Cloud eLearning

Personalisation of learning using resources from the Cloud

Krenare Pireva

Supervisor: Prof. Tony Cowling &

Prof. Petros Kefalas

Department of Computer Science
The University of Sheffield

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To my daughter Ema!

Declaration

I hereby declare that except where specific reference is made to the work of others, the contents of this dissertation are original and have not been submitted in whole or in part for consideration for any other degree or qualification in this, or any other university. This dissertation is my own work which has been carried out since the official starting date of this PhD program.

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Abstract

With the advancement of technologies, the usage of alternative eLearning systems as complementary systems to the traditional education systems is becoming part of the everyday activities. At the same time, the creation of learning resources has increased exponentially over time. However, the usability and reusability of these learning resources in various eLearning systems is difficult when they are unstandardised and semi-standardised learning resources. Furthermore, eLearning activities' lack of suitable personalisation of the overall learning process fails to optimize resources' and systems' potentialities. At the same time, the evolution of learning technologies and cloud computing creates new opportunities for traditional eLearning to evolve and place the learner in the center of educational experiences.

This thesis contributes to a holistic approach to the field by using a combination of artificial intelligence techniques to automatically generate a personalized learning path for individual learners using Cloud resources. We proposed an advancement of eLearning, named the Cloud eLearning, which recognizes that resources stored in Cloud eLearning can potentially be used for learning purposes. Further, the personalised content shown to Cloud Learners will be offered through automated personalized learning paths. The main issue was to select the most appropriate learning resources from the Cloud and include them in a personalised learning path. This become even more challenging when these potential learning resources were derived from various sources that might be structured, semi- structure or even unstructured, tending to increase the complexity of overall Cloud eLearning retrieval and matching processes.

Therefore, this thesis presents an original concept,the Cloud eLearning, its Cloud eLearning Learning Objects as the smallest standardized learning objects, which permits reusing them because of semantic tagging with metadata. Further, it presents the Cloud eLearning Recommender System, that uses hierarchical clustering to select the most appropriate resources and utilise a vector space model to rank these resources in order of relevance for any individual learner. And it concludes with Cloud eLearning automated planner, which generates a personalised learning path using the output of the CeL recommender system.

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Chapter 1

Introduction

Within the larger context of artificial intelligence in eLearning systems, this thesis explores modeling personalised learning paths based on diverse learners' backgrounds, requirements and characteristics, using an automated planning approach. ELearning is defined here as use of technology to enable access to learning materials for learners, anytime from everywhere [4], including learners located - geographically - at a distance. At the eLearning courses level, a "one-size-fits all" approach has generally been employed, wherein the differences among individual learners have been ignored, in order to appeal to the masses. Oftentimes, this has produced weak learner engagement, which consequently erodes their learning potential. Despite continuing issues related to a 'digital divide', the growth of Internet penetration and improvements in personal computing has ameliorated many 20th Century usage barriers. In response, significant progress has been made in the 21st Century, in both accessibility of eLearning and also variety of platforms, implying also the type and frequency of communication (synchronous or asynchronous) between teachers and learners.

In recent years, new technology-enabled features and functionalities have enhanced teacher impact and learner experience. Furthermore, amidst growing recognition that content creation and learning activities are time consuming and labor intensive, the idea of content re-use, interoperable within various eLearning platforms, has emerged as a best practice in higher education. The conception of Digital Learning Objects (hereafter Learning Objects) has influenced the creation and representation of learning content and associated activities, as an efficient approach for creating, sharing, and reusing digital content.

The Learning Object, is a digital resource used and reused to fascilitate learning[5]. The learning objects further discussed in 2.3 are used to build the learning content and activities as building puzzles or as building blocks, an analogy of Lego building blocks firstly mentioned by Wayne Hodgins [6]. Furthermore, Wayne Hodgins, defined the learning objects as "a

collection of information objects assembled using meta-data to match the personality and needs of the individual learner".

The idea of learning objects reusability emerged in 1994 and further emphasized during last decades[7, 8] because there was a lack of common standardisation how to reuse the learning objects in various sources as well as in various contexts. In response, several organizations initiated standardisation initiatives, influencing the way that learning objects are created, represented, and organized, reflecting standards and protocols which influence how they can be shared, such as: Dublin Core metadata standard, Learning Object Metadata (LOM) metadata standard, Sharable content object reference metadata (SCORM) specification, to name a few. Usually learning objects are associated with files known as meta-data which tends to describe the learning object in a standard manner through tagging or description. Using the tagging or description approach increased the possibility of successfully re-using, sharing and retrieving learning objects for personalised use. The metadata description is represented and managed as part of a group of learning objects, as shown in Figure 1.1 and discussed further in section 2.3.
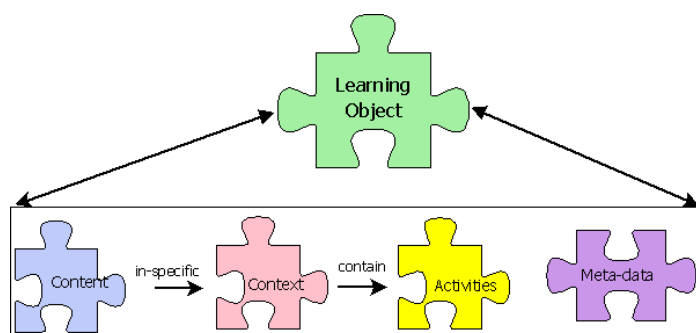
Fig. 1.1 The relationship of Learning Object and meta-data description

After 2000, the development phase of open education resources (OERs), the web 2.0 and personal learning environment technologies coincided, which contributed toward learning content creation and representation, as well as how it is shared and personalised to learners' needs. In this context the personalised eLearning means that the services (learning and related activities) of eLearning are offered based on learners' unique characteristics (the characteristics could be the learning styles of the learner, the level of learners' knowledge for a specific topic, the current interest of the learner etc). Above this, the personalisation is encountered by being able to adapt the environment and/or the content.

Today, learning objects are created by individuals, professionals, including practitioners, and institutions. Strategies vary depending on whether the content and the platform encourage open access. Increasingly, open access educational resource (OER) repositories observing international standards offer learning objects to the higher education community and beyond.

In addition, individuals make their content available through social media and open platforms which may or may not use common standards, as further discussed in section 2.3.

As a consequence, lately there have been various attempts to personalise the eLearning systems, using a variety of tools and techniques, in order to adapt teaching practices and adopt to pedagogical styles. Recognition of variety in learners' background and learning characteristics has, in turn, generated creation of personalised eLearning systems. The personalisation as an essential characteristic of eLearning systems, tends to adapt the system based on learners' characteristics in order to obtain the highest values of the learning process. The adaption of the system should consider the personalisation approaches including learning theories, learning stages, learning styles, learners' motivation and needs. Now personalised courses, which accommodate varying background and characteristics, are available for learners, as analyzed further in section 3.2. This shift in understanding has produced progressive recognition of the importance of personalised eLearning Systems.

However, as shown in the comparison of various eLearning platforms presented in section 2.2, many features that could contribute to personalisation, are missing. Their absence has an impact during the learning process facilitation[9], including such features as: personalisation of learning path, use of multi agent systems, ontology adaption, customisable learning path and so on. Furthermore, the advancement of technologies, especially the Cloud Computing as the fifth generation of computing has changed the processing approach, and this could be encountered as a positive aspect when dealing with scalability of learning resources further discussed in Chapter 4.

These findings so far, served as an inspiration to start this thesis, in order to be able to find possible ways to personalised the learning path of the learners based on various attributes, further discussed in Chapter 5. Lately, the use of cloud computing, knowledge representation, recommender systems and artificial intelligence automated planning technologies in eLearning systems have been introduced. However, there are still uncovered approaches how such technologies can enrich learners learning experience, and how these technologies can be used in respect of personalised learning paths, either as standalone system or through systems integration approach.

1.1 Motivation

The educational institutions that provide eLearning now develop courses and programmes using existing pedagogies and experiment with new ones. A typical eLearning course, whether it is open (Massive Open Online Course) or private (Small Private Open or Online

Course), consists of four main components, i.e. the pedagogy, the content, technological infrastructure and course administration.

The **pedagogy** should determine a number of characteristics for this course, such as the way in which the learning outcomes will be met by delivery and assessment methods as well as the learning path and learning pace of the group. Pedagogy will in broad terms define the balance between instruction and self-learning, implying also the type and frequency of communication (synchronous or asynchronous) between teachers and learners. The **content** will include a variety of text and media deemed as appropriate to give opportunities to satisfy the learning outcomes. The **technological infrastructure** is the set of Learning Technologies tools used by the teachers and learners in order to facilitate knowledge transfer and skill acquisition, such as Virtual Learning Environment (VLE), teleconferencing tools, wikis, file sharing, social interaction, support and e-feedback, etc. Finally, the **course administration** is a set of regulations and processes as well as their monitoring under which students enroll, attend, progress, etc. Irrespective of any combination of the above, eLearning inherits some rigidities of traditional face to face learning, with the exceptions of Massive Open Online Courses (mostly without credits).

The restrictions that characterise these types of learning approaches are: (a) **teachers apply predefined pedagogies**, (b) **the selection of material is largely done and/or recommended by the teacher**, (c) **the tools of the technological infrastructure are specified by the course provider** (teacher or institution), and (d) **regulations and processes are provider/institution specific**.

The big contradiction in this situation is that the learner, who is the receiver of the process, must abide by what the course providers have decided, with no or little involvement in the above. This common practice seems to be the "rational thing to do" for groups of learners, especially when providers are tied by the general educational framework in which they belong. Thus, for instance, Universities need to follow certain quality assurance requirements in order to award credits for courses and eventually degrees. But even then, course providers are often criticized because they do not apply a learner-centered approach, taking into account the individual characteristics (such as: learning styles, the learners background to name a few) and needs of each learner.

Today, the advancements of learning technologies, **knowledge representation, recommender systems, automated planning and cloud computing approach**, offer considerable promise. Traditional eLearning approaches could evolve into processes which place the learner in the center of educational provision by enabling personalisation, enhancing self-motivation, fostering self-pacing, encouraging collaboration and ensuring flexibility approach to the learning path.
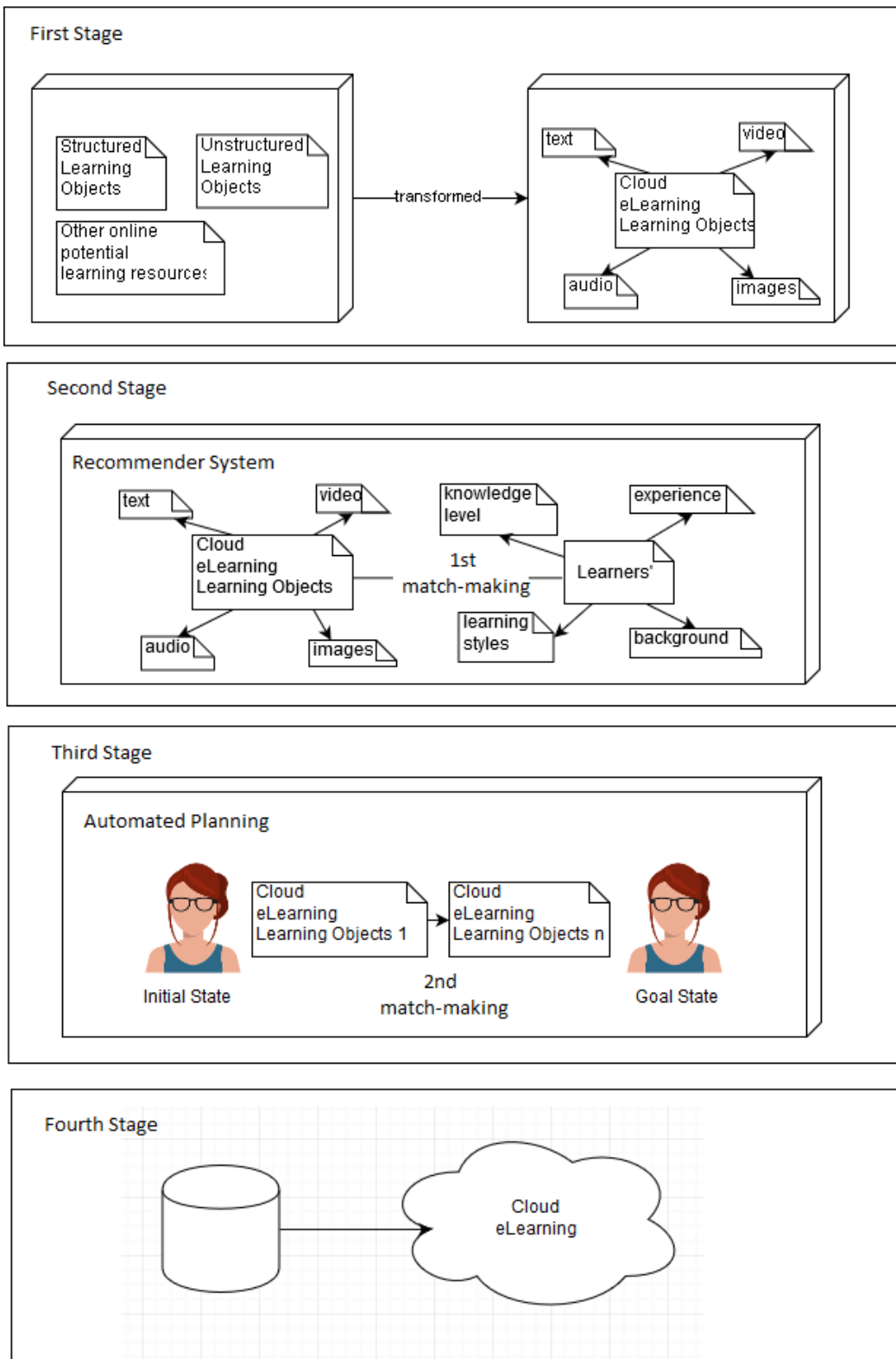
Fig. 1.2 The Cloud eLearning stages of development

In Figure 1.2 is depicted a chronological order of combining the technologies as a holistic approach followed by a set of activities taken within each stage.

Firstly, as per to use of knowledge representation technique disussed in Chapter 6, there is a need to represent the learning objects and the learners background in common standards, since the idea of re-using the existing content from various sources may end up in a complex situation, where various learning objects may be represented with different standards, which at the end could imply the lack of understanding/interoperability.

Secondly, the recommender systems technology disussed in Chapter 7 is used to be able to rank and predict the appropriate items of interests to particular type of learner. This contributes to filter a list of items of interest from a pool of items, which may not be of a learner interest.

Thirdly, the artificial intelligence planning technology disussed in Chapter 8, is tending through automatisation process to offer the appropriate solution/plan for a particular interest of a user in an automated manner. Toward this approach, in recent years planning as part of Artificial Intelligence (AI) has become an important field of research. It is used in autonomous robots, intelligent agents and furthermore transportation. From the aforementioned examples, planning has been used mainly in application domain (client side), albeit recent years the use of planning in web services has become popular.

And, the last but not the least, the fifth generation of computing, namely the cloud computing has reshaped the idea of computing and managing the online resources, especially when it comes to the point that we have to deal with big data, particularly with a set of learning objects, which are gathered from various sources with divers standardisation and representation approaches.

Today, given the ubiquity of technology in our everyday life, considerable attention now explores how to personalise and automate services in various domains. In this respect, the process of using the online open learning resources, and being able to offer in a personalisation sequences way through a combination of recent technologies could use a state of the art approach in order to propose a new paradigm of eLearning, namely the Cloud eLearning.

In this thesis, the advancement paradigm for eLearning, namely Cloud eLearning, is proposed and defined in chapter 5, as collection of available learning objects in a variety of formats derived from various sources, as structured, unstructured or semi-structured (depending on their represenation), and are located and distributed through the cloud. In this context, the artificial intelligence planning (hereafter planning) is used in the learning domain to generate a personalised learning path for individual learners which takes into consideration their advantages and differences.

Considering learning as planning process, facilitates the idea that the learner is in the very beginning, at some initial state of skills and knowledge already acquired through previous experience. It recognizes that the learner would like to change (learn) to attain a new desired state which will contain more skills and knowledge. So, the process of assembling the learning material to form a so called, learning path for individual learners, is equivalent to a planning process that promotes learning.

However, in order to be able to represent the AI planning in the learning domain and to fully realize the learning potential through AI planning, various technologies have been involved, such as: (i) **Cloud as knowledge generator**, (ii) **Knowledge Representation in Cloud**, (iii) **Recommender System** in order to filter the relevant learning resources from all existing ones in the Cloud, (iv) **Automated Planning**, to automatically generate a personalised learning path, and finally (v) the use of Cloud Services for a Cloud eLearning(CeL) approach. These technologies are discussed in chapter 6, 7 and 8, and the prototype of a show case have been elaborated in chapter 9.

1.2   Aim and research questions

The aim of this thesis is to explore and model technology-enabled learning environments with associated learning processes that could provide automatically personalised learning paths to all learners based on their interest, progress and related individual characteristics by using Cloud learning resources.

Therefore, four research questions are explored:

RQ1: Which artificial intelligence (AI) approaches could facilitate the personalisation of learning experience, based on learners' profiles, with the aim of creating a generalizable model for personal learning activities within Learning Cloud environments?

RQ2: What features could influence the creation of personalised learning paths as a planning problem, taking into consideration the involvement of agents?

RQ3: What are potential problems of linking a sequence of learning objects found on the Cloud and how can these be loosely coupled, so that there is adequate flexibility to change the coupling as the user progresses?

RQ4: How can the Cloud eLearning approach be evaluated? Should a new prototype be created? Should the evaluation target only the functionality of this prototype or do we need a user evaluation also?

Within the larger aim of enriching experiences and advancing knowledge through personalised learning paths that acknowledge diverse learning preferences and thereby enrich experiences and advance knowledge through courses, Chapter 2 presents the concept of eLearning. Identification of learning requirements and personalisation characteristics are first presented in Chapter 3 and then furthered through analysis of relevant projects and studies. In Chapter 4 is presented the eLearning with respect to Cloud technology, followed by the proposal of Cloud eLearning as a new paradigm of eLearning in Chapter 5. Chapters 6 to 8 deals with technologies used in our proposal, followed by the experimental show case and the result of this case shown in Chapter 9 and 10.

1.3   Research Contributions

The main contributions of this thesis are twofold. The first contribution of this thesis is the definition and the vision for a new enhanced eLearning paradigm, named Cloud eLearning (CeL). The second contribution is the identification of necessary technologies and their requirements for fulfilling the aim of CeL, with respect to user profiles, learning object specifications, recommender systems and automated problem solving. These contributions are part of various peer - reviewed publications, which has been published during my PhD studies.

Publication 1:   A proposal of Cloud eLearning as an advancement of eLearning is offered. Throughout this contribution the related concepts, the aim and the vision is defined.

Publication 2:   Through this contribution a high-level architecture is proposed, by defining the techniques being used for representing the knowledge in the Learning Cloud.

Publication 3:   Through this contribution, the "Learning Cloud" is defined as it is consisted of different sources and everything stored in it can potentially be used for learning purposes. Since the knowledge comes from various sources, the transformation process is describe by proposing the CeL metadata standard for enabling the coupling of "Cloud eLearning Learning Object - CeLLO" which are structured electronic learning resources represented as the learning objects in CeL.

Publication 4:   A methodology of matching the learning objects with learners' profiles is demonstrated through an experimental recommender, namely the CeL

recommender. Through which, it is demonstrated how intelligently the CeL RS identify and rank those objects which are relevant to a specific learner, considering her profile and desires.

Publication 5: The construction of Cloud eLearning as an artificial intelligence planning problem with the goal to find a personalised learning path for any learner with a specific profile and particular desires to acquire new knowledge and skills. The validity of the approach was demonstrated through an example.

1.4   Thesis Overview

The overall thesis is orginised into four parts from I to IV, as depicted in Figure 1.3.

Part I consists of chapters 2 to 4. Chapter 2, the eLearning, which gives a comprehensive overview of the eLearning concepts, and it further elaborates the various types of eLearning environment, standards and specifications, and how the content and learners are represented within the eLearning platforms. Chapter 3, Personalised Learning – Identifies the attributes of personalised learning, and which aspects of personalisation are being used for providing personalised learning in various eLearning platforms. It starts with the learning theories and ends with a list of AI techniques used to model a personalised learning path, which Cloud eLearning aims to achieve. Chapter 4, the approach of eLearning using Cloud Services– Elaborates on eLearning with respect to cloud technology. It gives an overview of Cloud deployment and services models and it further details the approach of using cloud services in order to offer Cloud eLearning services.

Part II covers the proposal of the new paradigm of eLearning, namely the Cloud eLearning, it starts with a high level architecture up to detailing aspects of the concept as well as offering a comparison of eLearning and Cloud eLearning. Furthermore, it elaborates on personalisation of learning path, as an adaptive learning approach for Cloud to Cloud eLearning learners. The architecture is depicted as a three layer architecture, where the top layer of the architecture is the "Learning Cloud layer" populated with knowledge and learners' experiences, which tends to emphasize the "Learning Cloud". The "Learning Cloud" is consists of different sources for CeL and everything stored in it can potentially be used for learning purposes.

Part III consists with Chapters 6 to 8, by describing how it amalgamates various technologies, including knowledge representation, recommenders systems, automated planning, in order to fulfill the CeL aim specified in chapter 5. Chapter 6 – Explores the knowledge representation aspect of Cloud eLearning which comes as a natural consequence of this knowledge representation technology. Further, it describes the various approaches for

representing the learning materials, as well as the learners for the eLearning applications. The chapter ends with the modeling of Cloud eLearning learning objects, and the Cloud eLearning learners, which constitute the Learning Cloud. The knowledge within the Learning Cloud is derived from structured and unstructured learning repositories and adapted as Cloud eLearning Learning Objects known as CeLLOs. In this respect, "Cloud eLearning Learning Object - CeLLO" are structured electronic learning resources represented as the learning objects in CeL. The CeLLOs, learners' profiles and experiences have been described through Cloud eLearning Metadata, a metadata standard inspired from the previous standards used in education, such as Institute of Electrical and Electronics Engineers Learning Object Meta-data (hereafter, IEEE LOM) and Dublin Core, which has a significant role in the overall architecture further explained in section 6.3. The "Cloud eLearning Metadata - CeLMD" is a metadata approach used to transform the derived Learning Objects (from various sources) into CeL Learning Objects. Chapter 7 – Describes recommender technology and proposes the Cloud eLearning Recommender System as a middle-layer of the overall Cloud eLearning architecture, in order to filter the most appropriate Cloud eLearning Learning Objects for a particular learner background and instant desire. The hybrid approach for building the Cloud eLearning Recommender System is elaborated, in order to rank the relativeness of learning objects through content filtering and the prediction of the learning objects through collaborative filtering. To conclude, the Cloud eLearning Recommender System (CeLRS) has a two-fold purpose: (i) a personalisation role, in order to provide personalised CeL Learning Objects, and (ii) a filter role, in order to filter the highest ranking CeL Learning Objects into an input list for the artificial intelligent planner. Chapter 8 – Describes an automated planning approach prior to proposing that planning offers learning opportunities. Further, a number of planners are listed and a list of techniques used from these planners are explained, and at the end the Cloud eLearning Planner is described as the final process of the overall Cloud eLearning approach. The "Cloud eLearning Planner - CeLP" synthesizes the right CeLLOs in the personalised sequence based on learners' backgrounds and learners' interests.

Part IV consists of chapters 9 – 11, by offering the description of the experimental show case, the results generated from the experimental show case and finally the Conclusion. Chapter 9 describes the evaluation process which firstly starts with demonstration of functionalities through the Cloud eLearning prototype. The second evaluation process as a complementary evaluation of the first approach, involves experimental users in testing the use of the system related to the proposed and fulfilling the online survey. And Chapter 10 – Concludes the thesis and proposes new ideas for future work. Furthermore, it emphasizes the contributions that has been made toward fulfilling the aim of the thesis.
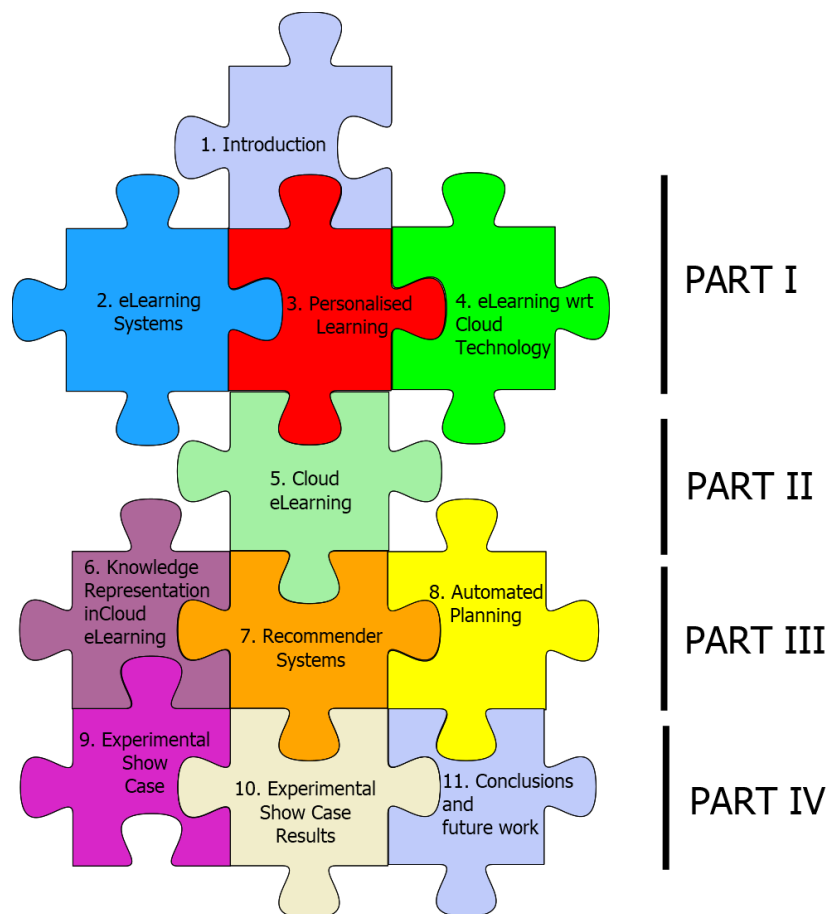
Fig. 1.3 Thesis Structure

Part I

The background with respect to eLearning, Personalised Learning and the use of Cloud Technology

Chapter 2

eLearning

This thesis extends the notion of eLearning by broadening the pool of sources required for a learner to all those available in the cloud. To make this possible, filtering and recommendation mechanisms are necessary to construct the final learning path for individual learner profiles. In order to set the background for our Cloud eLearning proposal, it is inevitable that we require to study the existing state of art in eLearning, identify gaps and discuss similar approaches.

This chapter defines and discusses eLearning systems together with the types of learning environment and how they support learners by storing and retrieving learning content. Learning Objects can be useful to some computation mechanism, i.e. retrieval, filtering, automated planning etc. only if a kind of standardization is applied that wraps around the learning objects with structured information about their content and its use. Thus learning objects are stored under some agreed standard specification format (meta-data) and form what we call Learning Repositories. ELearning systems draw objects from such repositories and manipulate them before they present them to learners. We present existing standards for meta-data which we will eventually use and extend later on in order to accomplish the aim of the CeL, i.e. personalized learning paths consisting of learning objects retrieved from the Cloud.

2.1   eLearning Definitions

The origin of using eLearning as a term dates back to the 1980's. However, many researchers used various terminologies and definitions before then for the concepts of network learning, distance learning, eLearning, online learning and virtual learning environments. These terminology discrepancies, are best explained through the review in [4] where the authors surveyed a considerable number of researchers in this domain worldwide in order to identify

the variation in meaning attributed to concepts of eLearning, distance learning, and online learning and their characteristics. While a majority of researchers perceived no differences among these concepts, others noted differences based on interaction processes or technology usages. Such variability in terminology illustrates the problem of inconsistent language and thereby findings in this research area. Therefore, this chapter begins with a review of studies, including definitions.

Generally, electronic learning allows people to have access to learning resources anytime and everywhere, using the technology. The "E" letter standing as part of the 'eLearning' term is used for electronic learning which overall combines all education network activities carried out by individuals or a group working online or offline through electronic devices [10]. Ruttenbur et al. [11] defined eLearning as the use of technology which has revolutionize the form of education. The authors further emphasize that the strength of eLearning is its ability to serve the right information, to the right people, in the right time. Clark and Mayer [12] define eLearning as instruction delivered through computers. Triacca et al. [13] emphasize that online learning is a type of online activity. Stamatis et al. [14] described distance learning as effective and low-cost approach form, whereas Moore [4] emphasizes the effort of providing access to learning for all the learners that are located geographically at a distance. Furthermore, King et al [15], goes one step further by differentiating the distance learning from distance education, describing distance learning as an ability and distance education as an activity within the ability. After considering the variation within the literature, we define eLearning concept as follows:

Definition 2.1: eLearning is offered through information and communication technology infrastructure, and whether it is offered as web-based platforms, programs, disks, and television or even through online or offline approach, it facilitates the learning process by providing learning opportunities for all learners.

Today, eLearning concerns vary depending whether the platforms are analysed from the ubiquitous availability, manageability, scalability, durability, usability, reliability, interoperability, accessibility or reusability perspective, to name a few. So, last decades, many researchers have tackle the problem of these *ilities characteristics, and tended to speculate and demonstrate how to increase them.

However lately, the research has been shifted to the customisation of eLearning courses and environment taking into consideration various personalised characteristics that might influence the overall learning process. The trends of new technology influencing these trends of research has been reflected in Figure 2.1, which depicts a roadmap of eLearning evolving history, influenced by Conole [16] and further we extended with the "Personalised Learning

Path" node, which have emerged with significant results after the evolution of computing processing power and massive data generation. The peresonalisation in general tends to shift the the eLearning paradigm furthermore by providing personalised learning paths to the learners, a learning path designed to meet the goals and characteristics of the learners. The Figure 2.1 reflects the history of eLearning in the last four decades, and it pinpoints the dominate trends, influential techniques and new technologies that have evolved the eLearning environments over time. And, in this regard, our approach is continuing the personalised phase, which in Figure 2.1 shows that its origin dates back to 2008, by analyzing the learners learning types, learning styles, other relevant characteristics that are related to the learners education background, their desires of acquiring knowledge in a particular topic and other characteristics that will be presented in the Chapter 5 and 6.
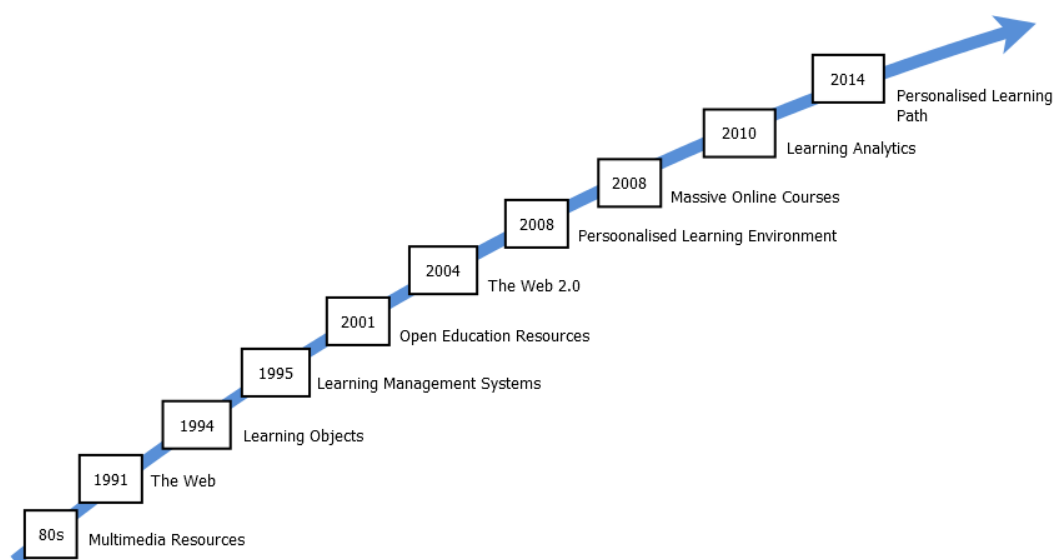
Fig. 2.1 The trend of development in eLearning

In analysing Figure 2.1, it is clear that from the development technologies of Open Education Resources and Web 2.0, the eLearning systems have experienced a spike development over the time toward personalisation features of learning process. With the introduction of personalised learning environments in 2008, the eLearning paradigm has progressively shifted toward personalised eLearning. These advancements resulted in eLearning system usage and its integration in our everyday life, especially to lifelong learners which are using these systems as a hub to their upcoming interests. As continuation of this approach, this chapter lists the types of eLearning environments, and continues with eLearning standards and specification used nowadays to formally model and represent the content and the learners' profiles as two important parts of the eLearning systems. In addition, within the framework

of these development trends, the Chapter 3 discusses the personalisation technologies used in eLearning and explains its impact on learning experiences.

