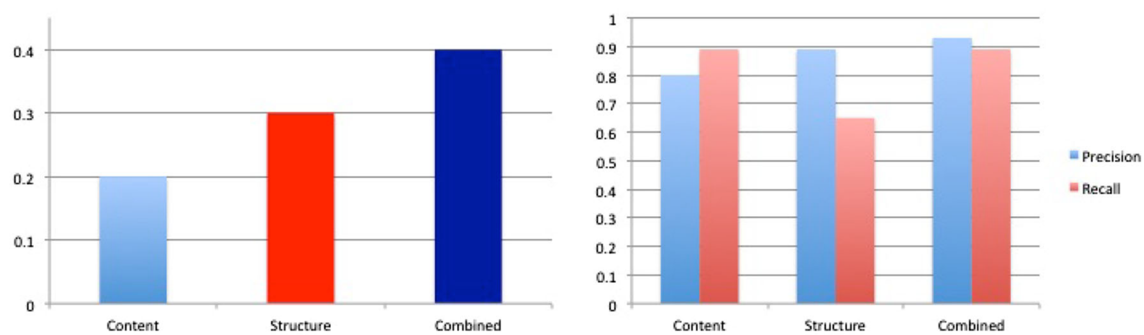

Fig. 11 Comparison of clustering techniques

the coherence of a cluster. An ideal cluster with only one member manually administered into the ALS (i.e. seed) has purity value 1. The higher the purity value the better is the quality of a cluster. Each time a new member is added to ALS, we recalculate the purity value as follows:

$$Purity(C_i) = \frac{1}{n_i} max_h(n_i^h) \tag{4}$$

In Eq. (3), C_i refers to a particular cluster or ALS, with size n_i and $max_h(n_i^h)$ is the number of objects that are from the dominant category. n_i^h is the number of objects of the ith cluster which belong to the hth category. A category could be one of PLOM metadata or classes. The objects to be clustered can be viewed as a set of vertices, and we employ K-Means to cluster them as follows:

1. Define the content and structural similarity thresholds
2. Filter irrelevant objects (associated with few terms)
3. Assign each relevant objects to the Top C existing cluster(s) based on the similarities (that above the similarity threshold) between the page and the corresponding centroids
4. The object will be one cluster itself if no existing cluster meets Step 3
5. Recompute the centroids of the clusters if its members are changed
6. Repeat Step 2 through 4 until all relevant objects are assigned and all centroids do not change any more

We arbitrarily select eight learning topics as part of this experiment: “Chemistry”, “Networking”, “Biology”, “Computer”, “Security”, “Electronics”, “Physics”, “Astronomy”. We would like to evaluate the quality of ALSs generated by the proposed clustering approach. First, Fig. 10 shows the ratio of a total of 200 PLOM objects clustered into the above topics, which could relate to particular ALS venues. These PLOM objects were simulated for the purpose of this experiment. Selected terms from each of the above learning topics were randomly associated with PLOM data values. Three clustering techniques were experimented based on content similarity formulated by Eq. 2, structure similarity formulated by Eq. 3 and combined similarity formulated by Eq. 1. An object could belong to more than one ALS or to a singleton cluster (if it cannot be grouped into existing ALSs). According to the experimental results, content-similarity identifies the most popular learning objects about the selected topics but fails to remove noise or separate objects that would normally belong to distinct topics. Structure-similarity could identify medium-size, tightly-related and more meaningful clusters, but suffers from low recall as we will see later on. The combined-similarity seems to give better results in terms of objects coverage and the quality of the obtained clusters.

To evaluate the quality of the clusters, we use two metrics: global metric (precision vs, recall) and local metrics (manual distribution vs. purity). To estimate these measures, we manually check the contents of the 200 clustered PLOM objects against each of the selected learning topics. Then, we make a judgement on whether each PLOM object is relevant to the clustered topics. Let A denotes the number of all clustered PLOM objects and B denotes the number of relevant ones. Then:

$$Precision = \frac{|A \cap B|}{|A|} \tag{5}$$

and

$$Recall = \frac{|A \cap B|}{|B|} \tag{6}$$

Precision and recall are used to measure the extent of noise removal from the generated ALSs, and their cohesion respectively. However in order to get a clear quality value of each cluster, we use “purity” to assess the ”goodness” of the resulting clusters. The purity of the clustering approach is the weighted sum of the individual cluster purities:

$$Purity = \sum_{i=1}^{k} \frac{n_i}{n} Purity(C_i) \tag{7}$$

The larger the purity, the better the clustering performance. The results of the experiment are shown in Fig. 2a. We evaluated the clustering of PLOM objects into the eight selected topics based on the purity of the resulting clusters. The content-based similarity results in coarse clusters with many noisy objects in the clusters. The structure based similarity is an improvement but combining both results in the best performance. Finally, Fig. 2b which compares the performance based on precision and recall using the formulas shown in Equation 5 and Equation 6, confirms the trend of the combined similarity criteria results.

The experimental study presented insights into the proposed clustering approach to realize ALSs as building blocks of our smart campus model. The results show the effectiveness of the suggested similarity criteria to drive PLOM objects to autonomically join appropriate ALSs.

7 Conclusion and future works

In this study we proposed a framework specification for ubiquitous learning in a smart campus model. We identified and modeled the main components of a smart campus environment to support ubiquitous learning experiences. We proposed PLOM, a structure to capture pervasive learning resources which meet the expectations of smart campus stakeholders, and provided the semantic PLOM relationships to achieve multi-modal u-learning and automatically generate instructional paths in a smart campus environment. We introduced the concept of Ambient Learning Space (ALS) to harness the complexity induced by a multitude of PLOM objects and used it as a gateway to the smart campus wide social platform. We also specified an autonomic u-learning ecosystem that exhibits capabilities such as self-organization and self-adaptation. To do this, we introduced the autonomic Web service (*AWS*) concept to reason about ALS members in inferring personalized learning paths to meet learner-declared goals. For our future work we continue with the realization of PLOM, ALS structures and *AWS* learning processes. We are also focusing our efforts on optimizing the clustering approach by measuring the effectiveness with different similarity functions. Various experiments within a university campus setting are planned to further evaluate our framework. Moreover, we continue to study the upper layers of the Ubiquitous Learning Resources Management and Sharing Architecture to administer the social infrastructure with required security and privacy parameters for the proposed smart campus. This also includes the study of the knowledge base that gears the behavior of *AWS*s and domain-oriented learning workflow applications.

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