2.2   Type of eLearning environment

The main users (actors) within the eLearning ecosystem are the learners and the teachers. Analysing eLearning from this perspective produces three types of learning environments. The first is teacher-centric, the second is learner-centric and the third is a so called "flat one"", which doesn't define any user hierarchy within the eLearning environments. Teacher-centric platforms offer an environment where the role of the teacher dominates and the learners are continuously guided through the content all the time, and all learners participate at the same activities. In contrast, learner-centric environments offer the opposite approach, described as independent learning, wherein the learner controls what to learn, when to learn, and from whom to learn. Finally, the flat approach describes an environment where there is no hierarchy between teachers and learners. Both roles might interact, collaborate and otherwise participate in various learning activities. In some scenarios, teachers are learners and learners are teachers, with traditional boundaries of producers and consumers blurred.

2.2.1   eLearning Platforms

Many universities use eLearning platforms to enhance students' learning activities by providing access to eLearning material anytime from everywhere. Overall, the key features of most eLearning tools or applications are how to increase collaboration, manage learners, their materials, facilities, announcement, notifications, delivering web-based courses, course assessment, mock exams, displaying scores and transcripts etc.

Still, researchers and developers struggle to create common terminology across various learning environments, national boundaries and disciplinary fields. Consequently, eLearning platforms are referred today as Learning Management Systems (LMS), Course/Content Management Systems (CMS), Collaborative Learning Environment (CLE), Virtual Learning Environments (VLE), Knowledge Management Systems (KMS) and so on. In [4], Gagné, Wager, Golas, and Keller in 2005 defined the CMS as a collaborative learning environment containing tools for developing and delivering courses with the aid of the Internet. Whereas, Wilen-Daugenti [17] in 2009 declared that the terms CMS, LMS and VLE should be used interchanged. Continuing, Trafford [18] defined Virtual learning environment as "a collection of software tools supporting academic administration, teaching and research". Furthermore, in [19] Virtual learning environment used interchanged with learning management systems

and content management systems concepts are defined as a "system for delivering learning materials to students via the web".

Having in mind the diversity of terminology used from various researches, within this thesis is given a number of definitions to emphasize the approach of each terminology as part of this thesis. Following this idea, the definition 2.2 encompasses essential elements of the Virtual Learning Environment:

Definition 2.2: Virtual Learning Environment (VLE) is a platform that offers an integrated environment approach of various resources that enables a collaboration among learners and teachers and interaction of learners with the content.

Within the VLE, the learners are not only active but also actors, in a sense that they contribute as well in content creation as part of social interaction related to a specific topic, in a direct or indirect manner. This includes:

   (i) synchronous and/or asynchronous communication,

  (ii) one-to-one, one-to-many or even many-to-many communication, and

 (iii) text, audio or video communication as three-dimensional communication.

The integrated environment approach mentioned above may be one product or an integrated set of various tools. In this regard, not only are students and teachers learning about eLearning environments and experiences but so do the researchers. They study how participants build individual and collective knowledge about the environments and because of the environments, especially as relates to information focused teacher-student interactions.

2.2.2 Massive Open Online Courses

The research conducted in [9] showed that Massive Open Online Courses (hereafter MOOC) have become one of the most attractive topics in higher education since the educational landscape are facing the reduced public budgets and soaring costs. MOOC represent online courses aimed at unlimited participation and open access via the Internet. In particular, they represent a dramatic stage in web-based education systems that has been enabled by the rapid growth of Internet access and increase in bandwidths over the past decade [20].The main objective of the MOOC development relies within the philosophy of openness in education, promoting that knowledge should be shared freely regardless to the demographic, economic, social, and geographical constraints.

The term MOOC on the other hand was first emphasized in 2008 by Dave Garner and Bryan Alexander to describe an online open course which was developed at the University of

Manitoba by George Siemens and Stephen Downes and had over 2200 learners from all over the world [21]. The course was perceived as an instantiation of the connectivist approach to learning, whereby learning is perceived to take place through making connections to knowledge resources and people in the network [21].

The biggest impact of MOOC in higher education was in 2011 when Sebastian Thrun and Peter Norvig from Stanford University opened access to their course Introduction to Artificial Intelligence for free. This course attracted 160,000 learners from all over the world and led to the foundation of the startup Udacity. After this success of Udacity, two more MOOC were followed within months, i.e. Coursera and edX, which together with Udacity are the main front-runners offering hundreds of MOOC from various elite universities around the world. In addition to traditional course materials such as videos, readings, presentations, audio recordings, and problem sets, MOOC provides interactive user forms that help design a community for students and teachers. The advantages and opportunities that MOOC offer for "massification" of courses' has created a great and convincing interest from governments, institutions, media and commercial organizations. The Cloud Computing technology have supported the scalability of this "massification" and it has accelerated the fast evolution and expansion of MOOC.

This evolution and expansion of MOOC has attracted the interest of more players in the market as higher education institutions and venture capitalists seek to generate revenue streams by taking advantage of this innovative approach in online learning MOOC provide [22]. MOOC remained relatively unknown until 2011 when a number of the most prestigious universities in the United States started to offer MOOC by putting their courses online and by setting up open learning platforms, such as edX, Coursera and Udacity. MOOC platforms require much efforts to care for the user experience [23].

Table 2.1 Features supported by LMS and MOOC

Features Capabilities		LMS	MOOC
Agent	Single-Agent	-	-
Interaction	Between users	+	+
	Within the course content	-	-
Personalisation	Assessment	-	-
	Learning Path	-	-
Ontology		-	
Taxonomy	Within Content	-	-

However, besides the common features that learning management systems and MOOC possess such as [9, 24]: customized environment, communication channel, testing and assessments, there are still features that are missed (Table 2.1), such features that could

contributes to personalisation, such as: personalisation of assessment, interaction with the course content, personalisation of learning path among others. As far as the interaction with course content concerns, it provides a faded interaction because even that some LMS or MOOC do provide it, the reactivity of the system for any input behaves the same. These findings will contribute to differentiate the new proposal, discussed in Chapter 5.

2.3   Learning Objects, Learning Object Repositories and metadata standards

Current eLearning systems have progressed based on the idea of creating learning object repositories (LOR) in order to be able to reuse learning content across different platforms. The learning object has been described and named differently by various researchers, such as: knowledge object [25], instructional object [26], sharable content object [27], content object [28], learning resources [29]. Based on [5] the learning object is defined as:

> Definition 2.3: Learning Object is a digital resource that can be used and reused to fascilitate learning.

Their popularity is attributed to their versatility. LOs can be used as part of a lesson, module or course within different eLearning platforms and they are provided through learning object repositories.

The most widely used Learning Object Repositories include: MERLOT, storing only links to the content resources and metadata; CONNEXION, storing the content and metadata of LOs; and ARIADNE used as a federated repository, gathering all the learning resources from existing LORs.

The professional literature reveals other repository resources as well. Zervas et al. [30] lists fifty different learning object repositories, presents indication of their scopes, details size of Learning Objects collections and offers number of registered users. These parameters could reasonably suggest impact and popularity of the respective LORs, as they reflect if people appreciate and use them. Ochoa & Duval [31] categorize existing LORs into:

(i) Learning Object Referatory (example: MERLOT[1]),

(ii) Learning Object Repository (example: Connexion[2], ARIADNE[3]),

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[1] MERLOT, merlot.org
[2] CONNEXION, cnx.org
[3] ARIADNE, ariadne-eu.org

(iii) Open CourseWare Initiatives (example: MIT[4]),

(iv) Institutional Repositories and Institutional Repositories - University.

McGreal [32] divided the learning object repositories into only three categories, according to providers:

1. Content of Learning Objects and metadata

2. Metadata with links to Learning Objects in different sites

3. Hybrid repositories from both categories 1 and 2, that host content and link to external Learning Objects

This categorisation reflects differentiation about whether a LOR offers LOs as content, content and metadata, only a link to content, or only a link to content and metadata.
In this thesis perspective, the learning object repositories are:

Definition 2.4: Learning Object Repositories (LORs) are databases containing either Learning Objects or metadata with links to Learning Objects or learning objects with metadata.

In order to expedite storage and retrieval of learning objects various organizations have established different metadata standards, such as IEEE LOM, Dublin Core (DCMI)[5], CanCore[6], and others. Learning Object Meta-data are used as a dictionary of tags for describing the learning content. For instance, IEEE is a LOM standard for creating a well-structured description of LOs. This model defines what vocabularies should be used to specify a Learning Object (Table 2.2).

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[4]MIT OpenCourseWare, Massachusetts Institute of Technology, https://ocw.mit.edu/index.htm
[5]Dublin Core, Metadata Initiaive, dublincore.org
[6]CanCore: Metadata for Learning Objects, https://eric.ed.gov/?id=EJ661421

Table 2.2 Elements and sub-elements of IEEE Learning Object Meta-data standard[1]

1. General	2. Life Cycle	3 Meta-Metadata
1.1 Identifier 1.2 Catalog 1.3 Entry 1.4 Title 1.5 Language 1.6 Description 1.7 Keyword 1.8 Coverage 1.9 Structure 1.10 Aggregation Level	2.1 Version 2.2 Status 2.3 Contribute 2.4 Role 2.5 Entity 2.6 Date	3.1 Identifier 3.2 Catalog 3.3 Entry 3.4 Contribute 3.5 Role 3.6 Entity 3.7 Date 3.8 Metadata Schema 3.9 Language
4. Technical	**5. Educational**	**6. Rights**
4.1 Format 4.2 Size 4.3 Location 4.4 Requirement 4.5 OrComposite 4.6 Type 4.7 Name 4.8 Min Version 4.9 Max Version 4.10 Installation Remarks 4.11 Other Platform Requirements 4.12 Duration	5.1 Learning Resource Type 5.2 Interactivity Level 5.3 Semantic Density 5.4 Intended End User Role 5.5 Context 5.6 Typical Age Range 5.7 Difficulty 5.8 Typical Learning Time	6.1 Cost 6.2 Copyright and other Restrictions 6.3 Description
7.Relation	**8.Annotation**	**9.Classification**
7.1 Kind 7.2 Resources 7.2.1 Identifier 7.2.2 Description	8.1 Entity 8.2 Date 8.3 Description	9.1 Purpose 9.2 TaxonPath 9.2.1 Source 9.2.2 Taxon 9.2.2.1 ID 9.2.2.2 Entry 9.3 Description 9.4 Keyword

IEEE Learning Object Meta-data standards produce specifications for expressing LOM model using XML and RDF, as shown in Figure 2.2 [1].

```
<lom xmlns="http://ltsc.ieee.org/xsd/LOMv1p0">
  <general>
    <title>
      <string xml:lang="en">Ecologues</string>
      <string xml:lang="la">BUCOLICA</string>
    </title>
    <language>la</language>
  </general>
  <technical>
    <location type="URI">
      http://classics.mit.edu/Virgil/eclogue.html
    </location>
  </technical>
</lom>
```

Fig. 2.2 IEEE Learning Object Meta-data is encoded in XML

The Dublin Core Metadata Initiative (DCMI) standard originated in 1995 as a cross domain resource description. However, in 2006 DCMI evolved into the Dublin Core Metadata Element Set, which resulted with new documentation terms from its usage board. DCMES facilitates the discovery of web resources through its 15 Dublin Core elements, divided into three classes [33]: (a) Content (such as title, subject, description, source, language, relation, coverage); (b) Intellectual Property (such as creator, publisher, contributor, rights); and (c) Instantiation (such as data, type, format, and identifier). The Dublin Core, uses Extensible Markup Language (XML) for representing a Dublin Core metadata description, as shown in Figure 2.3.

```
<meta name="dc.language" CONTENT="UK">
<meta name="dc.source" CONTENT="http://www.your-domain.com/">
<meta name="dc.relation" CONTENT="http://www.second-domain.com/">
<meta name="dc.title" CONTENT="a title">
<meta name="dc.keywords" CONTENT="more keywords">
<meta name="dc.subject" CONTENT="the subject">
<meta name="dc.description" CONTENT="A description of the content">
```

Fig. 2.3 Examples of the Dublin Core Metadata

Comparing to IEEE LOM, the Dublin Core defines no pedagogical metadata in leaning objects. The pedagogical part is added by teachers themselves [34]. The reason we emphasize this here, is that it makes us think whether there might be added new elements in existing standards that could facilitate the description of learning objects besides the listed elements in Table 2.2 toward of loosely coupling learning objects (coupling the learning objects in different context and in different learning sequence), as part of a personalised learning path.

2.3.1   LO Granularity and Intended Learning Outcomes of Learning Objects

One of the most important characteristics of Learning Objects is that they aim to be shared and reused. The definition of granularity of learning objects has contributed toward the reusability of learning objects [35]. Granularity refers to the learning time required to devote to a given LO for learning and it is proportion to the size of the LO. Examples include running time of a video, the number of pages in a book, or the effort allocated to completing a task, such as a written assignment or a test. The granularity of a LO could affect the integration of the learning object in various learning paths, it affects also the reusability of them in various contexts.

Reusability is one of the key characteristics of Learning Objects'. With this aspiration, developers know that the lower the granularity of a LO, the higher its chances to be reused in different contexts [36]. Admittedly, LO granularity is defined differently by different organizations and within different Content Models (SCORM, CISCO, Learnativity, IMS Content Packaging etc.) [37]. For instance, Cisco Systems has suggested that five to nine information objects could be combined to create a single LO, wherein information objects are defined as a set of raw data, such as text, video, images and photos.

The IEEE Learning Technology Standards Committee (hereafter: IEEE LTSC) envisions that an entire curriculum could be viewed as a learning object. Robson [38] suggests that the granularity of one LO should be between 5-15 minutes. Metros [39] recommends an LO as a digital resource only if it has at least: (a) one intended learning outcome, (b) one practice activity and, (c) one concluding assignment. Shoonenboom [40] describes different scenarios for determining the size of LOs, and the ability to reuse the modules in a personalised way. As it is shown, there is no standard definition about how the granularity of a LO should be defined, so it typically varies.

In general, however, in order to be able to create alternative learning paths, LO size should be smaller rather than bigger. This can map nicely towards gluing together LOs with intended learning outcomes. An Intended Learning Outcome or Objective (ILO) is expressed as what the learner should be able to do when a learning object is studied and assessed. Towards this direction, the condition of having the smallest number of ILOs as possible leads the course designer to use known taxonomies when assessing cognitive skills, such as the Bloom's taxonomy [41, 42], explained in section 3.2.

Modeling taxonomies of intended learning objectives could be difficult; however, there are initiatives which aim to implement educational metadata that include learning objectives and related attributes for learning resources using taxonomies' categorization. For instance,

Learning Resource Metadata Initiative (LRMI) [7] and Schema.org [8] aim to improve accessibility of all internet content, with or without an education orientation. LRMI references taxonomies and captures semantic content. In a complementary fashion, schema.org uses consortia of top search engines like bing, google, yahoo and yandex to make the web more effective through a framework for using standardized metadata.

2.4 Representation of Learners' profile

The representation of learners is another important component in eLearning, especially when dealing with integration of personalisation in the eLearning systems discussed in section 3.1. In order to design appropriate learners' profiles, various organizations have contributed to the invention of shared standards. Among them, IEEE LTSC Personal and Private Information (PAPI) standard and IMS Learner Information Package (LIP), are the most well-known standards which enable resource designs and describe learner profiles based on learners' personal information, interests or activities.

The representation of learners' profile varies based on the standards in use. For example, when using the IEEE Public and Private Information (PAPI) standard, the learners' profile is represented through description of six categories: (i) personal, (ii) relation, (iii) security, (iv) preferences, (v) performance and (vi) portfolio learner information.
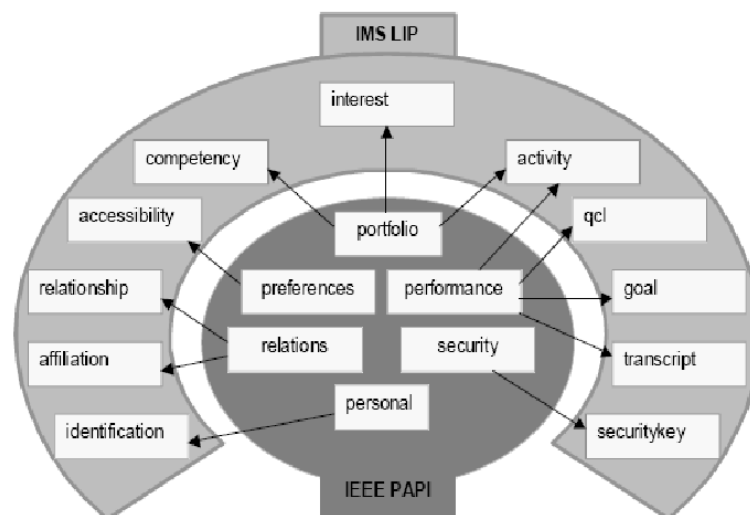
Fig. 2.4 The connections among elements in the LIP and PAPI specification standards[43]

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[7] http://lrmi.dublincore.net
[8] https://schema.org

Whereas, when using the IMS Learner Information Package (LIP), the learner is represented through the following categories: (i) identification, (ii) goal, (iii) Qualifications, Certifications and Licenses (QCL), (iv) activity, (i) interest, (v) relationship, (vi) competency, (vii) accessibility, (viii) transcript and (ix) affiliation categories. As shown in Table 2.3, the IMS LIP wraps the IEEE PAPI specification standard, visually illustrated in Figure 2.4, through the definition of relationships among the elements.

Table 2.3 IEEE PAPI and IMS LIP elements

IEEE PAPI	IMS LIP	Description
Portfolio	Interest	Information describing learner hobbies and recreational activities
	Competency	Information for skills, experience and knowledge acquired
	Activity	Information about learner latest activities
Preferences	Accessibility	Information for general accessibility, such as: language capabilities, disabilities, eligibility, and learning preferences
Relations	Relationship	Information for relationships between core data elements
	Affiliation	Information about membership in professional organizations
Personal	Identification	Information related to demographic and biographic elements of a learner
Security	SecurityKey	Credential Information
Performance	Activity	Information about learner-related activity in any state of completion
	QCL	Information which identifies the qualifications, certifications, and licenses from recognized authorities
	Goal	Information regarding learner targets, career expectation and other objectives
	Transcript	Information of academic achievements

Each of the elements contained in both standards are explained further, in detail, in Table 2.3. Both specification standards have been used and adapted by various eLearning systems for the purpose of developing learners' profiles. Relatedly, standards are improving over time.

Summary

This chapter sheds some light on fundamental concepts of eLearning, the evolution, its definition and the variety of eLearning types and platforms. Following analysis of other researchers' contributions, a working definition of eLearning and particularly virtual learning environment for this thesis was presented. Further, in section 2.3, use of different standards and specification is discussed in order to represent the status of existing knowledge about learner profile creation. A list of learning objects repositories is presented and analysed, in order to characterize the breadth and depth of open educational resources content available for educational use across the globe. Based on this analysis, the next chapter will focus on personalisation of eLearning systems, an important field of research, which has contributed greatly to investigation of potential learning processes with associated learning impact.

Chapter 3

Personalised Learning

Educational research has resulted in a number of theories which describe the way humans learn. This leads naturally to creating an individual learning type for each learner that describes the way that is more suitable for each of them to be guided to the acquisition of new knowledge and new skills. Personalisation in learning assumes that the type of learners is known before hand. More specifically, if we wish this personalisation to be automated, for instance in CeL, we must create a profile for each learner that will not only include their types but also their existing knowledge and skills as well as their desires and goals with regards to what they wish to learn and how. Therefore, related work is studied, so that we can identify all these elements that will be useful to our approach.

This chapter defines and discusses personalisation approaches that are encountered nowadays in order to offer personalised eLearning. A number of learning theories are studied and particularly focus is given to the Kolb and Felder and Silverman theories. The latter one is used to categorise the learners depending on their learning styles in Cloud eLearning. Furthermore, a list of techniques, mostly drawn from artificial intelligence, are analysed in order to acknowledge their contribution towards offering personalized learning paths. Overall, the intention of this chapter is to see how the learning theories are used to offer personalised eLearning and which artificial intelligence techniques are used so far in order to offer personalised learning paths to the eLearners.

3.1 Personalisation in eLearning systems

Nowadays, personalisation is an essential feature of a learning environment. It permits learners to customize the environment and the activities in response to their own ways of learning. Instead of a "one-size-fits-all" approach, the learner-centric personalisation approach in eLearning environments can be customized by learners to accommodate their

learning preferences. This necessarily requires prioritizing personalisation in design of the learning environment, learning materials, and learning activities.

A number of personalisation features are commonly used today to shift the paradigm of eLearning platforms from teacher-centered to learner-centered, namely toward the personalised eLearning approach. Personalisation features include: (i) knowledge representation, (ii) cognitive learning styles, (iii) adaptation to the learner needs; (iv) generalizing/specializing the search, and other relevant retrieval techniques.

Definition 3.1: Personalised eLearning encompasses the possibilities to adapt the environment and/or the content of the eLearning courses based on learners characteristics.

Based on [44], there are two main approaches of personalisation:

(i) the personalisation based on user profile and

(ii) the rule-based personalisation which in absence of a user profile, creates the personalisation based on decisions from predefined rules. Example: the learners can be grouped based on the visited topics, then the providers can manually set up a rule what experiences or content to propose to various group of users.

According to [44], when deciding to personalise an eLearning environment, a number of features could be considered, such as personalising the:

(i) environment,

(ii) content,

(iii) learning objectives,

(iv) learning content sequences,

(v) media,

(vi) navigation and so on.

The personalisation is an essential characteristic of eLearning systems, and in order to obtain the highest value from the learning process, the environment should be capable of accommodating many personalisation elements, including learning theories, learning stages, learning styles, learners' motivation and learners' needs. These personalisation elements enable personalisation of user environments, personalisation of learning paths and assessment methods, personalisation of learning activities, recommendations of learning material and

personalisation of communication channels and collaboration tools. In these various ways, eLearning systems are shifting from eLearning to smart or personalised eLearning as emphasized above. Influenced by the aforementioned approaches, personalisation is categorized according to:

(i) customized processes and/or

(ii) adaptive personalisation processes.

These processes imply the new systems, the use of adaptive hypermedia systems in eLearning, which tends to represent the adaptiveness of the system based on user profile. The customised personalisation process shifts the control of the environment to the learner by enabling the possibility of selection of options in an explicit way, whereas the adaptive personalisation process emphasises the important role of personalised elements in the use of the system. The adaptive personalisation process is an implicit process, which identifies items of potential learner interest based on the learner's profile while tracking learners' learning activities through intelligent tutoring techniques. To make more clear, the following definitions are used in this thesis for both kind of systems:

Definition 3.2: Adaptive Hypermedia eLearning Systems are systems that represent the learning materials through combinations of text, hypertext, hyperlinks, video, and audio and represent them to the learner by considering the selection of the most appropriate content based on learner's profile.

Definition 3.3: Intelligent Tutoring Systems are web and computer-based systems which incorporate Artificial Intelligence techniques for providing a personalised learning environment.

Since, in the very beginning we stated that the Cloud eLearning is comprised of various sources of learning materials and everything stored in it can potentially be used for eLearning purposes, then we suggest:

(i) that the presentation of learning materials will be in various formats such as it is in adaptive hypermedia systems(AHS), and

(ii) the proposed Cloud eLearning will provide the possibility to personalise the learning path through the use of knowledge representation, text mining, and automated planning which all reside within the artificial intelligence domain.

3.2   Learning Theories

Learning theories as a set of orginised principles explains how individuals acquire, retain, and recall knowledge [45]. By studying and knowing a various number of these learning theories, we can imagine and better understand how the learning as a process occurs. Furthermore, we could analyse how different style categories influence the learning process for various learners. Although the cognitivist learning approach is most relevant in this work, a brief overview of the landscape is provided here. Basically, a learner can acquire knowledge (learn) through two various learning processes:

(i) through formal structured activities (for example, attending formal lecture activities) and

(ii) through learning experiences (for example: learning by doing).

Definition 3.4: Learning is a process that is undertaken by learner in order to pursue new knowledge, skills and abilities.

The learning process itself is different for various learners, depending on learners' personality, cognitive and other previous learning experiences [46]. Therefore, it is important to take into consideration when designing a course, so a personalised set of learning theories, stages and styles could be generated and integrated into the learning experience.

Providing customisation features in the eLearning environment will increase the personalisation of the system, which will thereby facilitate the learning process, and as a result will increase the learning progress. For the sake of this, it is important to understand the importance of learning theories, learning stages (learning cycle) and learning styles present nowadays.

Learning theories are principles that define how learners acquire, retain and recall knowledge [46]. Among the many learning theories that explain how learning occurs, four that are encounter in our proposal are listed in Table 3.1, followed by the description of the process of knowledge creation with respect to learning activities [45, 46].

A number of theorists [47, 48] have contributed to the aforementioned theories. For example, in behaviourism, Skinner, Pavlov, Thorndike, Watson and others emphasized that behaviorism is concerned with observable and measurable aspects of human behavior. In cognitivism, the process of actively constructing knowledge passes through four phases: sensorimotor, preoperational, concrete operational and formal operational, and the theorists that contributed in cognitivism start with Piaget, Gagne, Vygotsky and so on. Social constructivism, according to (Freire, 1970; Illich, 1970) as cited in [49], emphasize the individual

Table 3.1 Learning theories

Learning theories	Describing the process of knowledge creation
Behaviorism	Learning is defined as acquisition of new behaviour or change in behavior. The knowledge of the learners' is increased through the shaping process, which is defined as the process of gradually increasing the desired behaviour which is manifested as learners' changing behavior .
Cognitivism	Learning is experienced through internal processing of information, where the learner retrieves, processes and stores information. New information is generated through refining prior understanding to advance more complex ideas that hierarchically structure problems and conceptually link models.
Constructivism	Learning is constructed based on learners' previous experience, prior knowledge, social interaction (between learners and environment), which is known as constructing knowledge through social processes.
Connectivism	Learning is acquired through a set of distributed connections in a network under an uncontrolled way. In the digital age, learners are consumers and producers of knowledge, able to create their own learning content through collaborative tools and share it according to their cognitive preferences. The connectivism theory emphasizes the importance of learners' connections rather than their current knowledge.

differences as well as the migration of the learning process from the teacher-centred to learner-centred, where the teacher is not encouraged only to transmit the information and the knowledge to the learners but also to facilitate the learners' identification of their own learning paths and processes, and the theorist that contributed in these theories starts with John Dewey, Jerome Bruner, David Merrill, Lev Vygotsky, Seymour Papert, Duffy T. and Cunningham D., Wilson B. Lately, the connectivisim theory known as the learning theory of the digital age, firstly mentioned by George Siemens[21] and then raised by Stephen Downes[35], emphasised the knowledge construction through relevant information patterns and new connections.

3.2.1   Learning styles and learning stages

Although the necessity to adapt teaching to the needs of learners' is generally accepted, there are a number of learning style models that have been developed, reflecting these differences, while only some of them have been the subject of studies in the engineering education literature, particularly [50]. According to Keefe 1979, as cited in [50]:

Definition 3.5: Learning styles are "characteristic cognitive, affective, and psychological behaviors that serve as relatively stable indicators of how learners perceive, interact with, and respond to the learning environment".

Learners perceive the information (acquire the knowledge) in different ways. Some of them perceive new information better through abstract and theoretical approaches, whereas others tend to acquire knowledge through practical approaches. Additionally, some learners prefer learning through visual presentation and others through verbal explanations. Furthermore, some learners tend to be influenced by active learning and so on.

Table 3.2 Learning styles [2]

Types of learning styles	Key theorists
Learning styles and preferences are largely constitutionally based including the four modalities: Visual, Auditory, Tactile and Kinesthetic Learning Styles (VAKT)	Dunn and Dunn, Gregorc, Bartlett, Betts, Gordon, Marks, Paivio, Richardson, Sheehan, Torrance.
Learning styles reflect deep-seated features of the cognitive structure, including 'patterns of ability'	Riding, Broverman, Cooper, Gardner et al., Guilford, Holzman and Klein, Hudson, Hunt, Kagan, Kogan, Messick, Pettigrew, Witkin.
Learning styles are one component of a relatively stable personality type	Apter, Jackson, Myers-Briggs, Epstein and Meier, Harrison-Branson, Miller.
Learning styles are flexibly stable learning preferences	Allinson and Hayes, Herrmann, Honey and Mumford, Kolb, Felder and Silverman, Hermanussen, Wierstra, De Jong and Theijssen, Kaufmann, Kirton, McCarthy.
Move on from learning styles to learning strategies, orientations and conceptions of learning	Entwistle, Sternberg, Vermunt, Biggs, Conti and Kolody, Grasha-Riechmann, Hill, Marton and Säljö, McKenney and Keen, Pask, Pintrich, Smith, Garcia and McCeachie, Schmeck, Weinstein, Zimmerman and Palmer, Whetton and Cameron.

This diversity of learners' characteristics is recognized through integrating various learning styles in eLearning systems. This approach is used in order to personalise the learning

process through adaptive personalisation methods mentioned in the previous section, in order to recommend a list of learning materials that match learners' preferences and thus learners' learning styles. In Table 3.2, a number of learning styles are listed in combination with the key contributors to particular types.

Each of the learning styles theorists tended to cover learners' preferences through learning style dimensions, which may be different, depending on the model proposed. As shown in Figure 3.1, David Kolb [51] proposed the experimental learning cycle model containing four categories in order to acquire learning, such as : (i) concrete experience (feeling), (ii) reflective observation (watching), (iii) abstract conceptualization (thinking), and (iv) active experimentation (doing). He argued that learning environments which neglect learning styles are most likely resented.
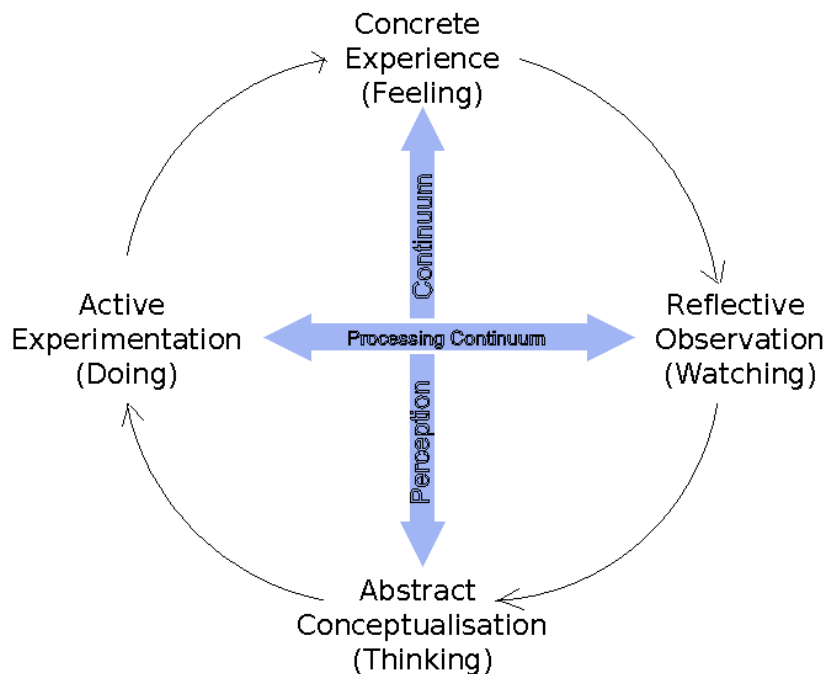
Fig. 3.1 Kolb Experimental Learning Cycle Model [51]

Indeed, as shown in Table 3.2, Allinson and Hayes, Herrmann, Honey and Mumford, Kolb, Felder and Silverman, Hermanussen, Wierstra, De Jong and Theijssen, Kaufmann, Kirton and McCarthy treat the learning styles as flexible stable learning preferences, wherein each learner has a preference for one or more of the dimensions [2]. However, there are researchers that treated the learning styles particularly from an engineering education perspective, such as Herrmann [52], Dunn and Dunn [53], Kolb [51], Jung's Theory of psychological type as operationalized by the Myers-Briggs Type Indicator (MBTI)[54]. Furthermore research studies from Felder and Silverman [55] targeted engineers when categorizing learners based

on the proposed of their learning model. The latter one was influenced by Jung's theory for sensing/intuitive dimensions and from Kolb's theory for active/reflective dimensions. Besides the characteristics of this theory, the experience of appling its theory in engineering students, as well as the positioning of the learners learning styles as flexible stable learning preferences are two key attributes that I encountered when deciding to use in our proposal.

Further, Felder and Silverman [55] proposed a four scale learning styles, which categories learners as:

(i) sensing/intuitive learners (how the information is taken),

(ii) visual/verbal learners (how the information is presented),

(iii) active/reflective learners (how the information is processed) and

(iv) sequential/global learners (how the information is organised).

The characteristics of the learning process based on the Felder and Silverman model are further described in Table 3.3.

Table 3.3 The Characteristics of Felder and Silverman Index of Learning Style

Scales	Descriptions
Active/Reflective	Describes the learners' participation in activities (active/passive)
Sensing/Intuitive	Describes the learners' perception of the content (concrete/abstract)
Visual/Auditory	Appreciates the content presentation format (visual/verbal)
Sequential/Global	Determines the content flow and progression (sequential/global)

3.2.2   Index of Learning Styles by Felder and Soloman

As described in [52], the learning style model was formulated by Richard M. Felder and Linda K. Silverman, and then the survey instrument (Index of Learning Styles) was developed and validated by Richard M. Felder and Barbara A. Soloman.

The Felder-Soloman index of learning styles includes (Table 3.3) most learning preferences approaches. It is designed based on four scales, where each of the scales has two opposite preferences, as mentioned in section 3.1. The Active/Reflective scale emphasizes how the learner prefers to process information, the Sensing/Intuitive reflects how the learner prefers to take in the information, the visual/auditory identifies how the learner prefers

the information to be presented, and the final scale, the sequential/global, highlights the preference of the learner for organizing the information. In order to identify the learning preferences of the learner, an assessment tool which tends to identify which student is in which categories they do belong using the Index of Learning Style (ILS) [56] which contains 44 questions. A number of ILS questions are shown in Table 3.4.

Table 3.4 A number of questions from index of learning styles[3]

Possible questions	Possible answers (single choice)	
I understand something better after I:	try it out	think it through
I would rather be considered	Realistic	Innovative
When I think about what I did yesterday, I am most likely to get:	a picture	Words
I tend to:	understand details of a subject but may be fuzzy about its overall structure	understand the overall structure but may be fuzzy about details
When I am learning something new, it helps me to:	talk about it	think about it
If I were a teacher, I would rather teach a course:	that deals with facts and real life situations	that deals with ideas and theories
I prefer to get new information in:	pictures, diagrams, graphs, or maps	written directions or verbal information
Once I understand:	all the parts, I understand the whole thing.	the whole thing, I see how the parts fit
In a study group working on difficult material, I am more likely to:	jump in and contribute ideas	sit back and listen
I find it easier:	to learn facts	to learn concepts
In a book with lots of pictures and charts, I am likely to:	look over the pictures and charts carefully	focus on the written text

Results can show that the learner may be equally balanced between the opposite dimensions within one scale, or they can dominate only in one dimension [3]. In each of these four dimensions you got a range from strongly active to strongly reflective and that we could use any number in the position of the learner for each of his/her positioning. However for

simplicity reasons in our thesis, we will categorise the learners only in two categories, based how the information that is presented: visual, verbal.

3.3   The use of cognitive domain in eLearning

Offering flexible content to the learners and still making sure that the learners advance their learning skills to achieve their learning goals presents a challenge. Today, a number of classification models are encountered that contribute toward this process, using taxonomies, ontologies and other relevant approaches to offer a personalised learning based on cognitive level. Following that way, a number of contributors [57–62] have proposed the use of Bloom taxonomy to model intended learning outcomes of relevant learning materials or even of the whole curriculum of a particular field. For example, if the aim of the learner is to move from novice to an expert for a particular topic, then learning objectives must reinforce that aim. A number of expert systems in AI [58, 63–66], they use Bloom Taxonomy to categorise the content difficulty. The Bloom taxonomy introduced by Benjamin Bloom presents a model containing three domain categories of human learning. Also known as KSA (Knowledge, Skills and Affective) categories, these domains include:

1. Cognitive: mental skills (knowledge);

2. Affective: growth in feelings or emotional areas (attitude or self) and

3. Psychomotor: manual or physical skills (skills).

The cognitive category, as the most important category for Creating and acquiring new knowledge is then divided further into six other subcategories which were modified in 2001 by Anderson and Krathwohl [41], former students of Bloom, as defined in the Table 3.5.

Each of the categories are identified by a set of verbs which could be used on creation of learning outcomes (LOs) for learning activities. For example, the category "Remembering" could be indicated in intended learning objectives (ILO) by using verbs like name, recall, state, list, and so on. Each of these categories are tightly dependent on the lower level categories, thus going from the down-top approach as the difficulty of the learning process increases. As it is shown in Table 3.5 the critical thinking is concentrated in the three top levels of the model. To make it clear and understandable, for example, in order to learn the topic "x", firstly it is enough to remember it. After that, it is crucial to understand the topic "x", furthermore before analyzing it, we should know how to apply it, and before creating we should evaluate it [41]. In this way, the evolution of learning process is accelerated going from bottom to up level. Besides the bloom taxonomy, there are other initiatives of taxonomies,

Table 3.5 Revised Bloom's Taxonomy [19]

Pyramid Levels	Key Verbs (keywords)
Creating	design, formula, develop
Evaluating	choose, support, relate, determine, defend, judge, grade, compare, contrast, argue, justify, support, convince, select, evaluate
Analyzing	classify, break down, categorise, analyze, diagram, illustrate, criticise, simplify, associate
Applying	calculate, predict, apply, solve, illustrate, use, demonstrate, determine, model, perform, present
Understanding	describe, explain, paraphrase, restate, give original examples of, summarise, contrast, interpret, discuss
Remembering	list, recite, outline, define, name, match, quote, recall, identify, label, recognise

such as: Learning Resource Metadata Initiative (hereafter LRMI) and Schema.org which aim to offer new opportunities for better accessibility of all Internet content. LRMI references the taxonomies and captures their semantic content, whereas Schema, made by a consortium of top search engines such as Bing, Google, Yahoo and Yandex, makes the web more effective by creating a framework for using standardised metadata. While the classification of intended learning outcomes using Bloom taxonomy is based on the verbs used, the other approach of classification, such as the use of ontologies, is based on the concepts used. Ontologies are seen as conceptualisation of a domain of interest that can be used in web resources to model, analyse and reason upon the certain domain. Since the ontologies contain a number of concepts and their relation between them, there are also tools that aid building and further extending the ontology using visual languages. However, at the end, the tools will be able to convert the visual languages into a machine understandable format, such as: OWL, XML etc. Using a combination of various classification approaches raises the chances to offer more flexible content. How to tackle the classification problem from a broader spectrum is further explained in chapter 7.

3.3.1 Flexible learning paths

Formerly, the learning activities, including the learning sequence of the materials, was dictated by the teachers and the learners did not contribute to this process. That is why the earlier eLearning systems have been described as teacher-centric.

As shown in Figure 3.6, a course contains materials, assessments units, a defined syllabus which was accredited from the appropriate agencies in order to award each learners' with

Table 3.6 Fundamental characteristics of Course

Course - main elements	
syllabus	What to learn?
material	What sources to use?
assessment	How to be assessed?
accreditation	How to get credits towards a degree?

the appropriate methods for getting the credits after completing successfully the particular course.

Nowadays, the new eLearning systems that tend to shift learning from teacher-centered to learner-centered consider the personalisation of learning paths as key features to accommodating learner preferences, learner-specific goals and learning objectives. The personalised learning path brings the learner in the center of the learning process, by enabling a learner in a course to elect a customized learning path and learning pace, taking into account the learning materials, learning activities, learning assessments and learning experience, to name a few. Currently, eLearning systems uses Learning Design Specifications as one of the specification metadata [67] which is used for describing the pedagogical models and educational goals for modeling learning process. Specifically, the IMS Simple Sequencing Specification is used for modeling the learning path using a set of learning materials and relevant activities. IMS Learning Design (IMS LD), more specifically IMS Simple Sequencing (IMS SS), is part of the Shareable Content Object Reference Model (hereafter SCORM) collection of specification standard used as a bookshelf for organizing the package of the content and for enabling the sharing and reuse of the learning objects on various platforms. The sequencing rules defined in IMS SS dictate the flow of the sequences of learning objects and tend to adapt the path during the learning assessments of the learner by proposing an alternative path based on the assessment result. However, this adaption of the content could lead the learner to circle in a loop with only a limited number of learning objects, since the result of the assessment may return the learner back to a particular learning object within the defined content package and may not have the ability to propose another alternative beside those that the learner has gone through before.

3.4 The use of AI technologies for personalised learning

Nowadays, new artificial techniques have been proposed in order to personalise the learning path, including such techniques as: fuzzy matching rules, the use of ontologies, artificial neural network, automated planning, and decision tree techniques, to name a few. Lately,

automated planning as one of the artificial intelligence techniques has also been proposed to be integrated in the learning domain, for being able to develop various learning designs. As an example, Garrido et al. [68] proposed a three-level approach procedure to generate learning designs using domain independent planners. The learning activities represented by XML schema are translated through metadata in automated planning, where:

(i) the course definition is presented as a planning domain,

(ii) the student's learning information are used as a planning problem of that domain and

(iii) the learning design is generated as a plan by a domain independent planner.

Each of the learning objects (LO) within the planning domain is presented as one or more planning actions, its dependencies relations as preconditions and its outcomes as effects [68].R-Moreno et al. [69] presented CAMOU as a tool to facilitate learning and acquiring knowledge through interaction between students and teachers and also to help the latter to design courses through Integrating Planning and Scheduling (IPSS), an integrated automated reasoning system in CAMOU which uses planning and scheduling modules as the main reasoning module. Garrido, Onaindia, & Sapena, [68] presented a way to personalise an eLearning path based on case-based planning (CBP), which is used for definition, memorization, retrieval and adaptation of learning routes. In order to provide solutions to a particular planning problem with respect to CBP, the following steps are followed:

(i) to retrieve plan that is stored in memory,

(ii) to repair the actual plan if any discrepancies are faced,

(iii) to test and revise the tested plan, and finally

(iv) to store as a new case in the library of case bases.

The previous CBP generated plans are stored as cases and can be reused to solve similar planning problems in the future. The best stored learning routes for each student's profile and course objective are reused further, so the system does not have to create a plan from scratch. In the meantime, if discrepancies are detected, the learning route is readapted and improved to meet new objectives, and finally a new learning route is stored. This proposal as explained contributes on the transformation process from eLearning template to PDDL (Planning description definition language) durative actions and CBP repository contains personalised learning information based on case-based planner. This LO repository could

be modified also by teachers, and the final approach is tested as an added value in open eLearning platforms, such as Moodle and ILIAS [70].

Vrakas, Kokkoras, Bassiliades, & Vlahavas in 2006 [71] proposed a system called PASER (Planner for Automatic Synthesis of Educational Resources) for synthesizing curricula using planning and machine learning techniques. The system is designed to use an automated planner, given the initial state, the available actions and the goals, which results in producing an entire curriculum. All aforementioned cases give arguments about how automated planning as a subfield of artificial intelligent is having an impact in the personalisation of learning processes, by being able to generate personalised courses and curricula respectively. Principally, creating an adaptive learning path which could be personalised, facilitates the process of achieving the listed learning objectives. This is accomplished by being able to follow a list of learning object that are appropriate for the learner, rather than follow a static approach which is designed for the masses and which might create a number of gaps for specific number of learners. Overall, the proposal of creating adaptive learning paths based on AI techniques, specifically on the use of recommender systems, multi agent systems, automated planning technique could contribute to personalisation of a learning path and this approach will be proposed in Chapter 5 and further elaborated through examples in Chapter 8, after giving a review in the following sections.

3.4.1   The use of Multi-Agent Systems in eLearning

The use of multi-agent system to produce a personalised learning has been explored in a number of research studies. Within multi-agent systems, the agent field integrates more or less the understanding, learning and planning components. Therefore, to build an agent which is able to take decisions on its own, planning, learning and communication problems must first be solved. Since the exact definition of an agent is still under debate, various researchers have attempted to contribute toward clarity. In [72], an agent is represented as an entity that can autonomously act in its environment. Russell and Norvig [73] define an agent as an entity that is able to perceive its environment through its sensors and take action toward the environment through effectors. Wooldridge [74], 2009 defined an agent as a computer system that is situated in an environment and is able to act autonomously in order to meet specified goals, whereas Jennings and Wooldridge [75], further state that an agent might be hardware or software-based, expressing properties of autonomy, reactivity, proactivity and social adeptness. The definition below combines these various ideas, as shown in Figure 3.2.

Definition 3.6: An agent is a software that is able to take decision pro-actively and autonomously to achieve goals as a result of the communication between environments and itself.
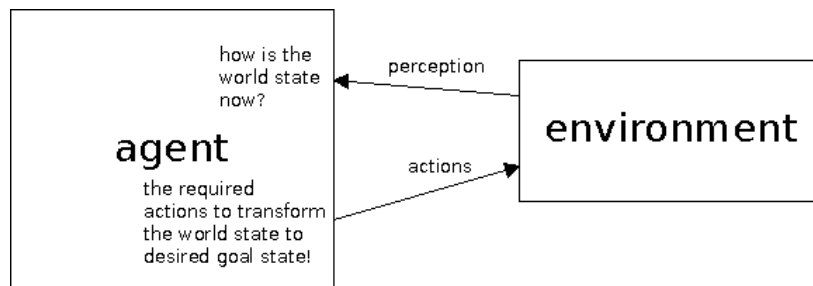
Fig. 3.2 An intelligent Agent abstract architecture

The basic concepts of agents and abilities are described in Table 3.7. However, is important to emphasize that not all agents are able to have all the abilities described in Table 3.7. For example, agents in the subsumption architecture do not have full collaboration and learning abilities and so on [76].

As shown in Table 3.7, agents have various abilities working independently, however their abilities have an impact also when we deal with a number of agents within a system. Here is where it comes the use of multi agent systems, which is defined as follows:

Definition 3.7: The multi agent systems (MAS) consists of a number of agents which collaborate or interact or negotiate or compete with each other in order to solve problems and achieve the desired goals that are beyond the capabilities of any individual agent acting on its own.

In order to have successful collaboration between agents in a Multi Agent System (MAS), the agents must interact, communicate, negotiate and coordinate with each other. Generally, the MAS architecture is defined as a collection of modules, whose communication and control flow are defined through boxes and arrows. Various agent architectures may be classified, according to the reasoning model developed by [76] as follows: (i) symbolic reasoning agent architecture, (ii) reactive agent architecture and (iii) hybrid agent architecture.

The idea of facilitating the process of network learning, open learning and distance learning through different MAS has been discussed in the last decade in various relevant publications, so this is not a new concept. For instance, Stamatis et al. [14] proposed a multi-agent framework for facilitating different phases of network learning through a number of agents. The paper proposed an architecture for courses, learners and virtual classes where the activities of the intelligent agents are based on searching, filtering and

Table 3.7 The list of abilities of an Agent

	Attributes	Definitions
Properties	Autonomy	Able to operate without direct intervention of humans and with full control of its actions
	Goal-orientation	Able to decide how and when to satisfy any direct request from other agents or humans
	Learning	Able to learn and change the behaviour continually based on experience
	Mobility	Able to move from one machine to another
	Reactivity	Able to perceive the environment and interact instantly
	Pro-activeness	Able to not only react to the environment, but also to take initiative as well
Social abilities/ Interaction	Interaction	Able to interact with the environment
	Cooperation	Able to work together to achieve the desired goals
	Coordination	Able to establish a hierarchical model by describing each agent's role and establishing communication protocols
	Collaborative	Able to discuss, refuse or modify the incoming request or even require further clarification for accomplishing the common goal
	Communicative	Able to communicate with other agents/humans for obtaining information in order to achieve curtain goals
	Negotiation	Able to negotiate when they want different things, by a defined model of negotiation process

data mining for assisting the network learning courses. In [77], intelligent tutoring based on MAS for distance learning was proposed. The architecture of the system is based on student, domain and pedagogical model, whereas the education model adds the functionalities for teachers. Each of the proposed models include a number of agents for particular processes, such as: exercises agent, tests agent, accounting agent and preferences agent. Finally, in [78], Fernandes-Caballero et al. proposed an architecture based on three different MAS: learning, teaching and interaction. Using the interaction MAS, the system can adapt to each user progress based on the information that different agents provide. Such agents are characterized as: accounting agent, preference agent, performance agent, and upgrading agent. Furthermore, agents were proposed as formative assessment in [79], personal tutors [80], [81], skill management [82], learning paths [83], personalised content search [84], communities for group collaboration, [85], affective facilitation [86, 87], and many more. Various applications in eLearning [88] and frameworks with MAS were also proposed [89–91].

3.4.2 Ontologies

In 1993, Gruber [92] defined an ontology as an explicit and formal specification of a conceptualization that can exist for an agent, or community of agents. In 1997 [93] Borst defined ontology as a formal specification of shared conceptualisation. Whereas, Studer et al. one year later [94], defined an Ontology as a "formal, explicit specification of a shared conceptualization". Furthermore, Swartout and Tate [95] defined Ontology as basic structure with which a knowledge based is built. Furthermore [96]:

> Definition 3.8: Ontology is defined as a formal description of knowledge in a specific domain. The foundational core consists of a generalization or specialization hierarchy of concepts and its relations which are represented in the form of conceptualization.

Therefore, conceptualisation based on Grubers approach [92], is defined as an abstract, simplified view of the world. Explicitly or implicitly every knowledge based agent is committed to some conceptualisation. For example, Genesereth and Nilss [97] explained the conceptualisation using a mathematical approach expressed as a tuple (D, R), where D – is a set of so called universe of discourse, and R – is a set of relationships to D. In general, researchers have attempted to combine the Semantic and Ontology approaches for the automatic processing of the web information. A good example to be mentioned here is Sampson et al. [98], who emphasized the influence of Semantic web and Ontology technologies in the new generation of eLearning systems. Furthermore, initial work of including ontology models as an integral part of eLearning systems for different purposes were presented in [99, 100]. In addition Kalou [99] used ontology to build and classify learning outcomes, and Valaski [100] used it for classifying learning materials. Following this approach, nowadays ontologies are used in various aspects of eLearning systems, such as:

- modeling learners knowledge background,

- describing the content of learning objects,

- modeling learning outcomes, and

- modeling the structure of learning objects toward a particular course.

In this respect, ontologies have the important role of semantically relating the learning objects to a logical domain. Furthermore, it allows for representation of knowledge to enable reason and inference for obtaining new knowledge. As explained above, today, ontologies are seen as mechanism that enable the interoperability of web resources. Toward this

approach, researchers have defined a standardized ontology language, the OWL (Ontology Web Language) based on XML (eXtensible Markup Language), RDF (Resource Description Language), RDFS (Resource Description Language Schema). Since the ontologies contain numerous concepts and relationships tools are needed to build and extend the Ontology using visual languages, with the aim at the end, to convert the visual languages into machine understandable formats, such as: XML and OWL. A number of ontologies exists, built by number of researchers and/or organizations for various domains, some of which are listed in [1]. Ontologies used widely in eLearning systems for modeling users' profiles, modeling courses, or describing the content include:

- ACM[2] Computing Classification System - classification system for the computing field as a poly-hierarchical ontology that can be utilized in semantic web applications,

- ODP[3] - An Open Directory Project, the most comprehensive human-edited directory of the Web, known as DMOZ

- Dublin Core[4] - specifications for resource description

Furthermore, how Ontologies are involved in our approach will be discussed in section 7.3.

3.4.3 The use of Recommender Systems in eLearning

Recommender systems (RSs) are used to personalise services based on various parameters, such as user profile, user interactivity with the content user adoption of collaboration features[101]. Last decade, RSs have been applied mainly for e-commerce services [102] into different domains, starting from those companies that offer reading and viewing materials, to those selling items. The related providers, such as Amazon, eBay, Kindle Store, netflix, GroupLens, alexa.com, Ringo, Expedia.com, to name a few, use recommenders' systems in order to satisfy the preferences of their users and eventually propose items of interest to each of them. Since that time, RS became popular and increased interest among human-computer interaction, machine learning, and information retrieval researchers. Ricci et al[101], defined RS as "software tools and techniques providing suggestions for items to be of use to a user" . In considering these various definitions and concepts, this definition emerged:

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[1] http://info.slis.indiana.edu/ dingying/Teaching/S604/OntologyList.html
[2] ACM, http://www.acm.org/about/class/class/2012
[3] ODP, http://dmoztools.net/
[4] DC, http://dublincore.org/documents/dcmi-terms/

Definition 3.8: A recommender system (RS) is a software that is capable of adapting the system to a user background and desire based on various algorithms approaches by filtering the relevant data, ranking and predicting relevant content to the user.

Recommender systems use various techniques and algorithms, such as Bayesian networks, Markov decision processes, and neural networks [103] in order to make recommendations based on user's preferences, goals and desires. This interaction is continuous since users' preferences often change. The algorithms discussed below classify RS as Content - based, Collaborative filtering, Demographic - based, Knowledge – based, Case - based, Constrained - based, Community - based, or Hybrid [101]. The content-based systems provide recommendation based on users' preferences by finding items similar to the items liked/preferred by a user using textual similarity in metadata. For instance, if a user has liked a book within the AI field, then the recommender tries to suggest other books in the related field. Collaborative filtering systems provide recommendations based on similarities of activities between common users with similar preferences. CF bases its prediction and recommendation on the users' rating and behavior. The demographic based RS recommends items based on demographic user profiles. For example, users could be attracted to a particular website because of their native language, country, or the other recommender items, or interest could be based on user gender, age, etc. The knowledge-based systems recommend items based on users' needs in a specific knowledge domain using case-based or constraint-based scenarios. In the case-based instance, the systems recommend items based on similarity metrics, whereas constrained-based recommendation are based on predefined knowledge that contain strict rules regarding the relation of user and item. The community-based model recommends items based on the user's network of friends. The hybrid RS uses a combination of two or more techniques of the above listed in order to better personalise the recommendation, by combining the advantages of artificial intelligence used techniques.

For example, Amazon uses item-to-item collaborative filtering which produces recommendations in real time, scales to massive data sets, and generates high quality recommendations [104]. A model is proposed for improving the item-based recommendation for Amazon by considering the total number of feedbacks beside the rating data per item [105]. Internet radio services (e.g. Pandora) and movie providers (e.g. Netflix) use content filtering models [106]. Other services (e.g. Ringo) use collaborative filtering by considering similarity of user profiles for recommending audio compact discs (CDs). Several commercial and open source Machine Learning (ML) products use various algorithms for processing data, while gathering, classifying and optimizing them, in order to recommend items. In Table 3.8, a number of commercial and open source recommender systems are listed, which provide recommendation by using either collaborative or content filtering technologies.

Table 3.8 Some of the recommenders using ML technologies

Provider	Implemented Techniques	Availability
PredictionIO	Collaborative - Filtering	Open Source
Amazon ML	Collaborative - Filtering	Commercial
Azure ML	Collaborative - Filtering	Commercial
Google Cloud Prediction API	Content - Filtering	Commercial
Seldon	Content - Filtering	Open Source
Vogoo	Collaborative - Filtering	Open Source
Duine	Content - Filtering	Open Source

Today, the same ideas applied in e-commerce are increasingly applied in eLearning platforms to guide the learner through the learning process, by suggesting materials that fits to the learners' preferences [107]. For providing recommendation of learning materials to the learners, it is necessary to match learning material with learner preferences and learning requirements/desire. Lu[107] proposed a RS for learning materials through a multi-attribute evaluation method to clarify a student's needs. In the proposed system, named PLRS (personalised learning RS), a fuzzy matching method is used in order to match the learning materials based on each learner's needs and personal information. In [108] is proposed, a feedback extractor with fusion capabilities for combining multiple feedback measures for personalising the eLearning environment based on users' preferences, which are gathered using collaborative filtering algorithm. [109] proposes, a system for monitoring users' activities and tracking the navigation continually. The data captured are processed with data mining using the algorithm "a-prior" for finding and optimizing similarities through "association rules" [110] and extended further using collaborative filtering, in order to recommend various web pages.

The above Recommender Systems rely on a single technique and they suffer from data scalability. Some approaches do not effectively address the sparsity challenge and the cold start situations (i.e., the state at the beginning of the usage of an RS, when the system does not have any information).

Summary

Besides elaborating the features that contribute to the personalisation of eLearning, we have also elaborated the learning theories as a set of orginised principles explained how learners can acquire, retain and recall their knowledge in order to better understand the learning process. Further, it has defined several instruments of categorising the learners' based on their learning styles. Furthermore, throughout this chapter we have discussed and elaborated

the personalization of learning paths from an artificial intelligence technique perspective, shedding some light on the technologies used for personalisation of learning paths as well as current needs in learning path personalisation.

This chapter has identified the basic elements that contribute toward personalised Learning. It has started with the elaboration of personalisation toward eLearning systems, starting with identification of features used nowadays to shift the paradigm of eLearning platforms from teacher- centered to learner-centered approach. It emphasis that personalisation features include the knowledge representation, the cognitive learning styles, adaption of the learner needs and the generalizing/specializing the search. Furthermore, it defines that when deciding to personalise the eLearning environment, we can start with environment content, learning objectives, learning content sequences, media etc.

Chapter 4

The approach of eLearning using Cloud Services

Our proposal, CeL, makes the assumption that everything, i.e. any structured or unstructured resource in the Cloud is potentially a learning object that can be used to facilitate learning of individuals, thus viewed as the Learning Cloud. The learning Cloud should be therefore introduced and illustrated as a collection of available learning resources located and distributed through the cloud, which are offered from various sources, into a variety of formats (e.g., text, video, audio, images, data, tests, etc.). Cloud computing and its services are central to our proposal. We would like to investigate how Cloud Computing is being used in eLearning and what kind of models deploy its services through the cloud.

This chapter explores eLearning approaches using Cloud services, with an emphasis on resources. We will list a number of options for how the eLearning services might be used as a service model, namely the Learning as a service (LaaS) or Education as a Service (EaaS). We intend to present an abstract architecture for how our proposal is associated with cloud technology.

4.1   The Learning Cloud

Learning Cloud is comprised of different sources located in the Cloud and everything stored in it can potentially be used for learning purposes. In order to combine the learning resources in a meaningful way and loosely couple them together and use them alone or together in various contexts, we firstly analyzed the state of the Cloud with respect to eLearning and how its services are deployed.

The potential of cloud services is recognized by a growing numbers of top universities which have opened their courses on the cloud. In [111] are listed universities that have decreased their costs by using cloud technology or even establishing a cloud architecture for their education services. The University of California software as a service model, supported by Amazon Web Services, offers a good example of cost effective use of the cloud. This initiative is continuing the University of Washington delivery model which uses the Microsoft and Google technology to offer education through cloud services to their users, to name a few[111].

Offering eLearning solutions that employ cloud computing benefits increases the system performance metrics while maintaining eLearning functionality performance. In [111], emphasized that using cloud computing there are a lot more other technical benefits than just performance metrics, including:

- Automation – offers opportunities to use different application programmable interfaces repeatedly, without having the need to reinvent the wheel.

- Auto-scaling – provides possibilities to scale in and scale out the application based on current demands without any human intervention.

- Pro-active life cycle - ensures more efficient production system, easy to clone.

- Improved test-ability - automated testing at any level during the development process.

- Disaster recovery - enables easy replacement of servers in case of catastrophic failures through geo-distribution.

- Overflow - ensures load balancing is adaptable, with capacity for regulation on demand.

Therefore, Cloud Computing is known as the fifth generation of computing, which goes beyond mainframes, personal computers, client servers and web services [112]. It offers IT capabilities (hardware, software, services) to institutions seeking cost-effective and efficient cloud services.

Today Cloud Computing offers eLearning services and associated activities through various providers with different services models. An eLearning system is provided through the main vendor infrastructure. Secondly, in the platform as a service model, educational institutions could customize solutions based on the provider's development interface. Thirdly, educational institutions can decide to use the eLearning as "software as a service", which can be accessed via different web clients. To better understand the aforementioned cases, all the types of cloud services as well as cloud deployment models will be elaborated further in this chapter.

Various definitions of cloud computing [113] exist today. One definition recognizes that the cloud is conceived as an access point which has a lot of different network devices, responding instantly to client requests. Report [114] defines cloud computing as "a style of computing where massively scalable IT-related capabilities is provided 'as a service' using Internet technologies to multiple customers". Considering the competing definitions for the term, this thesis uses this definition for cloud computing [114]:

Definition 4.2: "Cloud computing" is the use of technology to deliver IT tasks "as a service" through its resilient pool of resources.

4.2   Cloud deployment and service models

In cloud computing scenarios, users can distinguish different kinds of cloud deployment models. Today there are mainly four different models in use among cloud providers:

  (i) public cloud,

 (ii) private cloud,

(iii) community cloud, and

 (iv) hybrid cloud.

Each of these approaches may affect how the services are deployed through the eLearning systems. As one of the models of cloud computing which offers all services to the general public, the public cloud is owned by large companies which are also able to sell cloud services over the Internet. In the public cloud, data security is a key concern, because the data could be damaged if they are not encrypted while traveling in different locations. These services may be free or they may be charged based on pay-for-use model, on monthly usage per bandwidth and storage.

The private cloud is the most popular cloud for enterprises since the providers have more control on data security and increasing or decreasing IT capabilities is customizable to customers' needs. Usually private clouds are managed by the main organization or a third party. The data center is on premises or off premises [115] which are not available to the public. Some providers offer access to the isolated computing resources via virtual private networks (VPN) for extending the existing IT infrastructures.

The community cloud offers shared infrastructure services from several institutions with specific common concerns, such as: mission, security, etc. The infrastructure could be

located on premises or off premises and they could be managed by the owners or a third party.

Hybrid cloud infrastructure is a combination of private, community and public clouds that remains unique entities but are bounded by standardized technologies that enable data and application portability.

Furthermore, today many types of services are offered on the cloud, especially three main types: Infrastructure as a Service, Platform as a Service and Software as a Service. Understanding the types of services provided on the cloud further illustrate the cloud approach.

Infrastructure as a Service (IaaS) - known as resource clouds, provides resources as services to the users. There are different virtualization aspects, like virtualizing the operating system, CPU, embedded systems, memory, networks, storage etc. IaaS cloud customers are able to manage different software systems and different software applications.

Platform as a Service (PaaS) provides resources via platform where applications can be hosted and developed using programming languages and tools that are supported by the provider. PaaS supplies all resources required to build applications and services from the Internet without having to download or install software. The PaaS providers mainly doesn't offer to their clients the ability to manage cloud infrastructure, such as: servers, storage, networking, operating system except deployed applications. PaaS services include design development, web service integration, testing, database integration, security, state management, versioning, etc. The major PaaS providers are: Force.com, Google App Engine, Microsoft Azure etc. If a specific Platform developer decides to switch the infrastructure vendor, then the developer should redesign the part of the applications that rely on the core functionality of the previous vendor [116].

Software as a Service (SaaS) - offers the capability to use the provider's application running on the cloud infrastructure. At SaaS level, clients are able to run a provider application, those applications usually are accessed through thin clients' interfaces such as a web browser, e.g. web-based email, SalesForce.com, Google Mail etc. SaaS services are offered by: Google Docs, Salesforce CRM, SAP Business by Design etc. As is shown in Figure 4.1, in the SaaS model, clients do not have control of servers, storage, networks, security, platform of applications etc

Based on the aforementioned types, the three distinct logical layers [117] are categorized based on their main functions as shown in Figure 4.1.

So, Figure 4.1 gives further explanation about what clients can control or manage and what they cannot. Infrastructure as a Service layer could be thought of as the very bottom logical layer which virtualizes the hardware layer. In this level, the system can be scaled based on user requirements. If the system requires more computing power, the system will
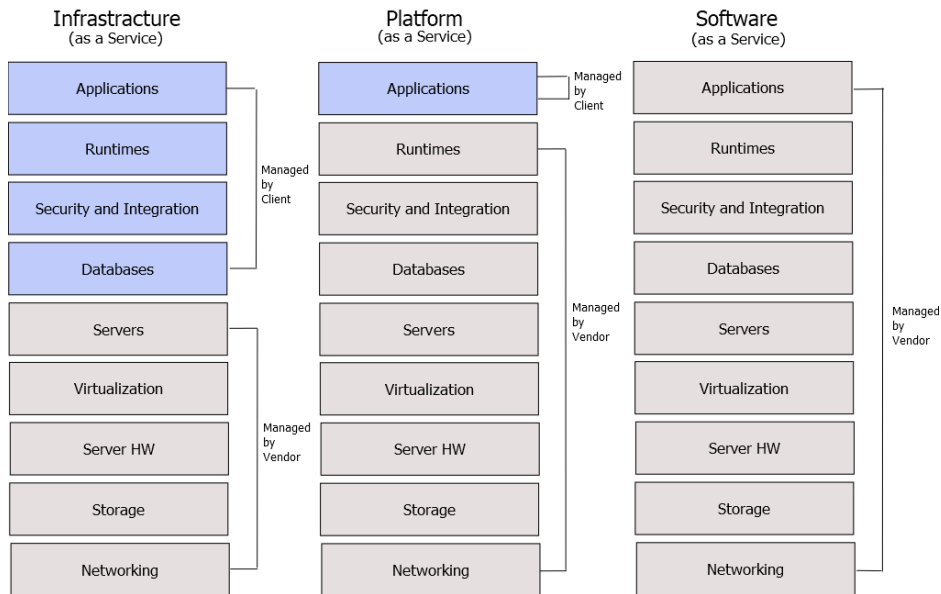
Fig. 4.1 Cloud Computing Service Models [117]

increase the system resources and vice versa. Comparing all three services models, PaaS provides the balance of manageability for customers and providers [118]. In this respect, the cloud technology has become popular for many factors, starting from the:

(i) quality of service,

(ii) stretch of the resources,

(iii) movement of the processing efforts from the local machines to the data center systems,

(iv) portability,

(v) reliability,

(vi) low cost, to name a few.

From the quality of service perspective, the scalability of the resources and the dynamical reconfiguration to optimum resource utilisation is guaranteed by the Infrastructure and the payment is modeled as pay-per-use which makes it affordable for customers.

4.3   Cloud in eLearning

To further demonstrate the feasibility of using cloud technology for organization services, especially for education institutions, a list of benefits will be highlighted, noting the number

of institutions that are using this technology in order to provide their education related services to learners.

The major technology companies were the first cloud computing players. Google offers Google Apps, Google AppEngine[1] and Google Classroom[2]. Google App is developed based on the model software as a service which covers: messaging, collaboration and security. Messaging includes google talk, gmail, and calendar whereas Google docs, videos and sites provides collaboration tools. Amazon[3] offers a number of services through their virtual environment that enables users to launch and manage instances within a wide variety of operating systems. Amazon extended Amazon web services to Amazon Elastic Compute Cloud which offers services to be rented by the users to run their own application while using the processing power of Amazon. The simple storage services, known as S3, provides web services used to store and retrieve data anytime. Furthermore, the Microsoft vendor has established a number of services known as Microsoft Azure, a suite including Microsoft Azure, SQL Azure and Azure.Net Services. Rackspace [4] by offering hosting and storage solution, to name a few. The various services offered by a number of leading companies are presented in the Table 4.1:

Table 4.1 Cloud Service Providers

Company	Offering	Hosting	Storage	Platform	App Services	Tools
Rackspace	Mosso	+	+			
IBM	Public and Private Cloud	+	+			
Google	GoogleApp Eng	+	+	+	+	
Amazon	Amazon Web services	+	+	+	+	
Microsoft	Azure Services	+	+	+	+	+
Salesforce.com	Force.com	+	+	+	+	+

While the vendors offer their services, the cloud architecture plays an important role in computing performance. The cloud architecture addresses key difficulties surrounding a large number of data processing activities. Difficulties include, but are not limited: to automatically scaling machine resources based on users' demands, finding as many machines as an application needs, coordinating large-scale jobs in different machine resources,

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[1]AppEngine, https://cloud.google.com/appengine/

[2]Google Classroom, https://classroom.google.com/

[3]AWS, https://aws.amazon.com/

[4]Rackspace, http://www.rackspace.com

switching data processing between different machines in case of machine failures, or even releasing resources when jobs are done. In the future, cloud architecture must decouple the physical resources that are located within the machines as they are working in different physical machines [119]. Today, in cloud computing there are no standards for following one particular cloud architecture model, but there are different architecture approaches depending on the capabilities and services delivered. The cloud architectures are divided in two different segments: front-end and back-end. The front-end includes client computers or mobile sophisticated devices which contains all necessary applications for accessing the cloud computing systems whereas back-end covers various cloud computing servers, which could be provided as virtual machines with powerful processing and a huge storage capacity within server farms. This makes cloud computing much more sophisticated than traditional model where the server side contained only one powerful server (machine).

Figure 4.2 presents a comparison of the traditional datacenter and a virtualized cloud datacenter, which tends to emphasize the virtualized datacenter architecture with respect to virtualized systems and its scalability depending on the number of the users.
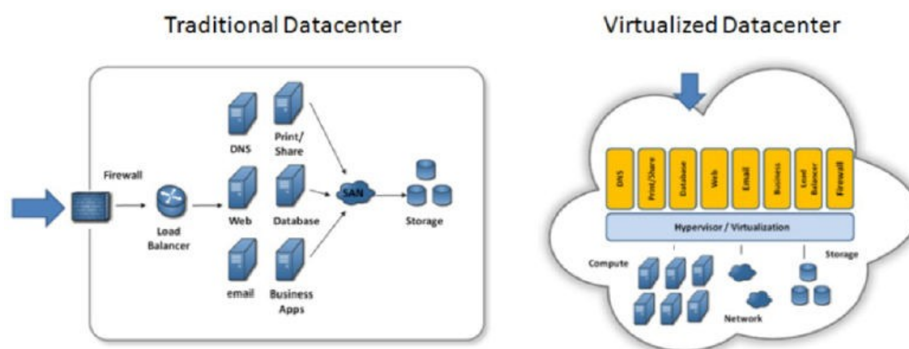
Fig. 4.2 Traditional versus Cloud datacenter

In [120], the analysis of cloud computing has been undertaken from the perspective of service-providers. While choosing an appropriate architecture for specific eLearning solutions, we analyzed all user-server requirements so the compatibility, availability, maintainability, and integrity could increase the performance of services. Besides that, the user requirements for using the cloud computing architecture perspective required integrity of data and services. In a nutshell, cloud architectures play an important role in cloud computing performance through infrastructure services, it addresses key difficulties, such as automatically scaling machine resources based on users demands, finding as many machines as an application needs, coordinating large-scale jobs in different machine resources, and switching data process between different machines in case of any machine failures, or even releasing the resources when the jobs are done. In the future, cloud architecture must decou-

ple the physical resources that are located within the machine as they are working in different physical machines [119].

In this context, the proposal of the new paradigm of eLearning, namely the Cloud eLearning, which is going to be described in the next chapter, has been inspired by the characteristics of cloud technology. By providing a simple search regarding cloud characteristics in any of the search engines, tens of characteristics could filter content, starting from the characteristics that increases *ilities of the system, until to the multitenancy approach. Cloud eLearning characteristics would be informed and enabled by cloud characteristics, most especially the top 6 characteristics listed in Table 4.2. As research papers [121, 122] elaborates, core cloud functionalities include on-demand usage, ubiquitous access, multi-tenancy resourcing pooling, elasticity and scalability, measured usage, resiliency, elasticity- to name a few. Each of the characteristics are described further in Table 4.2.

Table 4.2 Top Cloud Characteristics

Characteristics	Description
On-demand usage	the services are automated and they can be provided without human intervention
Ubiquitous access	the services provided through the cloud could be accessed through heterogeneous thin or thick client platforms
Multi-tenancy or resourcing pooling	the services are pooled together to be offered to multiple-tenant model with various resources
Resiliency and scalability	the services are scalable and also able to recover quickly in case of any downtime
Elasticity	the services are elastic since the users can start, stop and create virtual machines through web services [22][36][38]
Measured usage	the services are measured so usage is monitored and financed through various business models and fee structures

Since the Cloud eLearning (explained in the next chapter) comprises various sources of learning materials and everything stored in it can potentially be used for eLearning purposes, in the very beginning we speculated whether the services should be part on any of the service models that are described in Figure 4.1, or perhaps it would be more appropriate to propose new service model, namely the Learning as a service (LaaS) or Education as a Service (EaaS) shown in Figure 4.3. When thinking to propose/built a new service model based on the users/learners needs, a good example could be mentioned, the IBM Business Processes as a Service, which was built based on their client experiences[123].
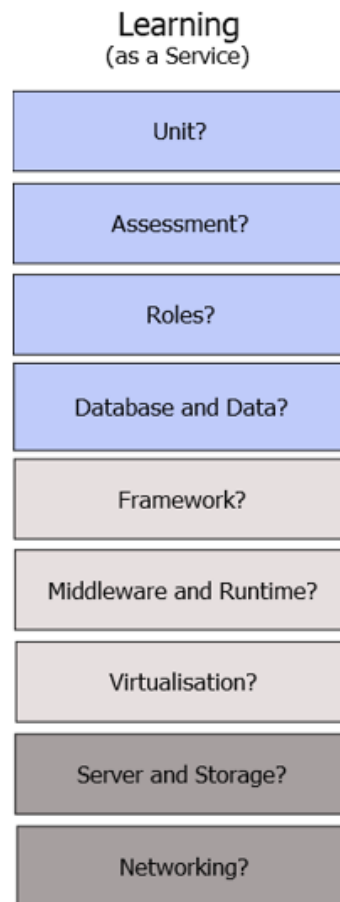
Fig. 4.3 CeL as Learning as a Service model

In this respect, then there is a need to analyse whether the eLearning services and the infrastructure are offered as a standalone service, for example: units, assessments, roles, database and data, framework, middleware and running, visualisation, servers, storages and networking. Then, there is a need to investigated which part should be controlled by the client and which by the distributors. Depending on the services that are provided by model depicted in Figure 4.3, the two bottom elements can be managed by the vendors, whereas the middle three elements can be managed by University Institutions and the rest by teachers and/or administrators.

Since these investigations are not part of this thesis, and also because of the time constraints, we have ended up with an abstract model in order to demonstrate how the cloud services are used in CeL experimental approach (Figure 4.4).
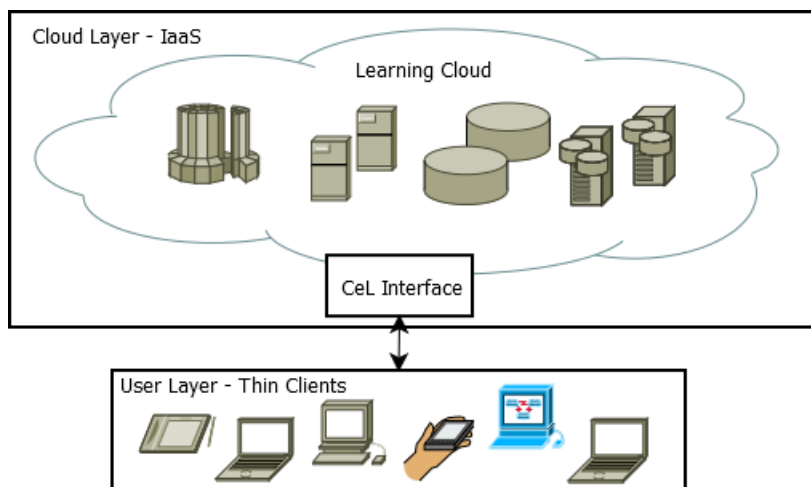
Fig. 4.4 The abstract model of CeL using IaaS as Cloud Services

So, in this regard, during the experimental show case described in chapter 9, we are using the Infrastructure as a Service model for testing the Cloud eLearning. To be more concrete, the experimental show case described in chapter 9 have used Amazon Elastic Compute Cloud as the main provider, beside that we have used Cloud eLearning also locally.

Summary

Throughout this chapter we have investigated how cloud computing is being used in eLearning services, and what kind of models are being used to deploy the services through the cloud. In addition, we have defined the learning cloud as a set of learning resources derived from various structure and unstructured sources, which are then located and distributed through the cloud. In this respect, we said that everything saved into the cloud could potentially be used for learning purposes. In 4.2, we have proposed a number of possibilities for how the eLearning services might be used as a service model, namely the Learning as a service (LaaS) or Education as a Service (EaaS). The chapter is concluded by explaining an abstract architecture, describing how our current proposal is using the cloud technology, which will be detailed in chapter 9. So, following chapters 2, 3 and 4, we are continuing with chapter 5 which will present the Cloud eLearning proposal, with its aim, vision and characteristics.

Part II

The Cloud eLearning Proposal

Chapter 5

The main proposal: Cloud eLearning

This chapter proposes Cloud eLearning as an enhanced model for eLearning. The 'big picture' vision for the proposed Cloud eLearning proposes a three-layered architecture system, which reflects an amalgamation of various technologies. Knowledge representation in the top layer creates the Learning Cloud, furthering the recommender technology in the middle layer used to filter relevant learning materials for each learner. Finally, the automated planning in the bottom layer serves as an automated processor generating flexible personalised learning paths for each learner. While various other technologies could facilitate processes for further enhancing these technologies, this thesis emphasizes these core technologies, which will be elaborated in more detail beginning in this chapter and continuing through chapters 6, 7 and 8.
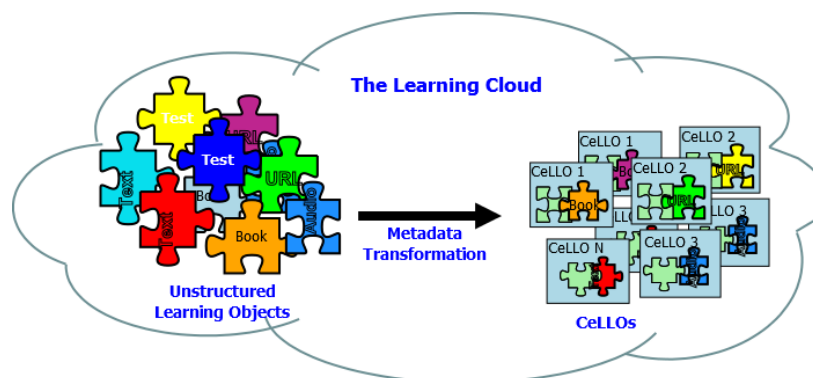
Fig. 5.1 The Learning Cloud in CeL

The definition 5.1 that will be proposed for the concept of a learning cloud suggests different sources for Cloud eLearning which, in this phase, consists of learning materials from structured, semi-structured or unstructured sources. These open learning materials are transformed into Cloud eLearning Learning Objects which are then further fed into the

recommender system, where the transformation process is explained in more detail in chapter 6.

With the enormous number of learning objects in the cloud, which is exponentially increasing over time, the filtering of relevant Cloud eLearning Learning Objects (hereafter CeLLOs) based on learners' dynamically changing needs poses a considerable challenge. In this phase, the Cloud eLearning Recommender System (shown in Figure 5.2) and further explained in chapter 7, has a twofold role. First, it filters the CeLLOs relevant to a learners' background, learning styles and learning needs and secondly, it ranks these CeLLOs from most to least relevant Cloud eLearning Learning Objects. Without filtering and ordering, planning would have to deal with an extraordinary large search space among all exiting CeLLOs, which is a known problem that might be facing in artificial intelligence planning.
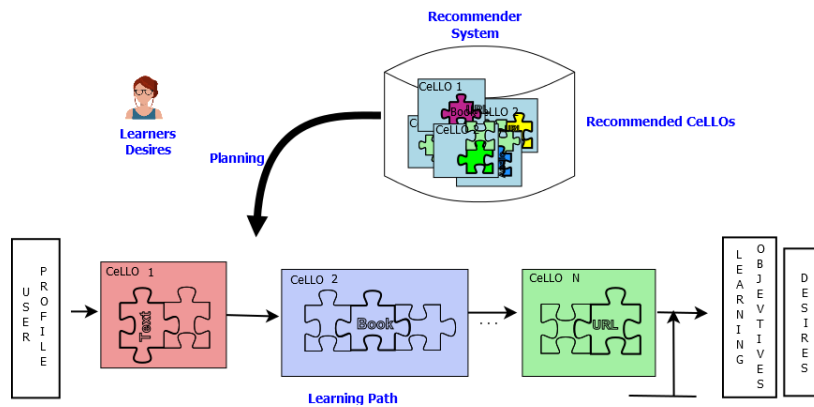
Fig. 5.2 The Cloud eLearning Recommender System and Cloud eLearning Planner

The filtered CeLLOs are further served as input learning materials to the Cloud eLearning Planner, which automatically generates a plan served as a sequence learning path. The logic of the planner implementation is further discussed in chapter 8.

5.1 The Vision for Cloud eLearning

The term Cloud eLearning currently is not a term that people have used, and so it has not been defined previously somewhere else, for that reason we firstly give a definition as proposed below:

Definition 5.1: Learning Cloud is the collection of available learning objects in a variety of formats (e.g., text, video, audio, images, data, tests, etc.) derived from various sources, as structured, unstructured or semi-structured, and are located and distributed through the cloud.

Definition 5.2: The Cloud eLearning (CeL) is an advancement of eLearning which aims to provide personalised services that will increase interaction among users (learners, teachers and institutions) by sharing a pool of experiences and knowledge available in learning cloud and suggest structured courses that match learners' preferences.

The important component in CeL is the Cloud and its open learning resources and the opportunities it offers together with its existing infrastructure and services. The Cloud has opened up a range of possibilities for:

- enhanced distant collaboration,

- instant availability to the web through a variety of devices,

- wide accessibility to information of different types,

- increased personalisation potentialities through combinations of services,

- a variety of tools and services.

These possibilities can be illustrated by considering some scenarios in Cloud eLearning, which will be elaborated in the following chapters. Table 5.1 presents' essential pedagogical and technological elements for contemporary higher education and suggest how Cloud eLearning characteristics could address these 21st century learning requirements.

Table 5.1 Fundamental open characteristics of Cloud eLearning

Cloud eLearning Scenarios - Fundamental Open Questions	
syllabus	What to learn?
material	What sources to use?
group	With and by whom?
learning path	How and in what pace?
assessment	How to be assessed?
VLE	What services and tools to use?
accreditation	How to get credits towards a degree?

The characteristics of Cloud eLearning as listed in Table 5.1 tend to open up the opportunities when it has to do with the creation of syllabuses, the materials that are being used in order to acquire the desired knowledge, the learning paths, the alternatives with respect to assessments, the tools and services that need to be used for being able to fulfill the Cloud eLearning aim. Starting with Collective creation of syllabus: Imagine that a collaborative environment could be developed in which learners would be able to determine

collectively the learning outcomes of a course. This could be done in accordance to some loose initial template that a teacher sketch. Learners will create a syllabus that emerges through individual preferences. Syllabi to meet emergent learning outcomes will then drive teaching and assessment methods to reflect learners' aims.

Collection of material through a variety of sources: Consider the variety of sources and their types (books, notes, libraries, video, audio, etc.) that exist in the web. Semantic annotation to learning resources and processes forms a cloud of knowledge from which learners choose. Suitability of resources would depend on a learner's learning style, past experience whether the resources have been useful or not, and popularity among learners and providers.

Selection of teachers, learners and providers: The learners would, in principle, be able to select by whom they are going to be tutored, while expressing the consent of the learned material through rating. In a cloud of teachers and providers globally accessible, a matching between learners and preferred tutors would provide better opportunities for better learning experience. The same could apply for the selection of providers as well as fellow learners with common interests and similar personal development plans.

Flexible Learning paths: Learning paths are personalised in terms of content, transition between steps, and pace for each step. This would assume existing experience of individual learners as well as other learners on similar course while taking into account individual learning styles, current knowledge level, personal commitments, to name a few.

Personalisation of assessment: Given variation in learning outcomes, diverse assessment methods would assess learning. The learners, who would definitely be of different learning types in terms of learning styles, and different capacity in terms of the level of knowledge, would be able to choose among the proposed assessments for them, thus having more opportunities with respect to the formats that could use, in order to achieve the aim of the course.

A customisable VLE: Users should be able to choose from a set of tools rather than dealing with the fixed set of tools provided by a specific VLE. Thus, every learner would have a customised environment in which all processes will be accommodated in a way that would not require extra effort or deviation from everyday routine. Similar customisation could apply to teachers also.

Configuration of course characteristics that may or may not lead to award of credits: Learners should be able to modify the proposed learning path of a course according to their need. Thus, it would be a different course which would satisfy personal interests, another which would be pursued for professional development and another which would lead to award of credits and eventually a degree. That would also need different levels of quality

assurance and accreditation that would be specific from case to case. It is important to note that the above characteristics of the CeL concept suggest that new ways for supporting learner engagement and motivation are required. A common assumption is that learners choosing their learning provides intrinsic motivation on its own, but this is a wrong assumption to make. As a number of studies [124, 125] suggest, MOOCs currently face this challenge since dropout rates are very high despite the fact that people choose what courses to attend. In fact, all the privileges and flexibility in learning content, pace, methods of delivery and assessment offered by CeL actually bear an increased responsibility for supporting individual learner motivation. A dynamic learning setting that can change from face-to-face to online, within a programme of study or even within a course, that consists of learners with different learning strengths, needs and backgrounds can be challenging and can easily lead to loss of learner motivation. Therefore, culturally responsive pedagogies that sustain the cognitive, behavioural and emotional engagement of learners must be a priority in CeL.

The essential elements of Cloud eLearning are: (a) learner-centered, (b) openness, (c) personalisation, (d) self-motivation and (e) collaboration. It is believed that CeL will be such a dynamic and complex environment that the learners could not manage it without help. This is where the involvement of automated planning is needed in order to automate the process, where each of the actions within the automated planning domain could be encountered as agents through which the personalised learning path is generated. There has been a major development toward this direction, however today there are emergent technologies that have changed the computation and processing approach, such as "Cloud" technology. The cloud has been transformed into the Learning Cloud which does not only accumulate knowledge in various forms (text, video, other media etc) but also provides a number of services for synchronous collaboration among users. It is exactly this opportunity that CeL attempts to capture in order to enhance the learning activity in a variety of ways.

5.2   The Cloud eLearning Layers

As it has been stated above in the discussion of definition 5.2, the aim of CeL is to provide personalised services that will increase interaction among learners, teachers and institutions by sharing a pool of experiences and knowledge available in cloud open courses and suggest structured courses that match learner's preferences. Cloud eLearning main actors are: (a) Learners, (b) Teachers, and (c) Institutions, and it is proposed to have three layers where each layer has its own functionality (Figure 5.3).

In the Cloud eLearning proposal, the foundation of a three-layered approach to Cloud eLearning is the open course layer or core layer aiming to offer personalised courses to

learners interested in gaining new knowledge or skills in specific domains, without interest in acquiring accreditation, credits or degrees. The core layer is encapsulated within the Credit Bearing Course layer aiming to extend further the functionality of the first layer, by offering personalised courses with credits to those learners who are interested in earning credits through completion of CeL courses. The courses listed in this second layer imply that learners who complete these courses should be assessed and receive course credits. Accreditation is required to be sought for Universities which provide such courses. And finally, in the third layer, the CeL should act as a virtual university which will inherit all characteristics of university establishments, such as accreditation, credits, quality assurance and monitoring, regulations, etc. This layer further extends the functionality of the second layer through offering services for those learners who are interested in acquiring degrees from CeL.
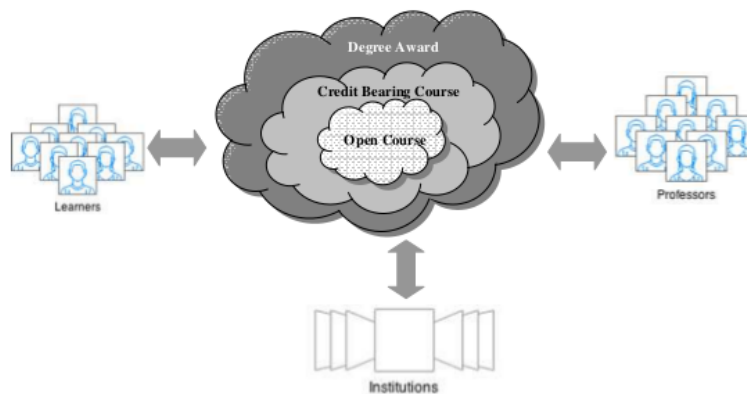
Fig. 5.3 Layers of Cloud eLearning and its main Actors

The three different layers have different inherent complexities. At the core level, CeL would not so much require collaboration between teachers and institutions. The outer level, where degrees could be awarded, would need rather complex arrangements which will ensure accreditation requirements and quality assurance. Thus, for instance, at the Open Course layer (the core layer), learners would need to collaborate for open syllabus as well as emergent collection of appropriate material which, after personalisation, would guide each leaner to follow an individual learning path with no further commitments with regard to assessment. In the Credit Bearing level, the teachers of an establishment need to collaborate in order to establish explicit requirements, including assessment, under which award of credits from that establishment would be possible. That would need compliance with local quality assurance standards. Finally, at the Degree Award level, various institutions need to collaborate in order to provide courses that meet national and international prerequisites for quality assurance

Table 5.2 Requirements for CeL layers and complexities implied

Requirements	Open Course	Credit Bearing	Degree Award
Collaboration among learners	necessary	necessary	necessary
Collaboration among teachers	optional	optional	necessary
Collaboration among institutions	-	optional	optional
Quality assurance at local level	optional	optional	necessary
Quality assurance at national level	-	optional	necessary
Quality assurance at international level	-	optional	necessary
Accreditation at discipline or university level	-	optional	optional

and accreditation. Actually, the outer level of CeL would form the virtual meta-University in which the learners should be able to choose among various University providers and available credit bearing courses. In brief, Table 5.2 summarises the requirements at each layer.

Within the three-layered approach of Cloud eLearning, the major work within this thesis has focused on the Open Course layer (the core layer), which aims to accomplish the open course layer functionality (Figure 5.3) and offer to the learners the personalised learning path by tailoring the open learning objects derived from various learning repositories, which is discussed in detail in the following chapters.

5.3   eLearning vs CeL

Standard eLearning in institution level is not well engaging and interacting. It is not well engaging because the courses are constructed with one size fits all approach, which tends to cover all learners no matter their background, learning experiences and interest. Whereas it is not well interacting, because the interacting tools that are offering are not personalized and the moment that we face an increment of number of users in the system, the system performance typically decreases. These problems lead the students to lack of motivation to learn further within these systems, or they use it because they need to for a particular reason, which may end up with the use of the system in very short term.

Nowadays, people have different needs, different individual learning or teaching methodologies, who are not satisfied with one size fits all learning methodologies. They are tending to use more the systems that are more familiarized with them, and which tends to personalize their services based on the users' needs and characteristics, which have been explained in the chapter 3. By combining the unrealized possibilities of eLearning and the potential benefits of open resource and cloud computing infrastructure, Cloud eLearning can potentially improve *ilities issues, so the learner will enhanced motivation to learn and to experience through

Table 5.3 Comparison between traditional eLearning and Cloud eLearning

	Traditional eLearning	Cloud eLearning
Learner	Learners access their university courses. They collaborate internally within their institution. They have access to the material developed by their local teacher. The discussion around the subject of study is mostly constrained within the University.	Learners are offered open materials that are developed by various institutions. They have access to other learners and teachers from other institutions. They use a variety of tools. They are flexible to decide what they want to learn, when to learn, from whom to learn and how to learn.
Teacher	Teachers are restricted to choose among traditional teaching, learning and assessment methodologies for learners, in a kind of one-size-fits-all way. They deal only with students within their institutional class. They are restricted to use the institutional VLE for all activities.	Teachers are open to collaboration and scrutiny from colleagues at other institutions. Competition will act as a driver to achieve better quality and disseminate best practices and inspiration to others. They will use a customisable VLE but some of them will be susceptible to resistance to change.
Institution	Institutions apply their internal monitoring of quality assurance. They define their own programmes and curricula. Learners and teachers abide by the institutional regulations and procedures.	Institutions will be forced to provide better service to learners and better policies for teachers. They will have to negotiate quality assurance and accreditation and as a result upgrade the standards of education provision in global competing market.

personalised learning paths, as compared with the standard eLearning versions as discussed in Chapter 2. Also, Table 5.3 lists the differences between traditional eLearning and Cloud eLearning from learner, teacher and institution perspective. Cloud eLearning uses Cloud infrastructure for providing services as well as increasing performance and reducing costs. In addition, when further comparing the various eLearning platforms discussed in chapter 2, a number of additional advantages emerge.

5.4 The personalisation approaches in Cloud eLearning

Before any personalisation is even considered, the main problem that CeL needs to address is the heterogeneity of electronic resources that form the Learning Objects (LOs). The Learning Cloud is populated from existing learning objects that are found in various sources. Depending on which sources are gathered as the learning objects, candidate learning objects

suffer from: (a) no or little semantics/annotation, (b) variety of granularity, and (c) no means for gluing them together in adaptive order to create a coherent course. Such learning materials can hardly fit together in a sensible learning path because of their different standards (Figure 5.4).
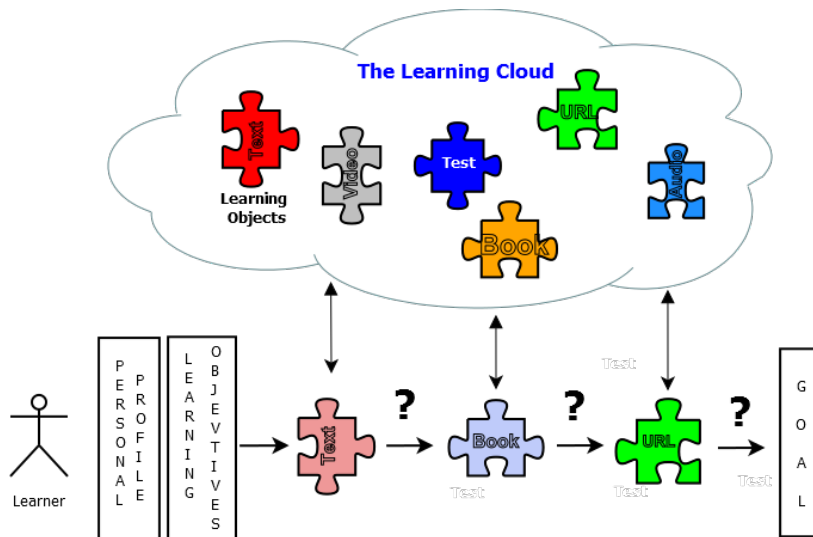
Fig. 5.4 Learning material coming from the learning cloud fail to form a coherent learning path

For instance, a learning object may not fit with another learning object directly, because of different metadata standards or different learning objects standards or inconsistent intended learning outcomes and desired cognitive level. In Figure 5.4, besides the learning objects, the question marks are representing the challenges one might experience when trying to tailor them together.

In Cloud eLearning, a proposed process takes these unstructured learning materials and adapts them for being able to create a coherent sequence. In contrast, in current eLearning approaches, structured LOs are stored in repositories (LORs) and they are used within the context of their repositories to create personalised learning paths. In contrast, in CeL, the heterogeneity of unstructured or semi-structured electronic sources makes customised learning a challenging task.

It is, however, inevitable that the study of Learning Object metadata (LOM) and its use in repositories will greatly facilitate the accomplishment of proposed goals, which is discussed in Chapter 6. The variety of existing organisation and specification standards are discussed in section 6.3. Then, ways to adapt these specifications to new specifications for CeL learning objects (CeLLOs) are explored, in order to represent Cloud eLearning learning objects within Cloud eLearning. Among other functionalities, the selected Cloud eLearning

Learning Objects should be glueable with other Cloud eLearning Learning objects and create a coherent personalised learning path as shown in Figure 5.5.
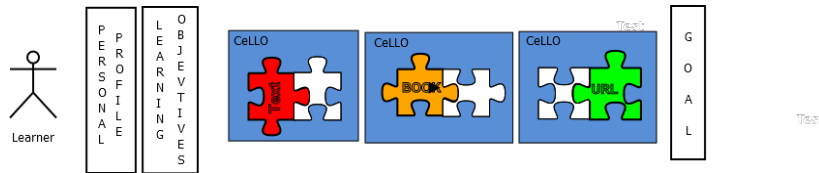
Fig. 5.5 A sequence of CeL Learning Objects forms a coherent personalised learning path

However, the idea of providing structured learning objects for a particular course within Cloud eLearning remains very challenging. The challenges were encountered from the moment that we derived the learning objects with various metadata descriptions up to the interoperability within various learning objects that were derived from various sources, which has challenged the combination of a set of learning objects in a specific order in various contexts.

5.5 Personalisation in respect to adaptive learning paths in CeL

In Figures 5.6, 5.7, 5.8, 5.9, various scenarios are depicted to illustrate how users can use Cloud eLearning by selecting one preferred topic and customizing resources for a personalised learning environment.
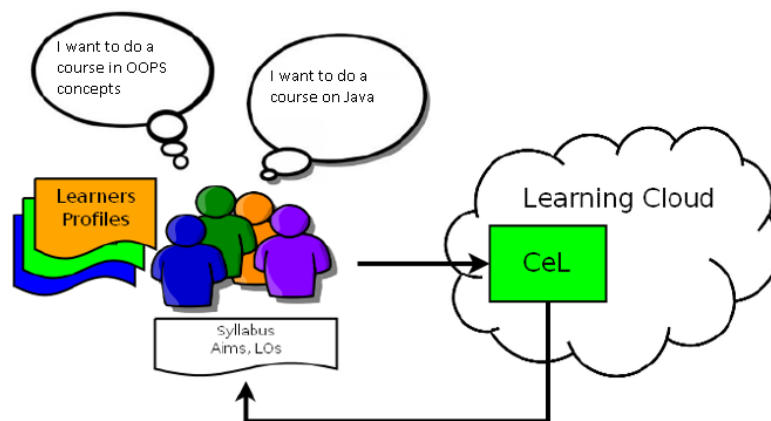
Fig. 5.6 CeL identifies preferences of learners and creates individual syllabi

Figure 5.6 shows the big advantage in CeL, that is, learners could personalise their syllabus based on their previous knowledge, select the desired learning methods, preferred

tools, and selecting topics from different teachers by always matching the particular course intended learning outcomes.
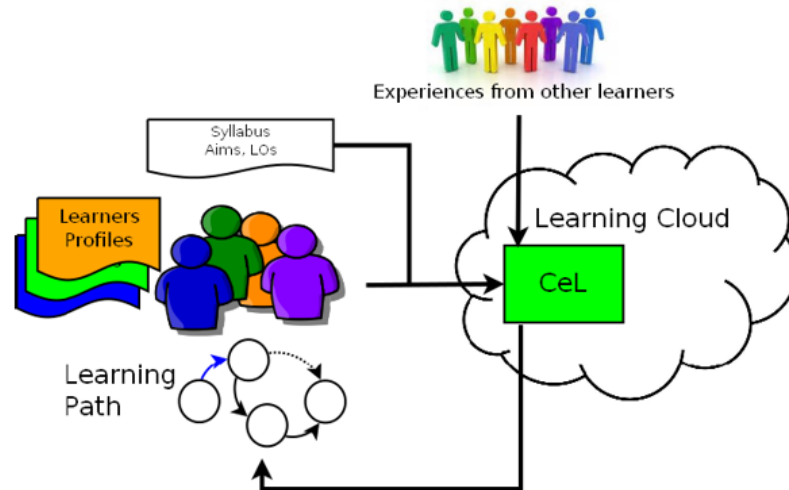
Fig. 5.7 The enhancement of syllabi with abstract learning paths for particular learners

In Figure 5.7, CeL proposes that learners follow a particular path for course syllabus creation, based on knowledge modelled, further discussed in chapter 6. The personalised learning path generated as part of an automated planner relies on intelligence emergent from previous users' experience while, at the same time, taking into consideration the learner's profile, attended courses and improvement of the overall experience of the system used under various scenarios from similar learners' profiles. The integration of user experiences will facilitate the improvement of the generated personalized learning paths, which tends to improve over time, by being able to integrate their feedback whether they liked the generated plan or not, whether they liked the particular learning object or not and so on.

In Figure 5.8, a learning path is proposed automatically based on learners' knowledge, however, it will have to be flexible on particular learners' preferences.

And, finally, within a Personal Learning Environment (Figure 5.9), the user will have a list of courses with personalised learning path, learning pace, learning tools, learning methodology and also the process of assessment while following different courses. The communication within these phases could be different each time the learners follow a particular course, based on the usage of the Cloud eLearning overtime.
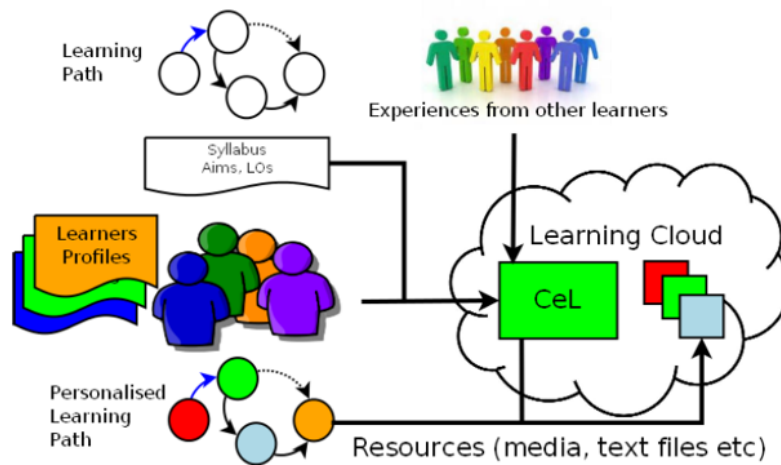
Fig. 5.8 The enhancement of the abstract learning path with resources of the learning cloud
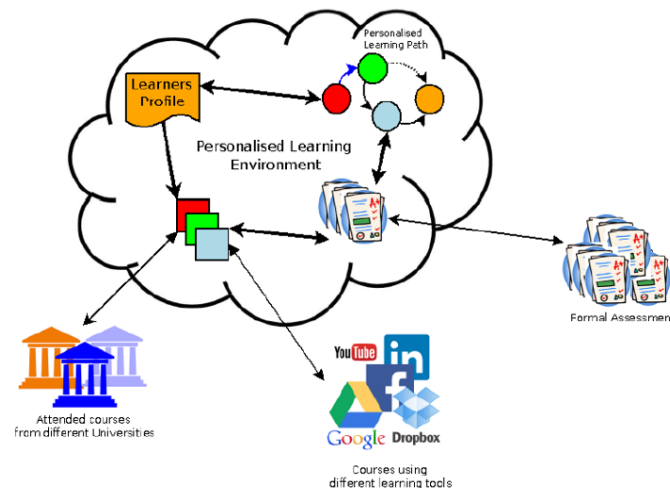
Fig. 5.9 Personal Learning Environment

5.6   Big picture of Cloud eLearning

Presentation of the 'big picture' of the proposed system illustrates high-level architecture of Cloud eLearning (Figure 5.10), and it shows how it amalgamates various technologies, including knowledge representation, recommenders' systems, automated planning, and cloud computing, in order to fulfill the CeL aim explained in Chapter 1.

The architecture is depicted as a three-layer architecture, where the top layer of the architecture is the "Learning Cloud layer" populated with knowledge and learners' experiences. The knowledge within the Learning Cloud is derived from structured and unstructured learning repositories adapted as Cloud eLearning Learning Objects known as CeLLOs (explained in chapter 6).

Fig. 5.10 Big picture of Cloud eLearning (CeL)

The middle layer contains the Cloud eLearning Recommender System (CeLRS) which has a two-fold purpose:

(i) a personalization role, in order to provide personalised CeL Learning Objects, and

(ii) a filter role, in order to filter the most ranking CeL Learning Objects into an input list for the upcoming layer, further discussed in chapter 7.

The bottom layer provides the "Cloud eLearning Planner", an artificial intelligent automated planner which generates a personalised sequence of learning experiences, which comprise a personalized learning path, using the planning processes, further discussed in chapter 8. And finally, the generated personalised learning path is evaluated through the use of learners, helping the system to learn over the time.

Summary

This chapter proposes the Cloud eLearning approach, which is encountered as a next step to eLearning. The Learning cloud was defined as a set of available learning objects which are located and distributed throughout the Cloud. Furthermore, the Cloud eLearning aim emphasized the importance of offering personalized services which will have an impact on the increasement of interaction between users, users and content by being able to share a pool of knowledge and experiences through which it is extracted a personalized learning path. Following this approach, the requirements for Cloud eLearning are listed, the layers of Cloud eLearning architecture and its main actors have been defined as well as the characteristics that associate the Learning Cloud and compared the eLearning with Cloud eLearning (Table 5.3) in order to differentiate the new proposal. The chapter is concluded with personalisation in respect to adaptive learning paths in CeL, which is the aim this thesis. Even though during this chapter we have proposed the whole big picture of Cloud eLearning, the main focus has been on the core layer (Figure 5.3) which aims to accomplish the open course layer functionality by tailoring the open learning objects derived from various learning repositories into a personalised learning path, which is discussed in detail in the following chapters.

Part III

The technologies used to build Cloud eLearning Prototype

Preface to Part III

This part provides the explanation of the technologies used in order to build Cloud eLearning prototype, and through the review of state of the art for each of the technologies it reason that the holistic approach of knowledge representation, recommender system and automated planning do provide unique results rather than using each of them as standalone technologies.

Within the scope of my PhD, it was impossible to implement the whole vision of CeL, taking into account the volume of features proposed, the variety of technologies that needs to be reviewed as well as the velocity of changes that we might experience in a such project scope. From the overall proposal which exceeds the work of one PhD student (all layers presented in Figure 5.11) we decided to build a throwaway prototype to offer a proof of concept and above that we aim in the next three years to enwrap the existing prototype with a stable version of CeL core layer, including better user interface and involvement of new advanced algorithms. This will show the significant results the moment that we possess more data which will be collected from the interaction of learners with the use the prototype.
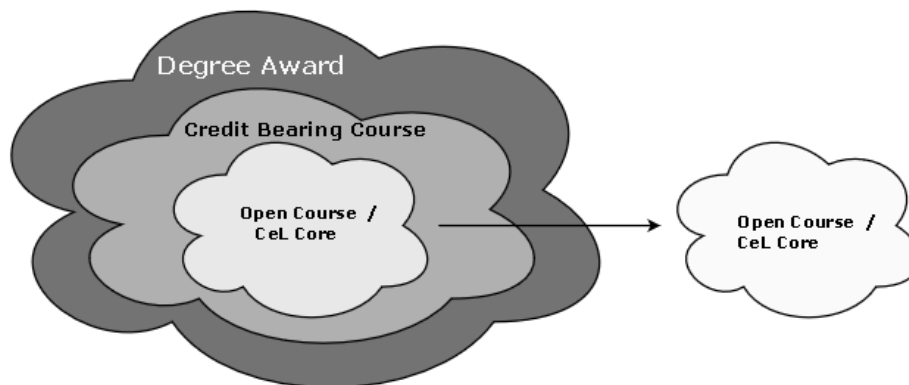
Fig. 5.11 CeL prototype as part of CeL Core

Before continuing the explanation of technologies and its impact in the overall Cloud eLearning prototype, please refer to the Table 11.1 which provides a comparison of attributes between what we have visioned (CeL Vision), what we have tackled for this PhD thesis (the cloud eLearnig core layer - open course layer presented in Figure 5.3) and what we practically build in order to demonstrate the feasibility of our proposal (throwaway prototype).

Chapter 6

Knowledge Representation in Cloud eLearning

Before discussing how automated planning can be employed to construct a personalized learning path we should look into more detail of how the Learning Objects that form this learning path are represented. Having a range of objects from totally unstructured to structured objects that are specified through meta-data, the automated task to put these together seems almost impossible for current techniques. Furthermore, the automated planning performance is also influenced by appropriate knowledge representation. Imperatively, we need to relate planning with the representation of learner profile and learning objects as well as their association. So, in order to generate a validated plan/solution, which will serve as a personalized learning path we need to offer a structured knowledge representation which is complete and unambiguous[126].

This chapter explores the knowledge representation aspect of Cloud eLearning which comes as a natural consequence of this knowledge representation technology. Further, it describes the various approaches for representing the learning materials, as well as the learners for the eLearning applications. The chapter ends with the modeling of Cloud eLearning learning objects, and the Cloud eLearning learners, which constitute the Learning Cloud. The knowledge within the Learning Cloud is derived from structured and unstructured learning repositories and adapt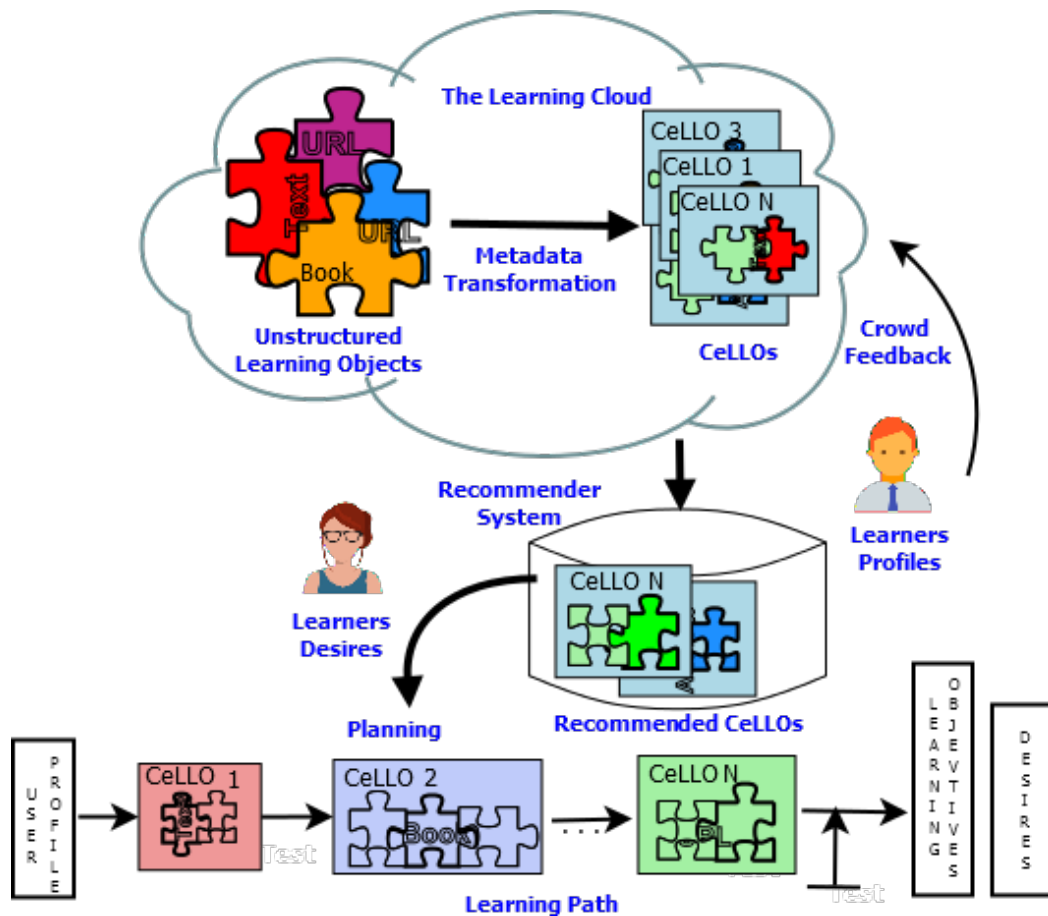ed as Cloud eLearning Learning Objects known as CeLLOs. In this respect, "Cloud eLearning Learning Objects - CeLLOs" are structured electronic learning resources represented as the learning objects in CeL. The CeLLOs, learners' profiles and experiences have been described through Cloud eLearning Metadata, a metadata standard inspired from the previous standards used in education, such as Institute of Electrical and Electronics Engineers Learning Object Metadata (hereafter, IEEE LOM) and Dublin Core, which has a significant role in the overall architecture further explained in section 6.3. The

"Cloud eLearning Metadata - CeLMD" is a metadata approach used to transform the derived Learning Objects (from various sources) into CeL Learning Objects.

Therefore, new models for knowledge representation are presented in below. Firstly, the Cloud eLearning metadata is proposed and then the Cloud eLearning Learning Profile is presented, which is used to model the Cloud eLearning learners' profiles. The transformation process of integrating the learning objects into Cloud eLearning Learning Objects has been followed in order to offer structured representation of content since forming appropriate knowledge representation is mandatory for the process planning as emphasized above, which tends to work better when having to deal with structure objects.

6.1 Knowledge representation

The knowledge and the representation of knowledge are two distinct entities which have an important role in intelligent systems. Knowledge representation is commonly used to understand and design software that is able to get the information and reason about the next steps for acting similar to human activities, whereas the representation concerns how the knowledge is encoded. In this manner, the knowledge derived from information, which in essence is derived from data goes through continual process shown in Figure 6.1.
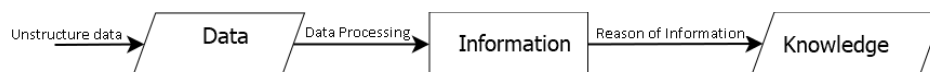
Fig. 6.1 The knowledge creation process

As shown in Figure 6.2, knowledge is of different types and, depending on the type of knowledge there are various possibilities to use the appropriate techniques for knowledge representation.

There are various representation techniques such as logic, rules, frames and semantics networks which are generated mainly from human information processing. In this thesis, knowledge is represented using the metadata approach. The metadata are expressed in a XML format as a syntactic form of knowledge representation of the CeL pool of learning resources as well as for representing the learners' profiles. Using information in the XML format, the problem and domain definition are modeled using the planning language named Planning Domain Definition Language (PDDL) for automatically generating a plan, which in this context is a personalised learning path. In the Cloud eLearning Knowledge representation, the learners' profile and intention must be represented properly in order to generate the successful personalised learning path. In the initial state, the current knowledge level, the
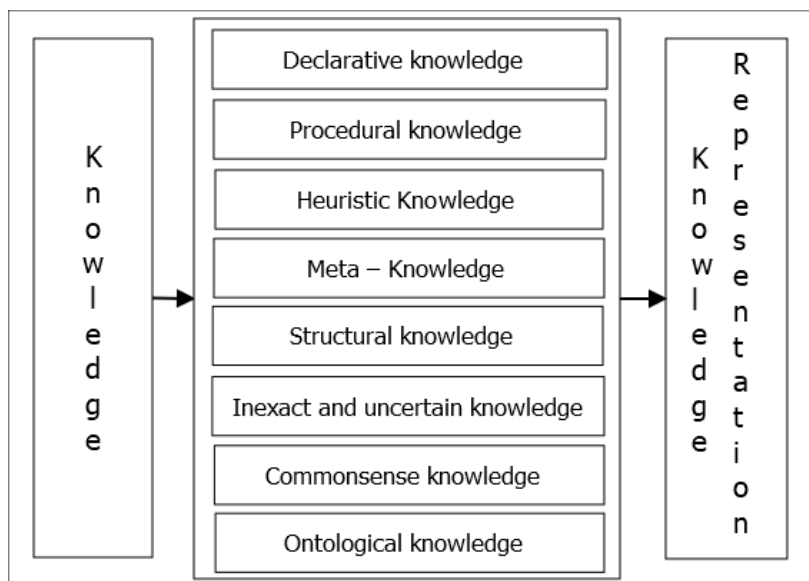
Fig. 6.2 The types of knowledge and its representation

learning style and the learner desire are represented, whereas in the goal state, the learning objectives are defined, as derived from the learners' stated desires.

The initial state and the goal state are represented properly through a formal language. The formal plan solution then is adapted through informal language so that the users can understand it. In continuing sections, the models are presented that have been used for modeling the learners' profile and the knowledge domain in general, and in Cloud eLearning specifically. Furthermore, the learning objects are described including the existing learning object repositories, which offer the learning objects associated with metadata or even those learning objects that do not have description at all.

6.2   Modeling of knowledge domain and learners

In order to achieve the aim of Cloud eLearning, the cloud eLearning learning objects and the learners' profiles need to be represented appropriately in order to increase the accuracy of the tailored process of providing Cloud eLearning learning objects for each learner in a suitable and satisfied manner.

Today, there are various approaches for how the learning objects and the learners' profiles are modeled. For example, in web and computer-based applications known as Adaptive Hypermedia Education (see definition 3.1) and Intelligent Tutoring Systems (see definition 3.2), Artificial Intelligence techniques are incorporated for personalising the learning environment. The architecture of intelligent tutoring systems is mainly divided into one of four

models: knowledge domain model, student model, tutoring model and the learner interface model. Therefore, the knowledge domain model deals with learning materials which will be offered to the learners, whereas the student model contains learners' characteristics, such as: knowledge level, preferences, needs, and other related profile information. Typically, student and knowledge modules are the most important parts of the architecture and the main difficulties could be encountered during the modeling and development of these two modules.

6.2.1   The learning object and its characteristics

With improvement in computational technology, new ways of generating knowledge while creating and maintaining content and distributing it further for teaching and learning purposes has gained increased attention and advanced usage. The process of building and developing knowledge through different platforms is complicated by incompatibility issues. The idea of designing a content model for a particular course and segmenting the course into standalone objects, catalyzed the possibility of reusing the learning objects in different courses. As described in section 2.3, "learning object" as a concept has been used for many years, and there was no common definition until the Learning Technology Standardization Committee (hereafter IEEE LTSC) proposed a standard definition. Following the approach of a learning object, David Merrill [127] developed a system of knowledge representation based on knowledge objects, in which components are used to represent different domains of interest. The properties' components were associated with process, entity and activity (PEA-net) relationship through which the author represented integrated knowledge. Activities are initiated by students as actions, and the actions triggered a process in order to change some properties. These processes were conditional, and they could be executed only if the conditions were met. The idea of a learning object was also derived from the theories of Object Oriented programing, where a single object is developed as an entity, with its own attributes and behaviors, and could be reused continually. Thus, a learning object is referred to as: study content, exercises, study tasks, etc., which is provided through different multimedia formats, such as: audio, text, video etc. The learning object is conceptualized as the smallest segment of content that could stand as an entity on its own, as a smaller object than the course itself (as a sub-part of the course), which could be used and re-used in different courses. For marking up the learning object (LO) for retrieval and to be able to structure it internally, the description, specifically the semantic annotation of the object, is needed. Each of the learning objects is described using metadata, which is stored separately from the LO, and reused in the context of learning so that they could be used efficiently in different courses. Recent decades have seen a tremendous growth in development of

metadata standardization for better describing learning objects and for ensuring re-usability and interoperability. The general view of a LO assumes conceptualising the study material, its content, context, pedagogy and metadata. The content refers the learning material that is expressed through different types, such as text, image, animation, video, audio, etc. The context defines the different domains where the LO could be used, and metadata is the description of the LO based on the content analysis, and it is used for search and retrieval purposes. However, in this thesis context, the metadata are also important for retrieving the CeLLOs, as well as for accomplishing the automatic coupling.

6.2.2   Learning object repositories and their standards

As specified earlier, the new eLearning systems advanced the idea of creating learning object repositories for re-use of learning content (LOs) across different eLearning platforms. Increasingly, open access learning object repositories have gained popularity because the learning objects can be used as part of a lesson, module or course on different eLearning platforms. The popularity of Internet searchable Learning Object Repositories (hereafter LOR) of high quality peer reviewed learning objects, with attributable authors' copyrights, is accompanied by development of various search capabilities. Approaches depend on whether the learning object repositories offer full content or only the description of learning objects and relevant links to different repositories. McGreal (2008) divided the learning object repositories into three categories of provider offerings:

1. Content of LO and metadata,

2. Metadata with link to LO that are located in different sites,

3. Hybrid repositories from both categories 1 and 2, that host content and link to external learning object.

During their indepth analysis of LORs, Ochoa and Duval (2009) categorized the learning object repositories into six types:

1. Learning object repository,

2. Learning object referratory,

3. Open courseware Initiatives,

4. Learning management system,

5. Institutional repositories,

6. Institutional repositories-University.

The categorization is derived based on whether the LOR is offering the LO as content, content and metadata, only a link of content, or only a link of content and metadata. The following descriptions offer examples of various categories of learning object repositories that are related to the above categorisation of learning objects repositories.

ARIADNE (The Alliance of Remote Instructional Authoring and Distribution Networks for Europe) Educational metadata is compatible with Learning Object Metadata (LOM). It promotes the use of electronical pedagogical material [128]. The repository, which was created for sharing and reusing LOs, is called the Knowledge Pool System. The description of LOs includes data elements which are grouped into six categories: General, Semantics, Pedagogical, Technical, Indexation and Annotations. The transformation of ARIADNE metadata into LOM metadata using XSLT was presented in [129].

MERLOT is a repository program of the California State University, which stands for Multimedia Educational Resources for Learning and Online Teaching. MERLOT is a free and open source learning object repository that provides links and annotations to peer reviewed assignments. It is developed to provide learning materials from different disciplines for teachers and students. This repository is made from contributions from individuals, higher education institutions and other partners with a common goal of improving worldwide education. OpenStax (then Connexions) is hosted by Rice University to provide authors and learners with an open space where they can share and freely adapt educational materials such as courses, books, and reports. The OpenStax CNX content is available in two formats: modules, which are like small "knowledge chunks," and collections, which are groups of modules structured into books or course notes, or for other uses. MIT Opencourseware is a repository initiated in 2001 at Massachusetts Institute of Technology. Since then, more than 2000 university courses have been digitized and published and made open and available for the higher education community worldwide.

The research project CWSpace [130], supported by MIT and the Microsoft Research iCampus program, has investigated and advanced metadata standards and protocols required for archiving the Opencourseware (hereafter OCW) material into the MIT institutional repository DSpace, and making the corpus available for learning management systems around the globe. Besides this, the Cloud eLearning developed in this research study contains learning materials from these repositories but it has a more open approach, by offering space also for those learning materials that are not controlled, but the reputation of each learning

material then is ranked based on the feedback (rating) that is derived from the users as part of their learning experience.

Standardization of Learning Object descriptions

Successfully re-using, sharing and retrieving learning objects for personalised use is only possible if LOs are tagged and described appropriately. This process of describing LOs through tagging can be accomplished manually and/or automatically [34]. Tagging the learning objects through fully automated process requires to investigate a number of research applications, where the process become even more complex when dealing with various formats of learning objects, such as: text, video and audio. Therefore for the scope of this PhD, tagging the learning objects manually or even semi-automatically is simpler when considering the time constrains that we have for this PhD.

International standardization of LO descriptions are essential for sharing and re-using LOs across different platforms. Nowadays, several metadata specification standards have emerged, such as:

- DCMI Dublin Core metadata standard,

- IEEE Learning Object Metadata (LOM) standard,

- IMS Learning Resource Metadata Specification,

- SCORM (sharable content object reference) metadata specification.

DCMI Dublin Core Metadata This international standard for cross domain digital content description originated in 1995. However, in 2006 DCMI was under the review of terms in Dublin Core Metadata Element Set (DCMES), which resulted with new terms documentation from its usage board. DCMES facilitates the discovery of the web resources through its 15 Dublin Core elements, divided into three classes, as follows [33]:

- Content (title, subject, description, source, language, relation, coverage),

- Intellectual Property (creator, publisher, contributor, rights),

- Instantiation (data, type, format, identifier).

Dublin standards have two levels - simple and qualified. There are 15 elements covered in Simple level and 18 elements in so called qualified level, adding: audience, provenance and Rights Holder as new elements.

IEEE Learning Object Metadata (IEEE 1484.12.1) is a LOM standard for creating a well structured description of learning objects. This model specifies how a particular LO should be described and what vocabularies should be used while describing a particular LO. Good vocabulary choices aid classification, avoiding redundant elements and even polysemy words (words with more than one distinct meaning). This standard also guides how to bind LOM data (e.g., how LOM records should be represented using XML, RDF) [1].
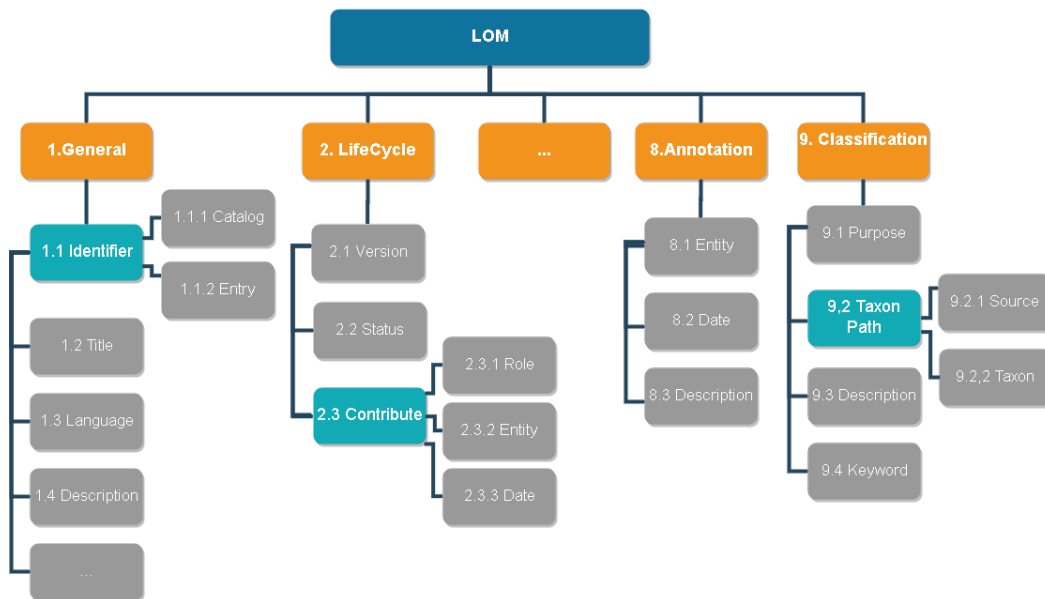
Fig. 6.3 Learning Object Metadata hierarchy structure

As shown in Figure 6.3, the LOM consists of 9 particular elements: General, Life cycle, Meta-metadata, Technical, Educational, Rights, Relation, Annotation, and Classification. Each of the elements is divided further into sub elements, and so on. The sub elements derive the context of their parent elements, which differentiate the final sub elements even with the same names.

IMS Learning Resource Metadata Specification is provided by IEEE and is based on early standard specifications which were contributed by the IMS Project and ARIADNE, from the United States and the European Union respectively. The collaborators chose to extend the LOM standard capabilities by introducing the best practices for describing the LO into the IMS learning resource metadata, binding them through XML based data structure and transforming XML instances into IEEE LOM using XSLT.

The ADL (advanced distributed learning) network was established in 1997, and its aim was to provide the highest quality standardized eLearning for the Department of Defense in United States, adapted for individuals' needs. Instead of achieving its goal, ADL developed and distributed the sharable content object reference model (hereafter SCORM) based on

XML and the ADL Registry, with financial support from the United States Department of Defense. The SCORM metadata elements are categorized into three groups: asset metadata, shareable content object metadata and aggregation metadata[28], which enable a successful sharing of LOs across different LMSs. SCORM metadata builds upon previous standards, such as the AICC (The Aviation Industry CBT Committee), IMS and IEEE, with the aim of creating a unified content model with associated metadata.

Using standardised metadata, most learning object repositories tend to enhance interoperability by using the two schemas, the Dublin Core and IEEE LOM. Some LORs provide LOs in content packages according to SCORM and IMS standard specifications, instead of being able to "transfer" the content into different LMS which support those standards.

6.3   Modeling the knowledge domain for Cloud eLearning

This research study recognizes that providing personalised courses with structured learning objects based on leaners' background and progress oftentimes requires reshaping learning object representation before placement in the pool of learning resources, in the Cloud. For avoiding the potential problems that could occur while linking the learning objects as discussed in Chapter 3, we have driven the process of adapting the learning objects throughout these three phases:

1. The granularity of learning object is segmented as small as possible, as a chunk object with a content that could stand as an entity by its own,

2. The existing learning objects are enriched with extra annotation for increasing the flexibility of coupling the learning objects with each-other,

3. The context alternatives of that smallest learning object are specified based on the new granularity of the LO.

These three mandatory phases are necessary conditions, because for a LO to be shared and reused the granularity of the content is very important, which is referred as the size of the learning objects. Noor et al. stated that the lower the granularity of the learning object is, it increases the chances to be reused in different context [36]. Whereas from the other side, Shoonenboom [40] has described different scenarios for determining the size of LOs, and the ability to reuse the modules in the personalised way.

After redefining the granularity of the LOs in the first phase, the learning object enrichment and the definition of context alternatives respectively, contribute to the flexibility of linking the sequence of Cloud eLearning learning objects. By increasing the flexibility, the

idea advances for combining the content and metadata of the learning repositories for offering loosely coupling of LOs in different sequences in different context [40].

Different context or domains refers to the number of domains in which a particular LO could be used. Wiley [5], expresses the different domains as the ability of reusing the learning object as "inter-contextual use". Analyzing each of the aforementioned phases, the evolution of learning objects into Cloud eLearning Objects (defined in definition 1.2) has come about naturally. The transformation process of Learning Objects into Cloud eLearning Objects is discussed further in the next section.

6.3.1 The evolution of Learning Objects into Cloud eLearning Learning Objects (CeLLOs)

As discussed in chapter 3, section 3.2, the pool of learning resources of various format and standards and, in this context, the creation of Cloud knowledge and its representation requires a common standard in order to be able to tailor a personalised learning path and create a coherent course otherwise we might end up with the situation as shown in Figure 6.4.
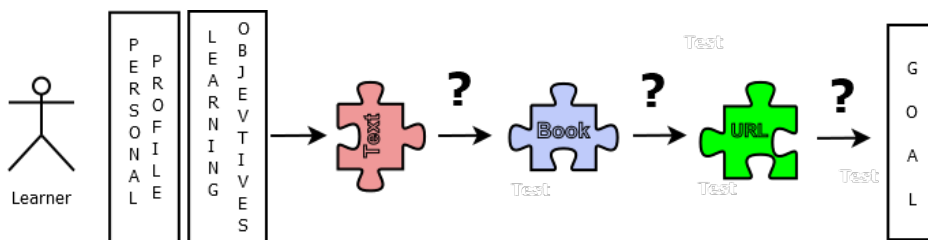
Fig. 6.4 A sequence of unstructured learning objects

In this respect, the learning objects that are derived from different sources, irrespective of whether these are structured in some standards and stored in some learning object repositories or if they are totally unstructured and untagged, have experienced a transformable process.
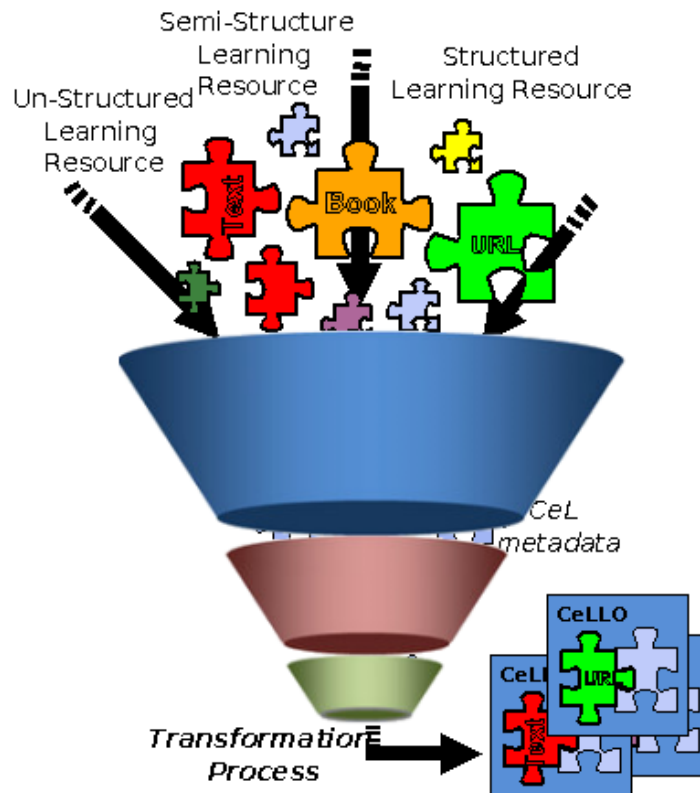
Fig. 6.5 Generating CeL Learning Objects from standard Learning Objects

This transformable process generates a new type of Learning Object that is usable, processable and applicable for CeL as shown in Figure 6.5. While this transformable process has created significant challenges, it has also made possible a coherent learning path of tailored learning objects. So, the result of the transformed process generetes Cloud eLearning Learning Objects, known as CeLLO.

Definition 6.1: The CeL Learning Object (CeLLO) as an advancement of learning object is defined as a structured electronic learning resource of a reasonable size and that satisfies an intended learning outcome.

The transformable process of integrating LOs into CeLLO is accompanied with addition of extra features/metadata to all existing learning objects to glue the LOs together in more coherent way. The additional metadata is added to each of the learning materials based on the extra information that are needed for the CeL framework. These additional CeL metadata together with existing metadata in LOs form the so-called CeLLO (Figure 6.5).

Definition 6.2: "Cloud eLearning Metadata - CeLMD" is a metadata approach used to transform the derived Learning Objects (from various sources) into CeL Learning Objects.

As shown in Figure 6.6, the elements of CeL Metadata are subsets of particular elements from existing metadata schemas, such as Dublin and IEEE LOM, with the addition of new elements that are required to achieve CeL aim.

The elements of Cloud eLearning Metadata are as follows: (1) Title, (2) Description, (3) Keyword, (4) Content, (5) Meta-metada, (6) Catalog, (7) Pre/Post requisite, (8) Relationship, (9) Intended Learning Outcomes, (10) Format, (11) Granularity, (12) Cognitive Level, (13) Context, (14) Credibility, (15) Crowd rating CeLLO, (16) Crowd rating set of CeLLO, (17) Date, (18) Language. The Figure 6.6, shows visually which of the elements are derived from Dublin Core and IEEE LOM. The extra added new elements are described seperately in Table 6.1.
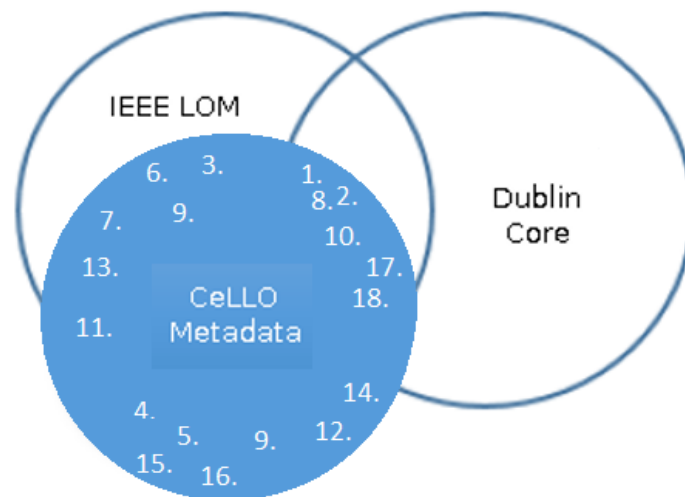
Fig. 6.6 CeL Metadata related to IEEE and Dublin core standards

The transformation of unstructured, semi-structured or fully standardised LOs into useful LOs for CeL could be done in a variety of ways ranging from manual, semi-automated or even fully automated which will be discussed as part of future work [34]. However, in this thesis we have proceeded with the manual option for reasons of simplicity and to avoid the associated complex situations which are out of this PhD scope.

The overall flow process of transforming LO into CeLLO is depicted in Figure 6.7, which describes the retrieval of a LO and its adaptation to CeL, as a CeLLO entity. As mentioned, the LOs are derived from different locations, which firstly were checked whether they already support an existing LOM standard. If not, the CeL metadata is applied fully to these LOs. Otherwise, if the LOs support already an existing standard, then the existing elements are inherited from that standard and the new CeL metadata elements are added manually.

Metadata elements such as Title, Description, Keyword, Catalog, Pre/Post requisite, Relationship, Format, Granularity, Context, Credibility, Date, Language, are reused from
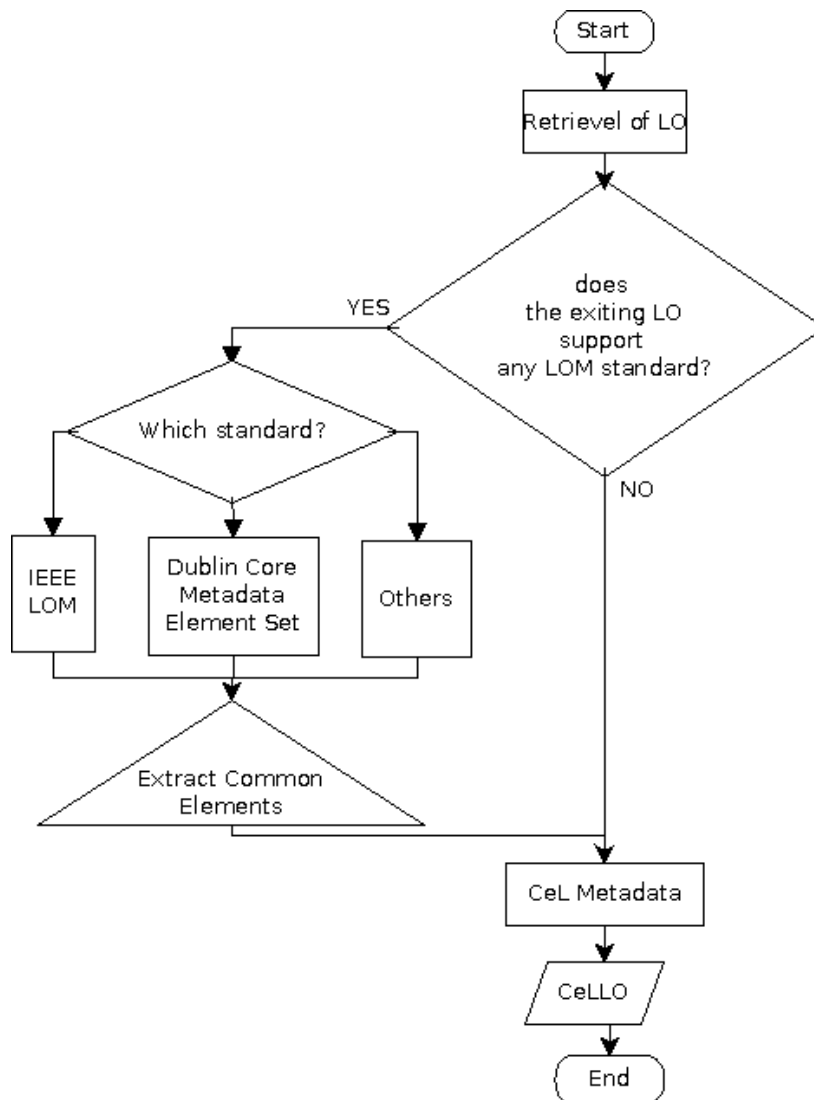
Fig. 6.7 The transformation process of a LO to a CeLLO

existing metadata schemas, such as Dublin Core and IEEE. The new elements that are required to achieve the CeL aims, such as intended learning outcomes, crowd rating, cognitive level, meta-metadata, and content are explained in Table 6.1.

In CeL context, a sequence of CeLLOs is generated from a planner (to be discussed in chapter 8) which automatically generates a coherent path, in which CeLLOs have pre- and post- conditions that correspond to what the learner knows and what the learner wants to achieve, respectively. CeLLOs are carefully selected from the pool of available CeL learning objects through a recommender system (discussed in chapter 7) that matches learners' preferences to suitable learning material. A concrete example is going to be demonstrated in chapter 9.

Table 6.1 Proposed Metadata Elements in a CeLLO

CeLLO Metadata Element	Description
Content	Content existing in the Learning Material for Text Mining
Meta-metadata	Information about the schema itself. Since the LOs are gathered from different sources, they may use different metadata schemata. These meta-metadata determine what kind of elements can be used within the existing metadata schema of a LO.
Cognitive level	Defining the level of cognitive difficulty of the CeLLO (using Bloom's Taxonomy)
Indented Learning Outcomes	Intended learning objectives of the CeLLO
Crowd rating	Indicating the perceived usefulness of the CeLLO

6.4 Modeling Learner for Cloud eLearning

The learner profile has an essential component when dealing with intelligent systems in online education. Online learners besides having different needs, have also different learning characteristics, starting from knowledge level, prior experience, learner learning styles, emotions, reactions etc. The information stored in the learner profile provides a gist on the personalisation of the eLearning process. Therefore, conceptualizing and modeling the learner profile properly could drive the overall process of personalisation services in a more advanced level. For providing personalised user services, the system captures users' interests and preferences. The actual existing systems do not accommodate of such changes, mentioned above. Either interests or preferences may change overtime, but not all existing systems are taking care of such changes, which may end to un-useful system after a certain amount of time, by providing inaccurate services. During the last decades, personalisation of the eLearning process has been an active research topic, which generated dilemmas among the researches concerning how to design an adaptive user profile, including the preferences of short and long-term interests, which all could contribute in the personalisation of an eLearning environment as effectively as possible. Various researchers speculated different approaches towards personalisation of learner profile, some of them linked with various theoretical backgrounds and others with models from different disciplines.

6.4.1   Learners Modeling Methods

As mentioned in 6.1, the modeling of learners is one of the most important part of any intelligent system. This challenge is derived from the idea, that different learners have different learning needs and different learning characteristics. And, in this respect in order to model the learner, the common characteristics of the learners should be elicited.

Based on Chrysafiadi [131], the common characteristics of typical learners are knowledge level, errors and misconceptions, cognitive features other than knowledge level, affective features, and meta-cognitive features. Generally speaking, when dealing with learners' modeling, there are plenty of available techniques. In [131], modeling learners' profiles, uses various methods, such as: the overlay, stereotypes, perturbation, machine learning, cognitive theories, constraint-based model, fuzzy logic, bayesian networks, ontologies models or even a hybrid approaches combined from two or more aforementioned technologies.

The overlay learner model proposed by Brian Carr (1977) is the mostly used model, which depicts the learner as a subset of the domain model by referencing the progress of the learners' up to the expert level knowledge of the particular subject. According to overlay student modeling approach the knowledge domain is represented as a set of elements, where each element could be a particular topic and concept. The stereotype learner model, used firstly by Elaine Rich (1979) for user modeling is a model of number of similar groups which have common characteristics and needs. The knowledge level of the learner could be presented as a limited number of conditions such as: novice, beginner, knowledgeable, advanced, expert or from the learning style perspective as visual or verbal, etc. The perturbation learner model [132] is counted as extension of overlay model by representing the learner as a subset of expert knowledge plus the learners' misconceptions. The learners' misconceptions are identified through learner's erroneous knowledge and wrong rules leading them to wrong answers.

The various cognitive theories explain the human learning as going through several phases, while a learner model is produced by knowledge tracing and model tracing [133]. A constraint-based model [134], models the learner profile by learning from performance errors. In this respect the Cloud eLearning has proposed a hybrid approach for modeling the learners' profile, which is disscused after reviewing learner specification standards in the following section.

6.4.2   Learner Specification Standards

Various organizations have contributed to standardizing the specific design of learner profile. Among them, IEEE LTSC Personal and Private Information Standard PAPI and LIP (IMS

Learner Information Package), are the most well-known standards which enable to design and describe learner profile based on learners personal information, interests or activities. Each of these standards has been described in section 2.4, which are the basis for the new proposal, namely the Cloud eLearning Learner Profile.

Both specification standards described in section 2.4 has been used and adapted by various eLearning systems for developing the learner's profile. For modeling learners' profiles, Musa et al. [135] has used a hybrid approach by using the union of elements of LIP and PAPI specification standards and additionally adding the learning and cognitive style elements. Wei et al. [136], presented an extended version of IEEE PAPI standard on their agent-based eLearning system, whereas Sawadogo et al. [137], presented an extended version of IMS – LIP by adding interactivity element.

According to Vogiatzis et al. [138], neither IMS LIP nor IEEE PAPI have enough elements to model an adaptive learner profile. Throughout their research the importance of modeling the learning profile through hierarchical structure is emphasized, starting from the user model definition, initialization, maintenance and implementation. Such conclusion is pertinent when analyzing both standards, which argues that none of previous approaches provides pedagogical information for the learners, such as: learning and cognitive styles, existing knowledge or lifelong learning goals, which are all missing [139].

6.4.3   Modeling Learner Profile with respect to Cloud eLearning

The existing IMS LIP specification standard is used as a basic model for modeling the CeL Learner profile (Ce2LP) characteristics, with a considerable extra number of features.

In order to satisfy the aim of CeL[140], IMS LIP (containing:(1) identification (2) affiliation, (3) relationship, (4) accessibility, (5) competency, (6) interest, (7) activity, (8) qcl, (9) goal, (10) transcript, (11) securitykey) is enriched with additional seven elements which contributed to model the Cloud eLearning learner Profile (Ce2LP) with respect to the CeL demands and continual changes overtime. Such elements as: Cognitive/Learning style, knowledge level, knowledge gained, short and long interests, social preferences and emotional state, described further in Table 6.2.

Table 6.2 CeL Learner Model Extra Attributes

CeL	Description
1.Cognitive/Learning style	The learning style of the learner
2. Knowledge Level	The knowledge level in particular topics/courses
3. Knowledge Gained	The knowledge gained (positive test result) in CeL
4. Short Interests	Interests which are shown in short terms (example: a topic that is visited in short term and never looked back again)
5. Long Interests	Interests (topics) that are studied continuously and, longitudinally and frequently visited (studied once and continually coming back to the same course/topic)
6. Social Preferences	Information related social activities (relevant information , example learners' opinions, feelings, likes etc.)
7. Emotional State	Information about emotional state, if the learner is confused, bored or even if the user is in the mood of learning simpler or more complex tasks at some particular moment

In this regard, the Cloud eLearning Learner Profile - Ce2L:

Definition 6.3: Ce2LP defined as metadata for Cloud eLearning Learner Profile is used to model and represent the learners of Cloud eLearning.

Further, the Cloud eLearning Learners profile (Ce2LP) is encoded using XML, as shown in Figure 6.8.

```xml
<?xml version="1.0" encoding="UTF-8"?>
<root>
  <row>
    <id>1</id>
    <topic>-</topic>
    <catalog>programming language</catalog>
    <knowledgeDomain>computer science</knowledgeDomain>
    <bloom_level>level_1/remembering</bloom_level>
    <test_results></test_results>
  </row>
  <row>
    <id>2</id>
    <topic>superviced learning</topic>
    <catalog>machine learning</catalog>
    <knowledgeDomain>computer science</knowledgeDomain>
    <bloom_level>level_3/applying</bloom_level>
    <test_results></test_results>
  </row>
  <row>
```

Fig. 6.8 An example of the knowledge level elements of Ce2LP

The features served for modeling Ce2LP are acquired in different phases, by explicitly asking the learners to complete the registration information, through questionnaires, or

through implicit manner, by monitoring learners' activities which is updated over time. For example, chunking all the elements of a particular user, the following data are derived either directly or indirectly:

- Directly: The personal data required from the user, such as:

    - name, birthday, address, gender, background knowledge, preferences, experience, domain of interest, role, username, password, etc.

- Indirectly: the data acquired from monitoring learner performance, such as:

    - learning style, knowledge gained, test results, rating of an item, item studied, click through, item visited, favourite, previous units, current units, progress achieved, overall time spent in the system, overall time spent in a unit, etc.

All aforementioned elements are represented using a combination of learners modeling methods explained above in section 6.5. The adaption of the learning environment using Learning styles has been implemented and evaluated in various systems. In this thesis the learning styles are represented using the stereotype model, by dividing the learners using the linear set of categories such as:

  (i) Visual,

 (ii) Auditory,

(iii) Tactile and kinesthetic learners.

Where the visual learners tend to learn more through visual approaches (for example: through videos), the auditory learner prefer the learning while listening, they often may read loud and listen to themselves. Furthermore, the tactile (touch) and kinesthetic (movement) learners prefer the involvement and memorizing of the learning through the interaction of objects[1] [141]. With respect to Cloud eLearning, as explained in section 6.5. the modeling of the learners' uses the hybrid approach, where stereotype learner model is used to represent the learners' knowledge level categorized as novice, advanced beginner, competent, proficient, and experts. The background of the learners' is used while following the overlay model, where the topics are saved to express the learners' progress as elements of knowledge domain. The cognitive theory is used to acquire learners' learning style. Above that, the learners' short-term and long-term interests are acquired using Text Mining technique, by modeling the vector of concepts extracted from searches and visited relevant sources and storing them as part of the learners' interests, shown in Figure 6.9.

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[1]http://www.nwlink.com/ donclark/hrd/styles/vakt.html
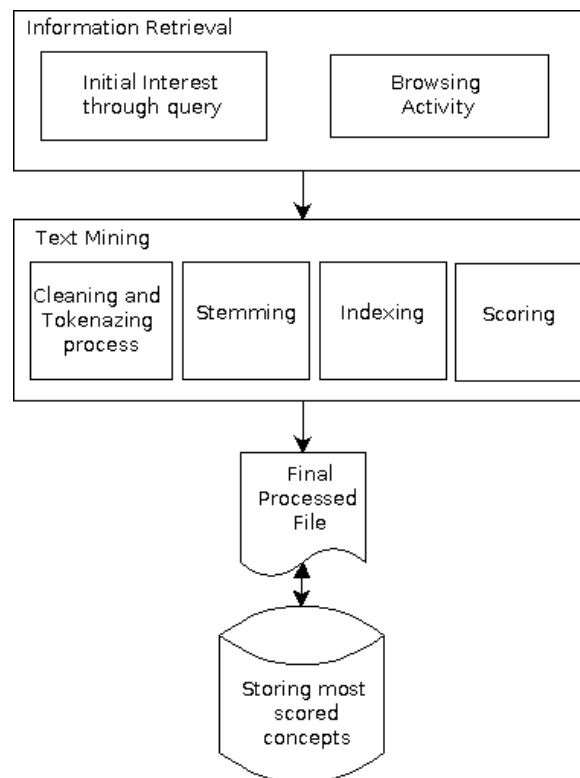
Fig. 6.9 Text mining technique for storing relevant concepts for user short-long interests

As shown in the process flow in Figure 6.9, the user's explicit searches, their browsing activities (example in social media and their overall browsing activities) together with the textual content expressed through direct queries are captured in a log file. The raw data stored in the log file are used for further processing throughout the text mining phase. In the very beginning the raw information are cleaned and tokenized. During the cleaning and tokenizing process, the html tags are removed and the sentences are chunked in words, so that semantically the similar words are matched together and indexed to the same indexing term. Further, the remaining data are processed under "stop word process", resulting with the removal of a list of stop words, such as: "the", "a", "and", "an" etc., which have the highest usage frequency overall. Then, the stemming process maps all inflectional forms of words to the same root form. For example, words computer, computation and computing are all derived from "compute", and only the root word, in this case the "compute" word is stored for the indexing phase. In [142], is presented the how the stemming algorithms is used to reduce the number of a word by mapping the nouns, adjective, verb, adverb etc. to its root word. The Portman stemming algorithm used in our approach is considered as the most usable algorithm which produced the most suitable output compared to other existing algorithms [142]. The final concepts are indexed and scored, where the top 5 stored concepts that are relevant

within the particular knowledge domain are stored in the learners' respective interests. These knowledges gained, are listed as topics/subtopics that the learner has completed after the CeL has proposed to the user.

Summary

This chapter reviews the contributions that have been made so far in order to provide knowledge representation. In this chapter a various number of theories and techniques have been analysed through which it has been clarified how the knowledge and learners' profiles are modelled so far. By reviewing existing systems and standards, we conclude that the new type of representing data and learners should be followed, namely Cloud eLearning meta-data and Ce2LP respectively which incorporates a set of elements (Table 6.1) which are missing in the existing standards. So, Cloud eLearning meta-data is based on IEEE and Dublin core standards and furthermore it has five additional elements described in Table 6.1, whereas the Ce2LP is based on IMS LIP specification standard and additionally adds seven extra features shown in Table 6.2. From one side, the Cloud eLearning meta-data facilitates the process of integrating the Learning Objects to Cloud eLearning Learning Objects (CeLLOs) through the transformation process depicted in Figure 6.7. From the other side, the CeL Learner profile (Ce2LP) with the seven extra elements models a dynamic learner with a number of characteristics explained in Table 6.2. Both approaches, CeLMD and Ce2LP facilitate the process of generating automated personalized learning path. However, since we are dealing with huge numbers of CeLLOs as part of CeL, the artificial intelligence planner will not be able to cope with such searching space, therefore we are obliged to implement a threshold filtering through recommender systems explained in the next chapter.

Chapter 7

Recommender Systems

Even if the learning objects are represented in the proposed standard form discussed previously, it is obvious that the Learning Cloud is a huge space to search in order to find those CeLLOs that should be presented to the learner arranged in a sequence of personalized learning path. In addition, combinatorial explosion creates an inevitable computational problem in any automated process, such as planning, that attempts to construct such paths. The main issue in classical techniques of artificial intelligence automated planning is the experience of exhaustiveness when dealing with the huge number of nodes in the search space (searching for numbers of objects as part of the search space). So, in this regard it is important that the pool of appropriate Cloud eLearning learning objects is relatively small so that we avoid combinatorial explosion (which tends to have many actions and states) during planning, which is the main limitation factor when trying to generate a solution from one engine in a single run [143].

So in this context, the Cloud eLearning recommender system (hereafter CeLRS) is involved between the knowledge representation and AI automated planning, which helps us to reduce the search space as well as to prioritise the Cloud eLearning Learning Objects that would be in the final learning path. We intend to introduce the basis of recommender systems and its related technologies which are being used in order to create a successful recommender system which filters a list of CeLLOs that matches with the learners' profile.

So, in this chapter recommender technology is described and we propose the Cloud eLearning Recommender System as a middle-layer of the overall Cloud eLearning architecture, in order to filter the most appropriate Cloud eLearning Learning Objects for a particular learner background and instant desire. The hybrid approach for building the Cloud eLearning Recommender System is elaborated, in order to rank the relativeness of learning objects through content filtering and the prediction of the learning objects through collaborative

filtering. To summarise, the Cloud eLearning Recommender System (CeLRS) has a two-fold purpose:

(i) a personalisation role, in order to provide personalised CeL Learning Objects, and

(ii) a filter role, in order to filter the highest ranking CeL Learning Objects into an input list for the artificial intelligent planner.

7.1 The Basis of Recommender Systems

In order to provide recommendations to user, a recommender system interacts with the user to acquire the users' preferences and the users' goals and desires. The interaction occurs continually in order to record and infer accurate data, since users' preferences often change over time. The acquired data are passed through various processing phases, facilitated by algorithms which generate item recommendations as search results. Recommender systems (hereafter RS) rely on the accuracy of data processing which results with successful recommendations by matching users preferences to "items" of interest which will be defined a couple of paragraph below.

The data within recommenders are organized in a matrix form, where columns are items and rows are users. In general, acquiring the data could be very difficult, and in order to build successful and reasonable recommenders there are various techniques for filling the data within the matrix.

Table 7.1 Rating Matrix (also known as Sparse Matrix) for two users and three items

	Item 1	Item 2	Item 3
User X	2	?	5
User Y	?	4	?

The term "Item" is used to determine what a system recommends to the users, whereas the term "rating" is used to denote the users' preferences, for that particular item. Practically, the rating is expressed for particular item as a triple attribute: (User, Item, Transaction)[144], expressed with range of "number of user" x "number of Items", as shown in Table 7.1. In this case, the transaction is expressed using rating, where rating for User X with respect to item 3 is "5", whereas the unrated items are represented as question marks. And, the aim of the recommender systems is to predict these question marks, based on the data collected.

The development of recommender systems requires a multidisciplinary effort, involving researchers from Artificial Intelligence, Human Computer Interaction, Data Mining, Decision Support Systems, Marketing and Statistics disciplines, and as a result of this collaboration

today we find recommenders that are developed by using different technologies of Artificial Intelligence, such as Bayesian networks, Markov decision processes, neural networks, to name a few.

Depending on the domain of the recommender system, the item could be a learning object, a book, a movie, a document etc. The suggestions made by the RS aim to facilitate their users in various decision-making process, by providing them enough information for deciding what learning object to study, what movie to watch, what document to read and so on.

The recommendation techniques could be classified [101] as knowledge poor or knowledge depended. Through knowledge poor techniques, the system tries to retrieve the preferences of users:

- Directly through test and questionnaire (or induced), through constraint-based techniques, where some constraints come from users and others from the items. Those items that satisfy the constraints are reasonable to suggest.

- Using data representing the user experience or activities during the navigation, rating, commenting, buying or

- A combination of the above

Whereas, through knowledge depended techniques, the system acquires the data using ontological description of the "user" and/or "item", or through user interaction and other social activities. Inspired from contributions elaborated in section 3.2 the Cloud eLearning uses the CeL recommender system, as a middle layer in CeL architecture as shown in subsection 5.6, to recommend and also rank the appropriate learning materials, from the overall pool of learning resources. The CeL recommender system in general, and the overall functionality, particularly the algorithms used to achieve the CeL aim, are described in subsection 7.2.

7.2 Semantics

Since the data gathering from the user profile and its interaction with the content over time is important to concretize the recommendation of the appropriate learning materials, the representation of data plays a key role in this matter.

Previously, the web content was targeted for human consumption, since the meaning of the data was not machine-accessible which is why many times there were difficulties while searching particular data for relevant items. So, to generate a specific search for data located

in different items required performing several steps. The first step was to generate different data, analyze the response and extract the needed information [145].

Therefore, the need to facilitate and automate the knowledge representation in web technologies resulted in the Semantic Web. With the rise of Sematic Web technologies, knowledge became organized in conceptual spaces according to its meaning. And furthermore, the web was organized either for human or machine retrieval. The use of semantic web as a new generation of Web has promoted the new paradigm of World Wide Web, aiming toward automate search, reuse of web resources as machine readable resources. The contribution of semantics has promoted in the understanding of the machines, example: interoperability, applicability across agents and services, usability etc.
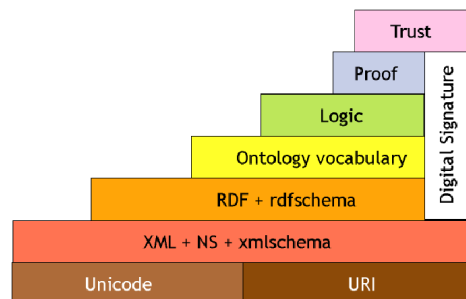
Fig. 7.1 Semantic Web Layers [146]

As depicted in Figure 7.1, the bottom- up layers needs to be followed when developing semantic webs[146]. The XML + NS + XMLschema is used for writing structure content with defined vocabulary. The next layer, the RDF (Resource Description Framework) + rdfschema applies basic data model like Entity Relationship Diagram (ERD) which has an Extensible Markup Language (XML) syntax in its own. Following Ontology Layers, the vocabulary defined here is used to provide a shared understanding of domain for improving the web search accuracy. The logic, proof and trust Layers establish the truth of statements, and so enable intelligent reasoning with meaningful data [147]. For using semantic web that will be shared and reused in different applications it is necessary to create conceptual boundaries for that particular domain. Ontology (further discussed in subsection 7.3) is used by all users for locating and reusing the resources as building blocks for creating meaning and furthering relationships.

Many approaches could have been used to establish concept and resource boundaries through extracting the preferred meta-data and minimizing the inevitable inconsistencies. In order to enhance knowledge based on the eLearning environment, in [148] a new approach is proposed for enriching domain ontology, by extracting concepts using a combination of contextual and semantics. The proposal in [148] follows an observation matrix, which

exploits the statistical feature extraction by using frequency of occurrence of common terms, font size and font type. Those concepts were scored further through selection of appropriate words for describing the particular item. Those concepts that were used at the highest level, are then selected as concepts for enriching the Ontology.

Another layered model for picking up new concepts and also updating the latest modification in order to avoid inconsistency is suggested in [147]. The concepts were gathered from: the learning domain layer, learning resources layer and profiles of learners' layer. The extracted concepts from the learner profile layer were used to enrich ontology with users' profile information. Based on that information the framework suggested courses that could be of interest to users and also created a relation between users with common competences and learning goals. The automatic selection of keywords called LVD-F (Lesk Visualness and Disambiguation with Frequency of Occurrence) [149] selected the most appropriate keywords for representing video lectures and describing topic content. The selected keywords from categories and titles were tokenized. All the same words that had different meanings were passed through a filter to distinguish them. Each word then is processed to calculate visualness values and occurrence frequency. The combination of visualness and frequency of occurrence informed generation of the most appropriate word for enriching the Ontology.

7.3   Ontologies

As discussed in section 3.4, the use of Ontologies as a formal specification of shared conceptualisation could be used through various purposes, such as for modeling learners' knowledge background, describing the learning materials, modeling the learning objectives/outcomes[99] and also for modeling the structure of learning materials as part of a course[100], which furthermore could be part of a particular curriculum.

Cloud eLearning (CeL), for the sake of personalising the learning process for specific learners, uses the ACM Computing Classification System. The ACM CCS ontology is used because the learning materials that will be proposed to the learners, as part of the Experimental show case that is demonstrated in Chapter 9 deal with Computer Science domain, specifically with Programming Language otherwise the selection of the ontology would need to have been reconsidered. The ontology needs to be reconsidered because ACM CCS currently provides the ontology only for computing domain.

In Cloud eLearning case, the use of ACM CCS made it possible to generalize and/or specialize the learners intentions and interests. Technically, the ACM CCS uses a hierarchical approach, by constructing the concepts and their relations as topics/subtopics of the computing domain. The coverage, the user-friendliness of the interface, the use of a

hierarchical approach of controlled vocabulary and a well-planned classification system, are among the reasons prompting ACM CCS selection [150]. The partial taxonomy of ACM CCS is depicted in Figure 7.2.
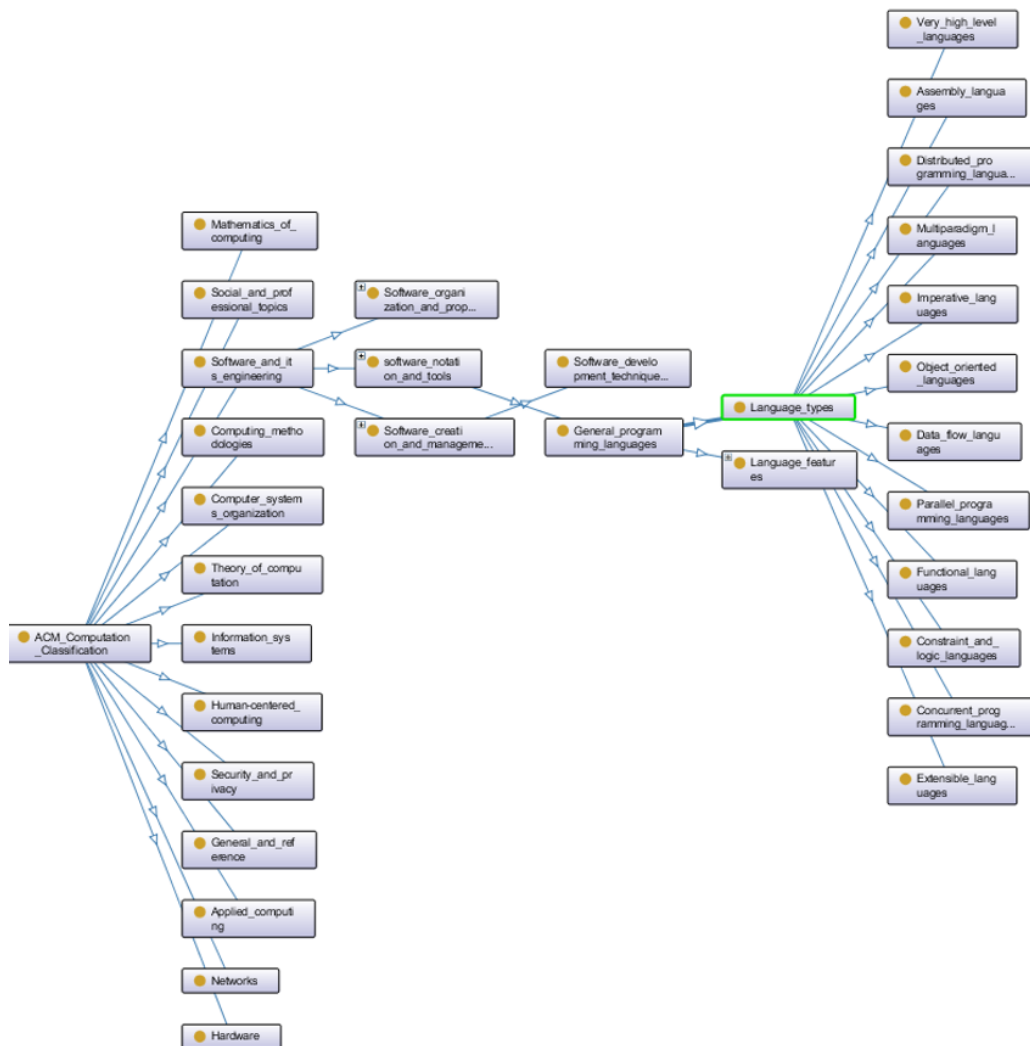
Fig. 7.2 The ACM Computer Classification System - A partial tree architecture

The overall process of using ACM CCS Ontology to generalize the interest of the learners in order to filter the appropriate Cloud eLearning Learning Objects (CeLLOs) is going to be described in the following sections. We selected the ACM CCS Ontology because the case which will be represented in Chapter 10 is part of computer science domain. Further, the Cloud eLearning Recommender System, proposed in chapter 5, combines the Semantic and Ontology technology in order to represent the CeL Learning materials (CeLLO), and generalize/specialize the learners' desire, respectively. Accordingly, to this, the CeLRS in general, and the functionality of CeLRS in particular is described in the following sections.

7.4 The Cloud eLearning Recommender System

In Cloud eLearning, the Cloud eLearning Recommender System serves as a middle layer in the overall architecture of Cloud eLearning, serving as a filter of the combinatorial explosion of learning materials. Filtering and identifying the most relevant learning materials for any specific user, requires various processes. In the very beginning, the learner profiles and the CeLLOs are represented through several features, which are encoded in the xml files. Beside this, as an input data is also the learners desire which in a particular moment, could be expressed as their desire to learn something new on a subject through an unstructured query. This, together with any rating information for the required subject as well as the overall learner profile (knowledge cognitive level of some subject expressed as in Bloom taxonomy and learning style [50] constitute the overall learners' desire as follows:

$$desire_{Li} = \{query, subject, knowledge_{level}, learning_{style}, ratings\} \tag{7.1}$$

In CeLRS, the direct unstructured query text is processed through word segmentation, stop-word removal, and stemming processes. The Term Frequency and Inverse Document Frequency (TF-IDF) [151] technique is used to find the weighting factors in CeLLOs and decide how relevant a cluster of CELLOs is for learner $learner_{Li}$ and her desires $desire_{Li}$ The CeLRS process will be discussed in detail in a future section, which will emphasize the important aspect of deploying the hybrid approach in one recommender system. In this aspect, CeLRS uses content and collaborative filtering as combined techniques for providing prediction and ranking which will be discussed further in subsection 7.4.3. The content-based filtering recommends the CeLLOs based on the learners' desires whereas, the collaborative filtering is used to weight higher the most popular rated CeLLOs and recommended $CeLLOs\{c_1, c_2, ..., c_n\}$ based on the k-nearest neighbours user and item approach. Therefore, the CeLRS can be viewed as:

$$CeLRS(desire_{Li}, CeLLOs) = \{c_1, c_2, ..., c_n\} \tag{7.2}$$

Each of the $CeLLOs\{c_1, c_2, ..., c_n\}$ provides the smallest granularity of a particular subject and must satisfy at least a single intended learning objective within the desired knowledge level of the subject.

7.4.1 The CeLRS Process

CeLRS is expressed through a number of steps as shown in Figure 7.3. Each of the steps represents a particular phase of the CeLRS. During the initial phase, the information retrieval phase, the existing learners' data and the learners' desires are determined.
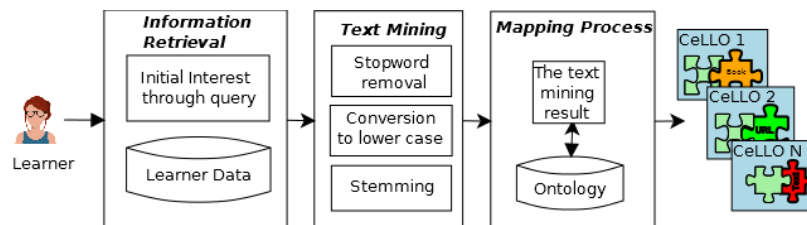
Fig. 7.3 The CeLRS process

During the text mining phase, the query is segmented to single words. The remaining word list is processed further through the stemming process using the Porter algorithm [152]. Finally, through the final phase, specifically through the mapping process, is used the ACM CCS ontology. Through this phase a vocabulary of the cluster containing CeLLOs is built, which in combination with the learners' desire produces a ranked list of all CeLLOs within the most similar cluster. In general, the data retrieval have impact on processing time, also the ranking of information in order to classify the most relevant and least or non-relevant CeLLOs could have an impact on the overall response time. In this context, clustering helps to partition the input space of CeLLOs into subsets on the basis of similarity metrics, such a learners' desires, and by taking into consideration that ranking may or may not be known at the beginning of the clustering process. In CeL, we tend to use any available learning object in the cloud as part of the enormous number of CeLLOs. That's why, the combination of clustering algorithms and ranking techniques are applied so that CeLLOs are listed in order of relevance per cluster. In general, the clustering algorithms are categorised in hierarchical, partial, density-based, grid-based, graph-based approaches, whereas the ranking algorithms could be content or linked-based [153].

As a result of this, in the CeL Recommender System, we have implemented the hierarchical approach for clustering similar CeLLOs and a vector space model, a kind of content-based approach, for ranking most relevant CeLLOs within a cluster.

7.4.2 Hierarchical Clustering in CeLRS

Within this context, hierarchical clustering techniques produce a sequence of clusters within a knowledge domain [154]. There are two categories of algorithms used for hierarchical clustering, agglomerative (bottom-up, starts with singleton clusters and continues by merging

clusters that are the most similar) and divisive (top-down, starts with a macro cluster and splits it further as it progresses). In the CeL context, the hierarchical clustering of CeLLOs produces a tree, representing parent-child relationship among the entities, which could be expressed as topic-subtopic relationship in a subject hierarchy. In CeL case this is done through the use of ACM CCS ontology that defines the computer science and engineering knowledge domain. To be more concrete, assume that a learner in CeL aims to acquire new knowledge or skills through CeL in the Computing domain, e.g. "Software and its engineering". The use of ACM Computing Classification Taxonomy depicted in Figure 7.4 demonstrates the hierarchical clustering process. As shown in Figure 7.4, the ACM classification schema defines various sub-domains within computing.
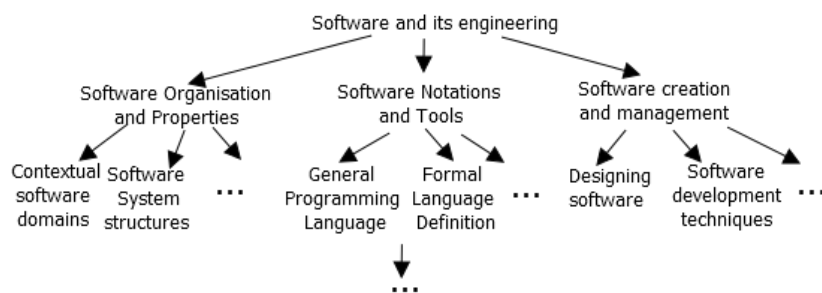
Fig. 7.4 A sample of the hierarchical classification of ACM Ontology

7.4.3   Vector Space Modeling in CeLRS

The Vector Space Model (VSM) is an algebraic model that is commonly used for information retrieval [155]. The idea behind the model is to represent the clusters and the data through vectors in a multi-dimensional space, and to compute their similarity through cosine similarity measure. For simplicity reason, the concepts of the clusters shown in Figure 7.4 are denoted as follows: assume C1 represents "Software and its engineering" as the main topic of interest (Figure 7.4), then C1 will be partitioned further into C2 which represents "Software Organisation and Properties", C3 "software notations and tools" and C4 "software creation and management". In turn, C2 continues to be partitioned further to subtopics, C5 "Contextual Software Domains" and so on, as shown in Figure 7.5.

Applying the divisive clustering approach to ACM taxonomy (Figure 7.5) results in a structure clustering as shown in Figure 7.6.

Then, the cosine similarity between the $desire_{Li}$ and the ACM cluster terms as resulted in Figure 7.6 are weighted as product between the *Term Frequency (TF)* and the *Inverse Document Frequency (IDF)* [151]. The TF-IDF weight is a statistical measure used in retrieval processes for evaluating how important a specific word is to a particular CeLLO
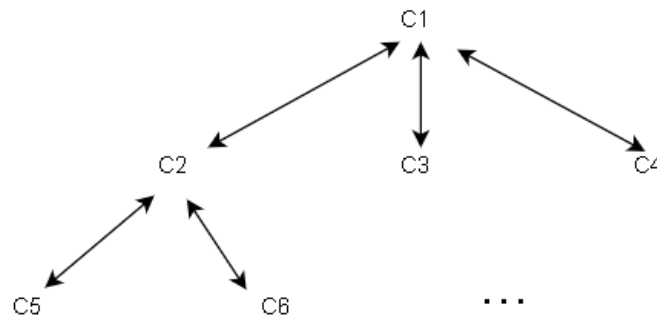
Fig. 7.5 An abstract approach of the hierarchical classification of ACM Ontology
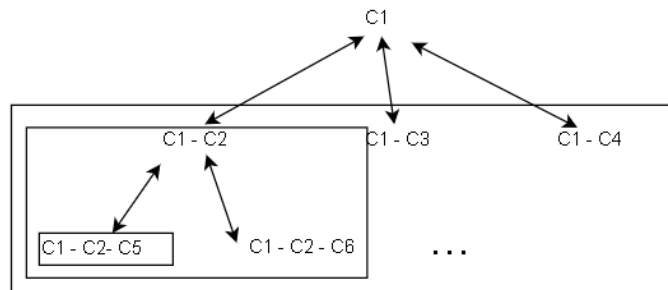
Fig. 7.6 The divisive clustering used for CeL based on ACM Computing Classification Taxonomy

that is part of a cluster. TF [151] provides the information how often the required term is found in using the expression as follows:

$$TF(t,c) = \frac{\sum t}{\sum atd} \tag{7.3}$$

where $\sum t$ represents the number of times the term "t" appears in a CeLLO. Whereas $\sum atd$ represents the total number of all terms in the CeLLO. In contrast, IDF [151] expresses through logarithm, the total number of CeLLOs in CeL divided by the total number of the CeLLOs in which the term occurs:

$$IDF(t) = log\frac{\sum c}{\sum c(t)} \tag{7.4}$$

where, $\sum c$ represents the total number of CeLLOs, and $\sum c(t)$ represents the number of CeLLOs containing the term "t".

Finally, the weighting of CeLLOs is calculated as shown in equation 7.5:

$$weight(t,c) = TF(t,c) * IDF(t) \tag{7.5}$$

The whole process is repeated until all the terms within a query are covered, and the final weighting is accumulated and represented as the final result:

$$Result(query, cellos) = \sum_{t \varepsilon query} (TF(t,c) - IDF(t)) \qquad (7.6)$$

The recommended CeLLOs are listed from most to least relevant CeLLOs by computing the function of cosine similarity of the angle between respective vectors in the VSM using:

$$cos\theta = \frac{v(q) * v(c)}{|v(q)| * |v(c)|} \qquad (7.7)$$

where θ represents the angle between the $desire_{Li}$ represented as $v(q)$ and the respective CeLLOs , $v(c)$ as part of a particular cluster.

7.4.4   A concrete example of using Vector Space Modelling

To be more concrete, assume that CeL contains two CeLLOs. The 1st CeLLO contains the following content, "You will be working with numbers and with strings in Java", as represented in Table 7.2. So, in the Table 7.2 are listed all tokenized words as well as its frequency.

Table 7.2 The 1st CeLLO content

you	will	be	working	with	numbers	and	strings	java
1	1	1	1	2	1	1	1	1

Continuing with the 2nd CeLLO, containing: "Learning data types in Java and how to declare them"

Table 7.3 The 2nd CeLLO content

learning	data	types	in	java	and	how	to	declare	them
1	1	1	1	1	1	1	1	1	1

A vocabulary is created containing all the words of CeLLO1 and CeLLO2, and the CeLLOs vector is represented based against the vocabulary as shown in Table 7.4:

Table 7.4 Vocabulary against CeLLO1

and	1
be	1
data	0
declare	0
how	0
in	1
java	1
learning	0
numbers	1
strings	1
them	0
to	0
types	0
will	1
with	2
working	1
you	1

Table 7.5 Vocabulary against CeLLO2

and	1
be	0
data	1
declare	1
how	1
in	1
java	1
learning	1
numbers	0
strings	0
them	1
to	1
types	1
will	0
with	0
working	0
you	0

Assuming that the learner is searching for: "data types in java"

Table 7.6 Vocabulary against learners' desire

and	0
be	0
data	1
declare	0
how	0
in	1
java	1
learning	0
numbers	0
strings	0
them	0
to	0
types	1
will	0
with	0
working	0
you	0

The cosine similarity between the initial query and the CeLLOs are calculated where the terms are weighted as product between the Term Frequency and the Inverse Document Frequency as explained in expression 1 to 4. The process is repeated until all the terms within a query are processed, the weighting is accumulated and finally the list of ranked CeL Learning Objects are listed from top-to-least relevant learning materials compared to the initial query In the above example, the 2nd CeLLO will be ranked higher with cosine similarity 0.47, followed by the 1st CeLLO with cosine similarity 0.14 .A concrete example will be given in the following section.

7.5   CeLRS example

So, assume the list of available CeLLOs, listed in Table 7.7, are of different format type such as: videos, audios, podcast and texts. In addition to those, there are also self-evaluation tests CeLLOs in order to assess the progress of the learners which will be part of future work. Results from such tests are updated in learners' profile on a continuous basis. Also, the prerequisites and cognitive level are defined according to Bloom Taxonomy. For example, in order for a learner to be able to work with numbers in "Java", s/he should be able to understand the basic concepts of "General Math" (defined as math(1)) which is prerequisite

for CeLLO "c10". In this stage, CeLRS besides the content, it considers all features of CeLLOs, such as: the level of difficulty of the CeLLO, the format of the CeLLO as shown in Table 7.7.

Table 7.7 Sample CeLLOs in some abstract format

Type of learner	Available	Cello ID	Bloom Level	Topic	Prerequisites
audio	podcast	c1	1	data abstraction	none
audio	podcast	c2	3	instance variables	algorithm(1)
audio	podcast	c3	3	objects and classes	none
audio	podcast	c4	2	control statements	none
visual	text	c5	1	data types and variables	none
visual	text	c6	1	boolean algebra	math (1)
visual	text	c7	5	interfaces	none
visual	text	c8	1	object and classes using java	none
visual	video	c9	3	array lists and arrays	java(2)
visual	video	c10	1	working with numbers in java	math(1)
audio	podcast	c11	6	objects and classes	none
audio	podcast	c12	1	classes	none

A *Learner*$_{L1}$ is interested to learn how to create classes in object-oriented programming (cognitive level 5, i.e., Synthesis or Creating). Her/his current knowledge is only "programing language features" at cognitive level 1, which means s/he is able to understand the basic concepts of the overall "programing features" such as: data types, control structures, constraints, and so on. In contrast, learner L2 currently has "General Programming Language" knowledge (cognitive level 4, i.e., analysis), and would like to learn about "interfaces" (cognitive level 5). Both learners' profiles are listed in Table 7.8.

Table 7.8 Sample Learner Profiles

Learner	Knows	Learner	Desires
L1	Programing Language Features at level(1)	audio	classes at level(5)
L2	General Programming Language at level(4)	visual	Interfaces at level(5)

Therefore, the CeLRS filters the number of relevant CeLLOs to the *desire*$_{L1}$ and *desire*$_{L2}$ according to the process that are explained in sections 7.2.2 and 7.2.3. As explained in 7.2.2, in order to determine the relevance of CeLLOs, the ACM Computing Classification System is used. For example, *desire*$_{L1}$, is mapped with the cluster of "Language Feature" which

contains the "Classes and Objects" as part of it (found as follows: General -> Software and its Engineering -> Software notation and Tools-> General Programming Language -> Language Features -> Classes and Object) and will filter a list of CeLLOs that are part of 'Language Feature'. Hence, all CeLLOs with cognitive level 2 to 5, that are part of the "Language Feature" cluster, containing audio materials from "Abstract Data Type", "Control Structures", "Constraints", "Classes and Objects", and so on, which are under the "Language Feature" topic in ACM CCS will be listed, predicted and ranked. Therefore, in our example, the final result is listed in Table 7.9.

Table 7.9 List of recommended CeLLOs by CeLRS

Cello ID	Topic
c2	instance variables
c3	objects and classes
c4	control statements

Table 7.7 contain also the CeLLOs "c11" and "c12" which provide materials related to "objects and classes", as part of a "Language Feature" cluster, and are of "audio format types", and so are within the desired format range. They are, however, omitted from the list in Table 7.9, because the cognitive level 1 and 6 are out of the desired range 2 to 5.

For the example presented above, the implemented CeLRS and initial tests demonstrate that it successfully recommends the list of CeLLOs in Table 7.9 that are relevant to learners' desires because the knowledge at level 1 of the learner is already acquired (stated in Table 7.8), whereas the cognitive level 6 exceeds the cognitive level desired. Similar to this, if a learner will search a particular topic that might be at cognitive level 6, but in her profile shows knowledge expertise of level 3, the CeLRS will propose the CeLLOs from level 4 to 6.

Proposing the CeLLOs from cognitive level 4 and 5 as well, tends to avoid the gaps that could be generated inadvertently (currently having knowledge at cognitive level 3, and immediately jumping to knowledge level 6), and make possible a more grounded progress for the learner.

Summary

This chapter presents the CeL Recommender System prototype which intelligently identifies and ranks those CeLLOs which are relevant to a specific learner, considering her/his profile and desires. Through this chapter a concrete example is given, which demonstrates the applicability of the proposed approach. In order to match the most relevant cluster containing a number of CeL Learning Objects, a hierarchical technique is used. Specifically, a divisive clustering approach based on ACM Computing Classification Taxonomy defines various

sub-domains within computing domain. In addition, in order to rank the appropriate CeLLOs within the clusters, the vector space modeling is used, particularly the cosine similarity algorithm. The resulted CeLLOs of CeLRS, serve as an input list to CeL automated planner in order to generate a sequence of CeL Learning Objects as a personalised learning path, which is going to be discussed in the following chapter.

Chapter 8

Automated Planning

In everyday life, the usual tasks are accomplished intuitively as in reactive fashion without having to mentally process everything in advance. With the increasing complexity of tasks, there is a need to demonstrate a goal-oriented behavior, e.g. planning, which often entails the need to plan different alternatives in order to achieve certain goals.

Given an initial and a desired state of a world, planning is the process of generating a sequence of actions in partial or complete order so that, if these actions are performed, the desired goal can be achieved. In Artificial Intelligence, the planning process can be fully automated in a variety of ways depending on the nature of the problem as well as the constraints imposed for the final solution (plan).

Automated planning is being used in various domains for generating processes that must bridge between a current and a desired state. Learning can be seen as a process that guides a learner to bridge her current knowledge and skills to some desired aspirational ones. And in this context, this process can be viewed as a planning process. The learner is at some initial state with skills and knowledge already having been acquired through previous experience and would like to change (learn) to a new desired state which will contain new skills and new (or modified) knowledge. The process of assembling learning material to form a, so called, learning path is equivalent to planning.

In the CeL case, the main issue is to select the most appropriate learning resources to include in a personalised learning path. This becomes even more challenging in Cloud eLearning, where the resources can be anything that is stored in the Cloud. This chapter begins with a short explanation of planning as a key area of artificial intelligence, followed by an overview of AI planners and algorithms used, and it concludes with the explanation and demonstration of CeL Planner.

So, this chapter describes an automated planning approach prior to proposing that planning offers learning opportunities. Further, a number of planners are listed and a list of

techniques used from these planners are explained, and finally the Cloud eLearning Planner is described as the final process of the overall Cloud eLearning approach. The "Cloud eLearning Planner - CeLP" synthesizes the right Cloud eLearning Learning Objects in the personalised sequence based on learners' backgrounds and learners' interests.

8.1 Planning Principles

Planning is an important component of rational behaviour [156] and could be defined as the task to design the behaviour of entities that act individually, either on their own or as part of a group of activities [157]. The purpose of Planning as a subfield of AI is to cover the computational aspect of intelligence rather than just performing a plan as a set of activities for providing a solution to particular problems.

Often, Conceptual models are used to describe the elements of problems, through explanation of basic concepts, analysis of the requirements and representation of them. Mostly, a Conceptual model for planning requires general models for systems, such as expressed in Figure 8.1.
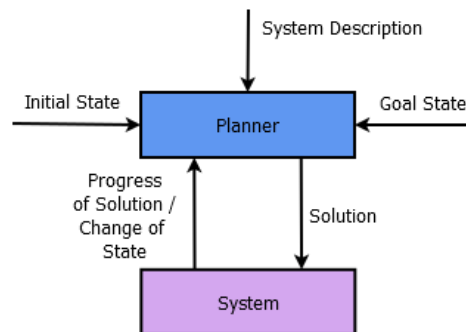
Fig. 8.1 Conceptual Model for Planning

As shown in Figure 8.1, the planner requires certain information, such as the planning domain with various actions for the system, and a problem describing the initial and goal state. Based on this information, the planner generates a particular plan based on the logic that the planner poses. As a continual process, the plan provides a set of actions that need to be taken in order to achieve the desired goal as stated in definition 8.1. Details will be discussed further within this chapter.

Definition 8.1: A Plan is defined as a sequence or parallelisation of activities or actions, which aim to achieve specified goals and satisfy the domain constraints based on some initial state given a priori.

8.1.1   Types of Planners

Planners involve the representation of actions executed by intelligent agents. Since there are various types of actions, there are different types of planners which are applied for various tasks, such as: path and motional planning, process planning, perception planning, navigation planning, to name a few. Each of them is further described in Table 8.1.

Table 8.1 Taxonomy of Domains for Planning

Planning Domain	Description
Path and Motional	Commonly used to find a path for a robot or agent, from the initial state to the defined goal. The algorithms are used in different fields, starting from bioinformatics, animation of characters, industrial automation, robot navigation, etc.
Perception	Processes the current state of environmental concerns, by gathering the information through sensors. It relies on decision theory of a problem, when, which and how the information is needed. For example, the perception planner is required when modeling a complex environment.
Information gathering	Assembles forms of perception while querying the system
Communication	Dialogues between various agents in order to justify when and how to query required information and which feedback to provide in the meantime
Navigation	Combines the path and perception planning in order to explore the environment. For example, it follows a particular road by processing and avoiding the obstacles.

In the other side, there are different approaches on planning, there could be domain specific/dependent planning or domain independent planning, online or offline planning, classical or temporal planning, linear or non-linear planning respectively[156]. The domain specific planners are specified precisely for particular problems and their drawback is that each planning problem is tightly connected with the domain problem. In contrast, domain independent planning relies on an abstract model, starting from the simplest model of action which allows a limited reasonable action to those advanced models with more complex capabilities [158]. Meanwhile, a partial-order plan or non-linear planner starts the initial state with a partial plan and continues to refine the plan until the goal state is achieved. The actions within partial-order plan are unordered, except those necessary, whereas, the total-ordered plan or linear planner generates a sequence of totally ordered actions, even when steps do not need to be ordered. Based on the algorithms used, each of the planning techniques is described in Table 8.2, and includes some of the planners used in each of the specified techniques.

Table 8.2 Taxonomy of Techniques for Planning

Planning Technique	Description	Planners
Total order	The total order technique or linear planning specify the exact ordering of the actions within the plan. For example, in state-space planning, a totally ordered plan is refined.	SHOP[5], HTAP[6]
Partial ordered	The partial ordering technique or non-linear planning specifies the ordering of the actions only when necessary. In plan-space planning, a partial-ordered plan is refined continually until the desired plan could satisfy the state goals.	UC-POP[7], NOAH[8], PL-PLAN[9]
Heuristic Task Network	The HTN planning approach provides a plan by dividing the tasks into smaller subtasks by heuristically selecting the best options among the possible ones until reaching the primitive tasks that can be performed directly by planning operators.	AltAlt[10], FF[11], GRT[12], LPG[13], VHPOP[14], H2O[15]
SATbased and Contingency	SAT as a logic-based approach converts the planning problem into Satisfiability problem and the plan is generated based on the efficient solution of the resulting satisfiability problem. In both techniques the actions are not deterministic, and their effects may or may not be observable.	SATPLAN[16], Madagascar[17], ZANDER[18], BlackBox[19]
Temporal	The temporal planning differs from the classical planning because the actions have durations and some of them might be executed concurrently.	LPG-td[20], TALplanner[21], OPTIC[22], CRIKEY[23]
Casebased	The case-based planning approach, adapts (reusing previous plans or partial plans) previous cases with similar initial and goal states by recalling them from the library and modifying the retrieved solution for new upcoming problems.	CHEF[24], CaPER[25]

8.1.2   Techniques for Planning

The scenario of classical planning could be defined as a static planning for one scenario, with a known initial state and deterministic actions performed one at a time. And, the algorithms used are usually categorized into state-space planning and plan-space planning [158]. The Plan-Space (PSP) planner differs from the State-Space (SSP) planner not only in search space but also in how the problem is solved. For example, PSP uses a partial planning with infinite actions that will be refined continually until the final goals are satisfied whereas SSP uses a finite sequence of actions that is proposed from initial state to final goal. For example, using SSP the node is the initial state and the arc is the transition, whereas using PSP planner, a node is defined as a partially specified plan, and the arc is the refinement operations to further complete the partial plan[156].

The scenario of neoclassical planning encounters the parallelized activities through graph-based planning and satisfiability algorithms, through AI planning techniques. The neoclassical planners provide an open planning approach while taking in consideration various extensions to classical planning, such as time, resources and information gathering action. The automated planning conceptualised as automated reasoning relies in domain independent approach and in order to solve a problem, the planners take as input the problem specification and the knowledge about its domain. Based how the planners do the reasoning as planning capabilities, there are identified:

- project planning,

- scheduling and resource allocation, and

- plan synthesis.

Throughout, the scheduling and resource allocation include temporal, precedence and resource constraints to be used from each action. A scheduling application takes the action together with resource constraints and optimisation criteria as input and returns the temporal organised plan with resource allocation which aims to achieve the defined input criteria. Generally, in automated planning, the Planning and Scheduling are related problems, where the planning deals mainly with how to generate a set of actions (the plan) in order to achieve the specified goal, whereas the scheduling is concerned with time and resource allocation for the set of actions defined previously.

During the last decades, a lot of research has been conducted on planning in different domains, by proposing new methods and techniques for improving the planning systems either by introducing new definition languages or by developing algorithms with improvement

performances in known and unknown environments. For example, [159–161] developed flexible and distributed planning of multi agent systems in dynamic environments.

8.1.3   The use of search algorithms in State-Space Search

The State-Space Search is used to conceptualise and solve general and specific planning problems. The search is performed from the initial state to the goal state using appropriate actions in order to generate a successor until a goal state is matched. As stated above, in State-Space Search model, encountering the node as the current state of problem and the arc as the transition of the problem state from the current state to the successor state one may raise the issue what methods could be used in order to pass this transition. So in this respect, following the transition from the current state to the successor or goal state, there are number of search algorithms that could be applied to the planning problem. Depending on the algorithms that are used, the transition generates a particular solution, or a plan which describes the set of actions that needs to follow in order to achieve the goal state.

Based on the algorithm approaches used, the search algorithms are categorised as uninformed or informed search algorithms, depending on whether the algorithms have information about what state to expand next or not, as shown in Table 8.3 and 8.4, information that dependes on the state itself. The uninformed search covers the Depth-First Search (DFS), Breadth-First Search (BFS), to name a few, whereas the informed search is categorized further in global and local search algorithms depending on whether the search is performed in all state-space or only in a part of that. The informed search usually uses heuristics for estimating the distance to the goal in order to increase the performance of the algorithm by reducing the number of explored states. In the first category of the informed search, the global searches category are covered through: Best-First Search (BFS), A*, IDA* or D*, ARA* or AD*, among others. In contrast, in the local search are covered: Beam Search, Hill Climbing, Enforced Hill Climbing, to name a few [162].

Table 8.3 A list of planning algorithms- Uninformed (Blind)

Category	Algorithm	Description
Uninformed	Depth First Search	A graph traversal algorithm, which performs an exploration of the graph by reaching the deepest node before backtracking.
	Breadth First Search	Unlike DFS, the BFS algorithm explores the graph by visiting the successors of a certain level before going one level deeper.
	Dijkstra	Dijkstra is a complete and optimal graph search algorithm, known as shortest path algorithm. It explores the successor nodes based on minimal positive cost of the path.
	Bellman-Ford	Bellman-Ford algorithm is similar to Dijkstra algorithm, which explores the successor's node of the graph based on the shortest path but encountering also the negative edge weights.

Table 8.4 A list of planning algorithms - Informed (Heuristic)

Category	Algorithm	Description
Informed (Global Search)	A*	The A* algorithm is a heuristic search algorithm which expands the path that has minimum value of function F which is defined as the sum of the path cost and the estimated distance to the goal.
	Iterative Deepening A*	IDA* algorithm is a heuristic search algorithm similar to A* but with lower memory usage. When exploring the graph it defines its successors which are most promising nodes, and it doesn't go to the same depth in each of the branches of the tree.
	Anytime Dynamic A*	AD* algorithm is a graph based planning. The plan could be refined iteratively when new update information is received. The order of visiting the successors is similar to A* but taking into the account the inflation of the heuristic.
	Anytime Repairing A*	ARA* is a variation of A* algorithm which can produce a sub-optimal solution quickly, and continually refines until the allocated time expires.
Informed (Local Search)	Hill Climbing	Hill Climbing algorithm, starts exploring the graph, bginning from an arbitrarily state, and iteratively selects its successors with the lowest heuristic value. It starts with sub-optimal solutions and iteratively improves the solution until the maximized conditions are achieved.
	Enforced Hill Climbing	EHC is based on HC used for local search, but it uses BFS when the algorithm ends in local optimum. The algorithm will find a solution only when the problem has dead-ends.
	Beam Search	Beam search is a complement to the Breadth First Search algorithm.While exploring the successor, it keeps a limited number of successors (specified as width) as the best among others in order to achieve the goal state.

8.1.4   Planning Formal definition

In the artificial intelligence planning, the planner is used to generate solutions/plans for a specific planning problem. Once a planner is aiming to generate a solution, a planning problem and planning domain representation is required. In order to represent the planning problem and planning domain usually is used the planning formal definition. Today, we have various number of representation languages, such as STRIPS, ADL, PDDL[163]. In principle, within the planning domain of a classical planner, three components must be defined: the description of the system, the initial state and the objectives (the goals). Formally definition, a planning problem is a tuple:

$$P = (S, A, E, \gamma, s_0, g) \tag{8.1}$$

where

- S is defined as the set of states;

- A is the set of actions which are going to be performed in order to achieve the stated goal;

- E is a set of events;

- γ is the state transition function denoted as $\gamma : S \times A \times E \Rightarrow 2^S$;

- s_0 is the initial state;

- g is the set of goal states.

Planning Domain Definition Language (PDDL) is a representation language standard notation used to encode planning domains. There are different versions of PDDL, mainly supporting different syntactic features such as [164]: conditional effects, basic strips style actions, specification of hierarchical actions, to name a few. The PDDL modeling language is inspired by STRIPS and ADL a previously specification languages for describing the system [163]. PDDL, as a domain definition language is supported by different planners, through which it could define the properties of the domain, the precondition and the actions. Using the defined properties, the planner is aiming to generate a plan for achieving the desired goal based on the planning techniques that has been developed. PDDL contains requirement clauses, such as: typing, strips, fluent etc which could be used further in the function and actions only if they are primarily declared. So, as part of the final process of Cloud eLearning, respectively the phase of Cloud eLearning Planner, the specification language for describing the system is used Planning Domain Definition Language . The

PDDL modeling language was chosen besides the STRIPS and ADL, because nowadays is supported by most planners. It is used to represent the planning domain and planning problem as two required compontents in order to be able to generate a personalised learning path (generate a plan).

8.2   Learning as a Planning Process

As specified in the previous section, Learning can be defined as a change of state in the learner's cognitive, psychomotor and affective domains [41]. Learning is based on learning outcomes, which in CeL case has been derived from the Bloom Taxonomy explained in 3.2, including the defined ways how to accomplish a specific task as specified in teaching and assessment methods.

Therefore, the learners are confronted with a series of learning materials, which we call Learning Objects (LOs), such as texts, videos, assignments, and exams that they can access in order to meet their learning outcomes. These objects resources form a learning path which can be seen as a solution to a defined planning problem.

Definition 8.2: Learning is a planning process that has an initial and a goal state. Where the inital state represents the actual knowledge of the learner and the goal state is the final state of the learner after acquiring new knowledge of their interest.

One could define learning as a planning process as follows:

$$Learning = (S_l, A_l, \gamma_l, s_{0l}, g_l) \qquad (8.2)$$

- S_l is the set of all possible states that characterise a learner;

- A_l is the set of all Learning Objects;

- γ_l a set of transitions which change the state of a learner;

- s_{0l} is the initial state of the learner;

- g_l is the set of learning outcomes to achieve;

In the case of Cloud eLearning, a simple example would be: Select a Cloud eLearning Learning Object (CeLLO) from the Cloud eLearning Recommender System (CeLRS) pool of resources using the Cloud eLearning planner for learner X.

Starting from the initial state and the desired goal of the learner, a plan is generated which will define through planning actions what the learner should study, and through scheduling, when and how to study it.

8.3 Automated Planning as the final process of CeL

As explained in Chapter 5, the Learning Cloud is populated with CeLLOs adapted from various sources as shown in Figure 8.2. The CeLLOs contains topics from various subdomains of computer science. A set of CeLLOs might contain similar topics which drive the learner to the same intended learning objective. Further, the similar topics provided from various sources, might be offered in various format, such as video, audio, text, to name a few.
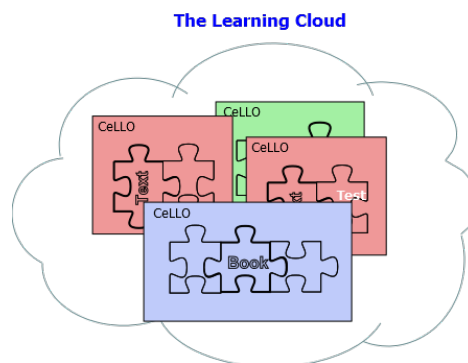

Fig. 8.2 CeLLOs of various formats

The Cloud eLearning Recommender System, represented in chapter 7, filters the number of existing CeLLOs in the Learning Cloud, based on the learner background, as well as the desire that the learner expresses over time. And, as a result of the processes expressed in section 7.3, the resulted list of CeLLOs encounters the most relevant CeLLOs based on content, intended learning outcomes, granularity, and crowd rating.

The personalised learning path (the plan) generated from Cloud eLearning Planner (CeLPLN), considers the background of the learner together with learner desire as initial state, and the achieved learning outcomes as the goal state. In a nutshell, the plan defines a sequence of CeLLOs having learning outcomes (LeOs) that correspond to what the student knows and what the student aspires to achieve respectively. Planning offers a reasonable learning path, and in case of any testing failure the failure triggers the CeLPLN to generate the new learning path which tends to replan the new alternative in order to meet the intended learning objectives (LeOs) as shown in Figure 8.3.
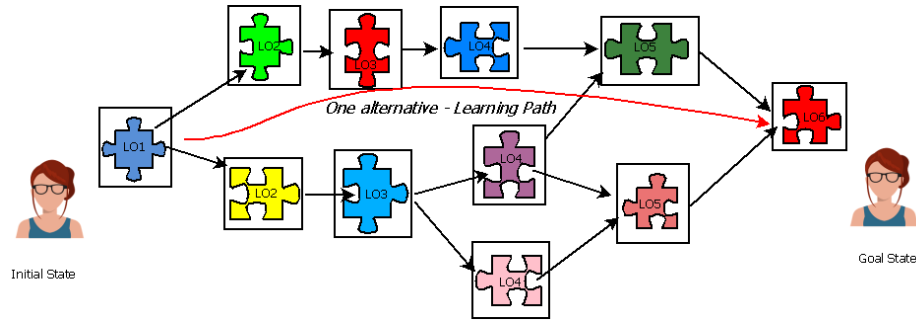
Fig. 8.3 The proposed learning path from CeL planner

8.3.1 CeL as a Planning Problem

Therefore, with the process described above we ended up with a pool of suitable CeLLOs that will take part in the planning process. Formally, the Planning in CeL is a tuple:

$$P_{CeL} = (S_{cel}, A_{cel}, \gamma_{cel}, s_{0cel}, g_{cel}) \tag{8.3}$$

where:

- S_{cel} is the set of all possible propositions that describe the user profile, knowledge, skills and desires

- A_{cel} is the set of all CeLLOs

- γ_{cel} is the set of state transition functions which given a state of a learner and a CeLLO returns a new state which includes new knowledge and skills that the learner has acquired through this CeLLO

- s_{0cel} is the initial state of the learner

- g_{cel} is the set of goal states that include the desires in terms of skills and knowledge by the learner

As discussed in the papers [165–167], all recommended CeLLOs are offered as part of the planning problem and the CeLPLN synthesizes the right CeLLOs in the personalised sequence based on learners' background and learners interest. The logic how the CeL planner is invoked is desribed using the pseudocode in Algorithm 1.

The CeLPLN has adapted the FF [168] planner, a planner inspired by HSP planner [169]. The FF planner relies on forward search, in the state space, guided by a heuristic function

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Algorithm 1 Invoking Automate Planning to generate a personalised learning path

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    Input: Recommended CeLLOs from the CeL and profile constraints of learner
    Output: Personalised Learning Path for the learner

 1: **if** *recommendedCeLLOs*! = *null* **then**
 2:      Action 1: Select the relevant existing CeLLOs;
 3:      Action 2: Generate the personalised plan to the learner;
 4: **else**
 5:      reInitiate the CeLRS;
 6: **end**

---

which estimates the goal distance by ignoring the delete lists (the negative effects from all operators), as was proposed by Bonet and Geffner [169, 170].

The FF planner as a search strategy uses the enforced hill climbing algorithm which initiates the heuristic function and the relaxed graph-plan [168] respectively, to estimate the goal distance, which at the end generates either a solution or a fail plan.

Unlike FF, the CeLPLN uses the backward chaining algorithm, which starts from the goal up until to the prerequisite required to accomplish the goal state. Basically, it starts from the intended learning outcome of the desire, and aims to produce the necessary prerequisite of CeLLOs. It firstly builds a planning graph until all prerequisite are satisfied for achieving the intended learning outcome, which is stated as the main goal.

The graph consists of alternating CeLLOs and action layers as shown in Figure 8.4. The number of CeLLOs that deal with similar topics construct an action layer. The next layer is constructed based on the prerequisites of CeLLOs that are part of the previous layer.

To be more concrete, it first constructs the final layer (the "n" layer) which contains all CeLLOs that fulfill the intended learning outcome of the learner desire. All the CeLLOs within a layer are CeLLOs which target the same topic/subtopic but it could vary depending on the CeLLO attributes, such as: format, type, granularity etc. Then, it goes backward to the second layer (the "n-1" layer) which contains all the CeLLOs which are prerequisite for the final layer and the process of constructing layers and CeLLOs as part of particular layer goes on until no prerequisites are required. So, when this phase is fulfilled, the graph plan is designed, and then the learning path is constructed from the initial state up to the goal state as emphasized in Figure8.4, by adding successors based on their granularity.

In addition to the previous examples, there might be a need to define the duration of each action (watch, study, take test etc.) that the learner should do. In such case, we should specify the time frames as constraints for the action, precondition and effects [171]. If we consider the same actions with planning and scheduling techniques, beside the constraints, the action
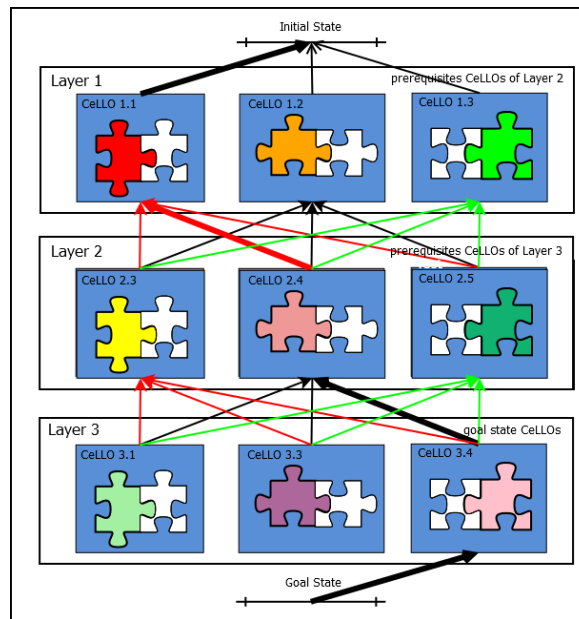
Fig. 8.4 The layered structure of states and CeLLOs

is specified with its resource requirements as well (which might be consumable or reusable resources) and three variables (starting time, ending time and duration).
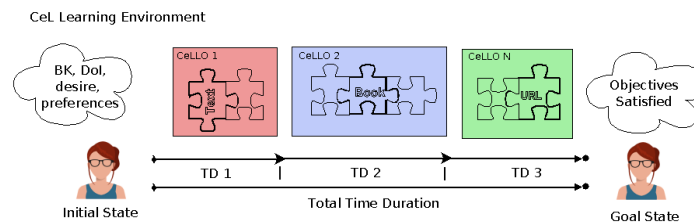
Fig. 8.5 The CeL Planning Domain

To be more concrete, a visual examples is modelled in Figure 8.6, 8.7, and 8.8 using the itSimple tool [172] which emphasized a more technical architecture of Cloud eLearning through UML class diagram. The itSimple tool offers the possibility to model the planning environment and the planning problem through a graphical interface. Figure 8.6 expresses the concept of CeL. As depicted in Figure 8.6, Learners are defined by: type, knowledge level and desire attributes, whereas CeLLOs are defined throughs: type, format, granularity, topic, prerequisites and intended learning outcomes attributes. Each of the CeLLOs has a defined time to study, respectively to test the learners knowledge. The Match-making uses the learners profile and the existing CeLLOs to produce a personalised plan, specifically a personalised learning path, which is characterised through a number of CeLLOs and its defined sequence.
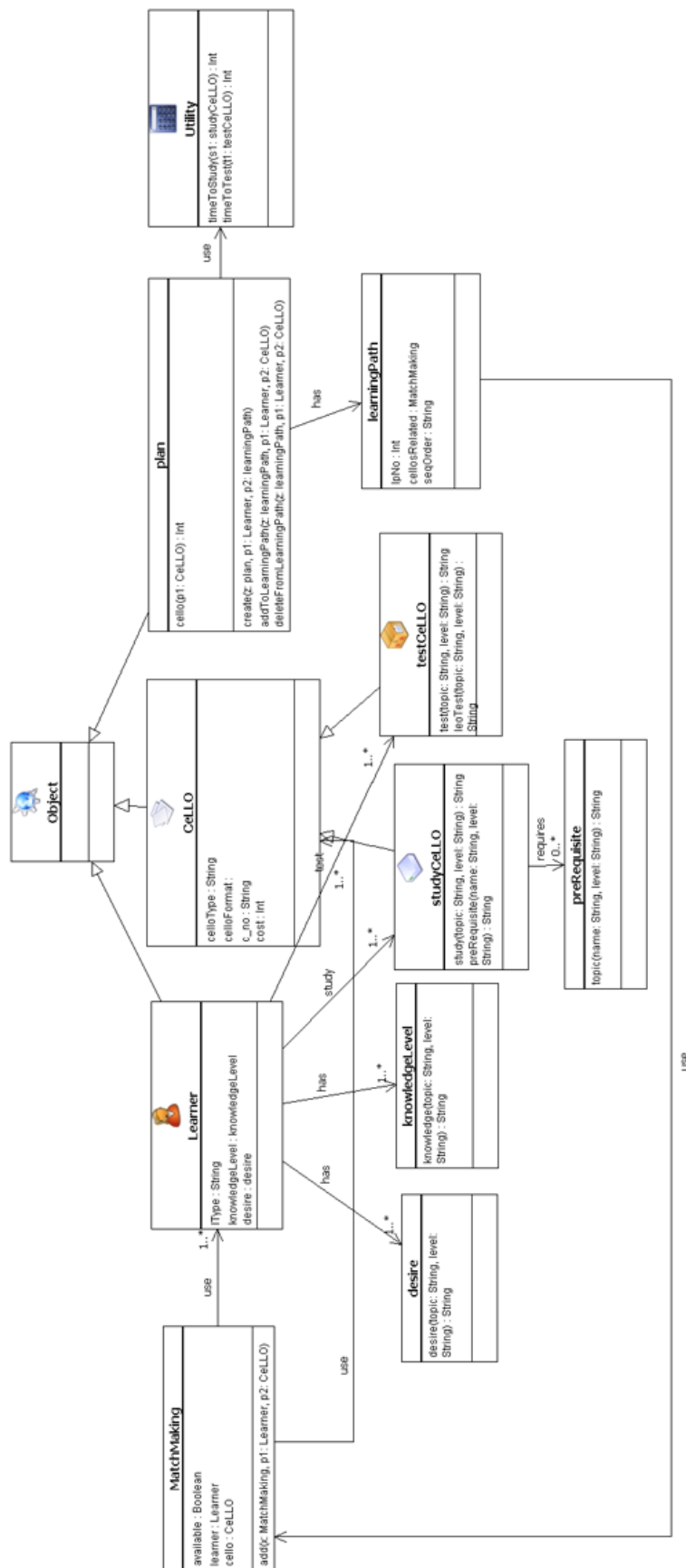
Fig. 8.6 The representation of CeL concept using itSimple

Continuing with the Figure 8.7 as required by the Cloud eLearning Planner, the learner should have an initial and goal state. So, the initial state is represented using itSimple in Figure 8.7 and the goal state in Figure 8.8 which lists all objects that are related to learners, CeLLOs and related attributes associated with all the objects. So, starting with the representation of initial state in Figure 8.7, we have an instance of the learner, following with learner desire, and the instances of all required CeLLOs based on the learners desire and its background.
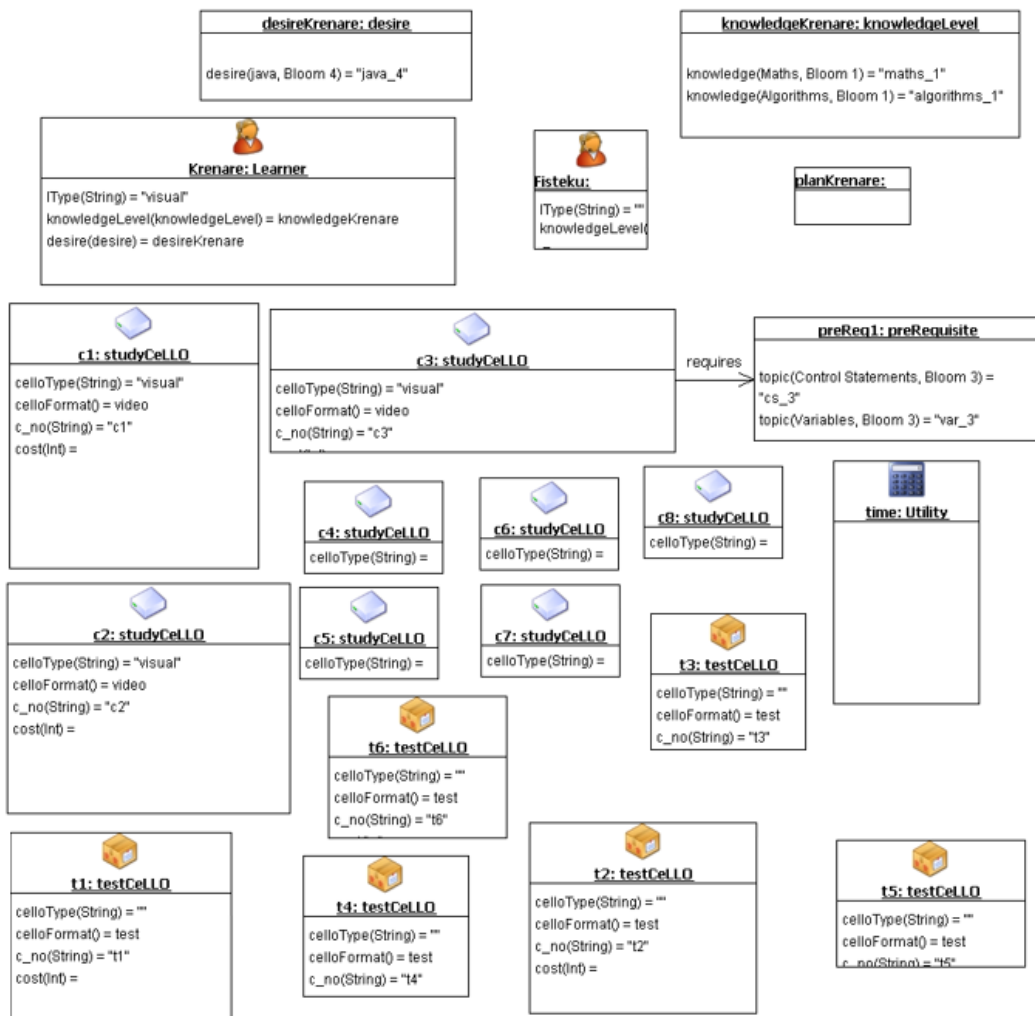
Fig. 8.7 The initial state in CeLPlanner

Following the Figure 8.8, the learner ends up with the desired goal, which defines the list of actions which needs to be followed in order to study the appropriate CeLLOs for satisfying the goal state.
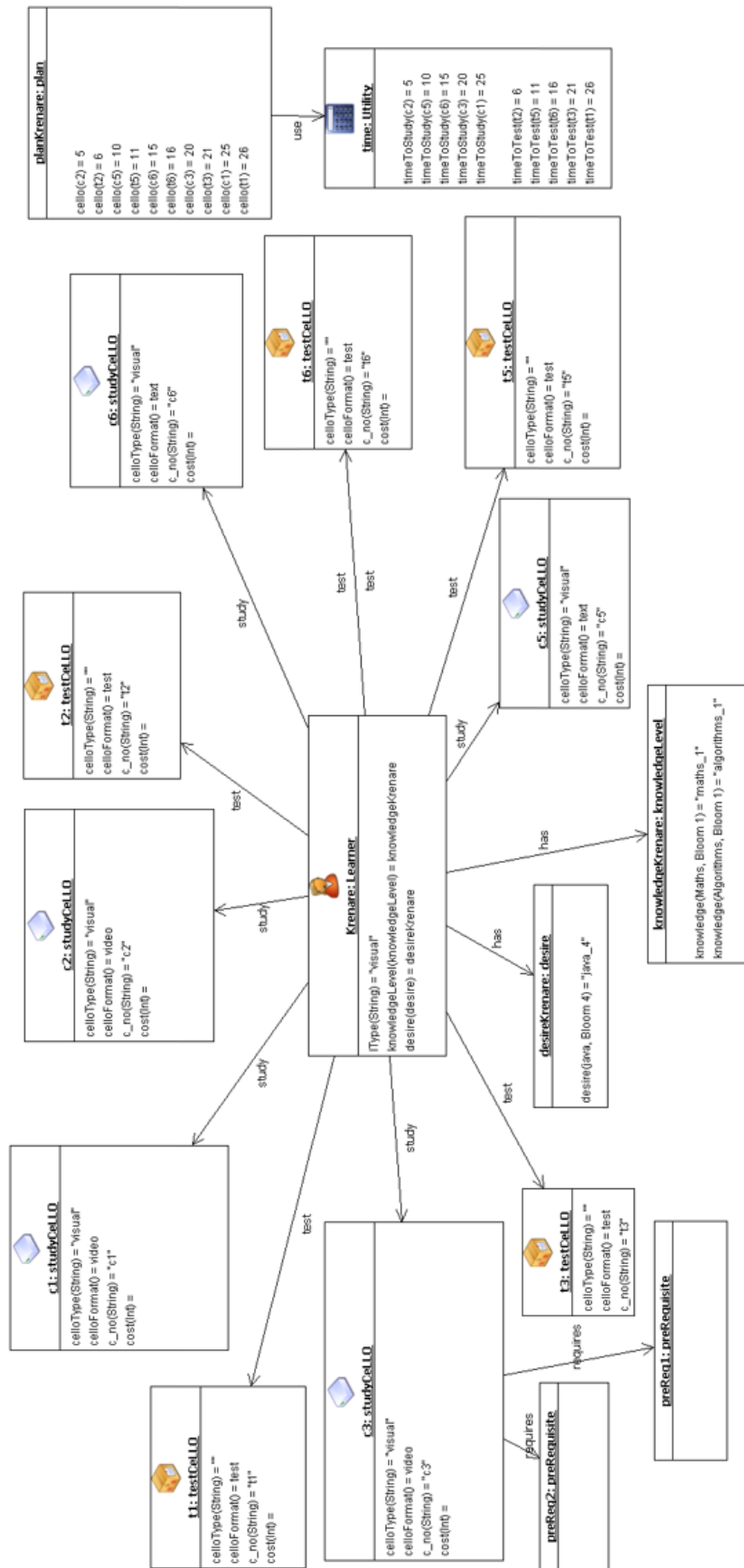
Fig. 8.8 The goal state in CeLPlanner

8.3.2   Planning in CeL: An example

For simplicity reason, here we present a trivial example avoiding the syntax and the graphical interface tools in order to demonstrate the generation of the personalised learning path.

As shown in Table 8.5 a learner (learner 1) is interested to learn java so that the learner can acquire skills at level 4 of the Bloom taxonomy, i.e. analysis. The learner profile is listed among other profiles in Table 8.5.

Table 8.5 Sample Learner Profiles

Name	Knows	Type of Learner	Desires to Learn
learner1	maths at level(1) and algorithms at level (1)	visual	java at level(4)
learner2	maths at level(3)	audio	ai at level(4)

Learner1 expresses her desire through an unstructured query (example: compare and explain classes and objects in java). The CeL recommender system filters the number of available CeLLOs which might be relevant to the desire of the learner. Relevance is determined also by the ontology related to the desire, in this case, java is related to variables and control statements of programming languages through the ACM ontology [173]. Some of these CeLLOs are videos, audios, podcast or others texts format types, while some others are self-evaluation tests to assess learners' progress (Table 8.6). The CeLLOs that are potentially relevant contain materials about algorithms, java, object oriented programming and maths. In each of the CeLLOs the cognitive level of the contained material is defined (Bloom level), as well as the pre-requisites required in order to be able to benefit from the content of the material.

Table 8.6 Sample CeLLOs in abstract format

Type of Learner	Available Format	CeLLO ID	Bloom Level	Topic	Prerequisites
visual	video	c1	4	java syntax	none
visual	video	c2	3	oop	none
visual	video	c3	3	algorithms	control statements at level(3) and variables at level(3)
visual	text	c4	1	maths	none
visual	text	c5	3	control statements	none
visual	text	c6	3	variables	none
audio	podcast	c7	3	control statements	none
audio	podcast	c8	3	variables	none
any	test	t1	4	java syntax	none
any	test	t2	3	oop	none
any	test	t3	3	algorithms	none
any	test	t4	1	maths	none
any	test	t5	3	control statements	none
any	test	t6	3	variables	none

For example, in order to deal with the topic "algorithms", one must deal with control statements and variables (CeLLO c3). An initial linear Planner creates a goal state that starts from the desires of the learner. The learner's profile forms the initial state. The plan generated is the learning path which consists of the most appropriate CeLLOs. In our example the personalised learning path for learner1 based on her profile and her desires is as follows:

1. Watch *c2*, a video on OOP;

2. Take the test *t2* related to OOP;

3. Study text *c5* on control statements;

4. Take the test *t5* related to control statements;

5. Study text *c6* on variables;

6. Take the test *t6* related to variables;

7. Watch the video *c3* on algorithms;

8. Take the test *t3* related to algorithms;

9. Watch the video *c1* on Java syntax;

10. Take the test *t1* related to Java syntax.

Summary

In CeL, the CeLLOs are treated as reusable resources, which have fixed duration, as shown in Figure 8.5. During learning, the learner may face problems, that is, fail to follow the personalised path for some reason, e.g. fail an assessment test. In such case, the planner should be able to define alternatives learning paths or to re-plan from that point of failure.

We have formally defined Cloud eLearning as a Planning problem with the goal to find a personalised learning path for any learner with a specific profile and particular desires to acquire new knowledge and skills. The validity of the approach was demonstrated through a graphical representation of an example using itSimple, following by a simple concrete example. We managed to implement the problem using linear planning, i.e. STRIPS notation, through PDDL. The Cloud eLearning Planner inspired by the FF planner, which has dominated in the last decade is integrated with Cloud eLearning Recommender System which initially contains a limited number of CeLLOs related to Java topic.

This chapter encloses the final process of Cloud eLearning proposal, and in order to deal with the planning as a learning process we had to go through the knowledge representation (Chapter 6), the Recommender Systems (Chapter 7) and ending up with the Automated Planning (Chapter 8). The following chapters will deal mainly with an experimental show case for CeL and the evaluation of the Cloud eLearning Prototype, which mainly was generated to validate the Cloud eLearning functionality.

Part IV

The evaluation process, results and Conclusion

Chapter 9

An experimental showcase for CeL

This chapter presents the system design and implementation of the experimental case. Since the Cloud eLearning consists of a number of technologies, finding a system with similar conditions in order to compare and generate results was impossible. Even though, if we divided the Cloud eLearning into three various segments, we could have compared each segment with number of systems that are reviewed. However, we think that comparing the segments and concluding for the total system is not the right approach, since we assume that the holistic approach of the Cloud eLearning, particularly the combination of technologies within the Cloud eLearning has an impact when discussing the final results. Therefore, in order to validate the research questions and Cloud eLearning functionality we developed a throwaway prototype using the Java and XML technology. The prototype served for concept-proof evaluation, and above that we applied the user evaluation approach to give an added value.

So, this chapter presents the requirements, design, development and implementation of CeL prototype, explaining in detail CeL prototype functionality with the help of various technical diagrams and at the end it presents the concrete Cloud eLearning prototype through a number of screenshots.

9.1 Design and Implementation of CeL prototype

In order to develop the throwaway CeL prototype an agile software development lifecycle was followed, going through the requirements, analysis and design, implementation, and the concept-proof evaluation processes as depicted in Figure 9.1.

The whole process of building the Cloud eLearning throwaway prototype was divided in two iterations where each iteration followed each of the processes presented in Figure 9.1. The creation of the Learning Cloud and CeL recommender system resulted in the end of the

first iteration, and then in the second iteration the CeL Planner was integrated to produce first version of the system which generates automatically the personalised learning paths as a the planning problem.
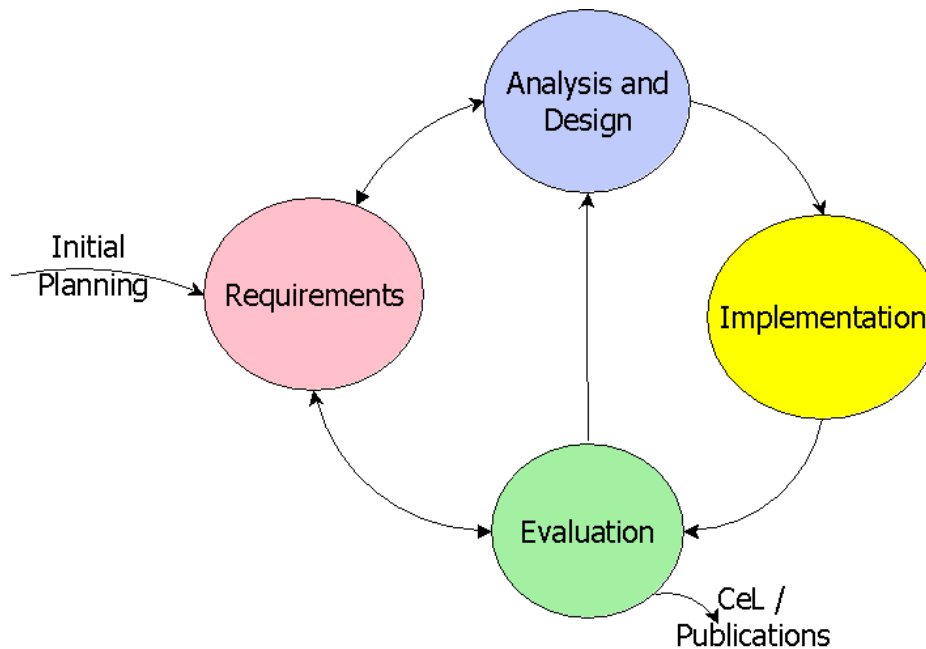

Fig. 9.1 The CeL prototype development lifecycle approach

Prototype preparation included generating a functional CeL prototype populated with learning objects, namely CeL Learning Objects (CeLLO) from various online sources discussed in subsection 10.2. From one side, learning objects were identified and adapted as CeLLOs per CeL requirements, whereas from the other side new learners' profiles were modeled and created in order to be able to test the functionality and validity of the CeL approach. And, finally, the prototype was evaluated by the experimental users' where the results are analysed and presented as part of Chapter 10.

Defining the requirements and understanding the overall concept of our proposal was a key step in order to proceed with the prototype. The list of requirements inherited from the proposal described in Chapter 5 was separated into functional and non-functional requirements. The main focus was on the functional requirements in order to create a functional CeL prototype which covers only the core layer approach presented in Chapter 5 (Figure 9.3). Following the proposal in Chpater 5, in Table 9.1 and 9.2 a number of functional and non-functional requirements are listed.

Table 9.1 Functional requirements of CeL prototype

	Functional Requirements prototype
1	Enable learner registration
2	Update learner profile
3	Update learner's progress
4	Validate learner's credential and update learner's preferences
5	List available CeLLOs for learners' intended interest
6	Enable learners' to rate the CeLLOs as standalone learning objects and the list of ranked and recommended CeLLOs
7	Enable the ranking of CeLLOs
8	Generate the personalised learning path of the learner

Table 9.2 Non-functional requirements of CeL prototype

	Non-Functional Requirements	
1	Usability	The system should be easy for a typical learner to use
2	Reliability	The system should be reliable enough that will not put off the users
4	Adaptability	The system will be able to adapt based on user characteristics
7	Resource Consumption	The system will be able to offer services for a massive number of users

The first iteration followed the identification of requirements and the proposal of the abstract architecture presented in Figure 9.3. Following the identification of requirements listed in Table 9.1, the list of use cases has been created and shown in Table 9.3.

Table 9.3 The list of Use-Cases

Use Case	System Operation
Register	registerUser()
Login	login()
Maintain/update system Functionality	createFunction(), updateFunction()
Get list of CeLLOs	getCeLLOList()
Rate the CeLLO	rateCello()
Rate the list of CeLLOs	rateCelloList()

For example, Figure 9.2 expresses the CeL use case, depicting the learners' interaction abilities with CeL. Such interactions, as being able to register, to login, to search for a desire topic and/or subtopic, be able to see the list of Cloud eLearning Learning Objects and furthermore to study them.
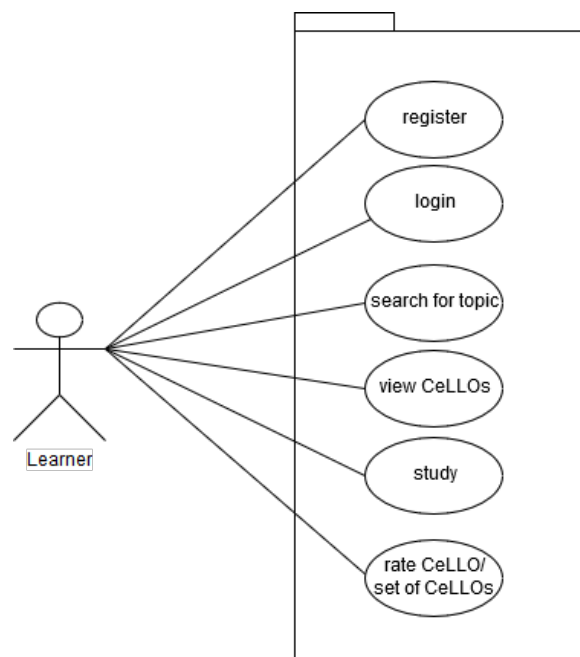

Fig. 9.2 The Cloud eLearning prototype use case

In order to generate the first prototype Java has been used, followed by the XML technology through which the metadata of the CeLLOs and learners has been adapted in structured manner.

The first desktop prototype generated the CeL recommender system and the CeL reposi-tory to enable the adaption of CeL learning Objects from various structured and unstructured resouces as explained in Chapter 6. Furthermore, the second version of the prototype included also the Cloud eLearning Planner which has been build using the FF planner concept as explained in Chapter 8, in order to generate automated personalised learning path for CeL learners'. The overall Cloud eLearning Architecture components are depicted in Figure 9.3, explaining the collaboration between the modules within the CeL prototype.

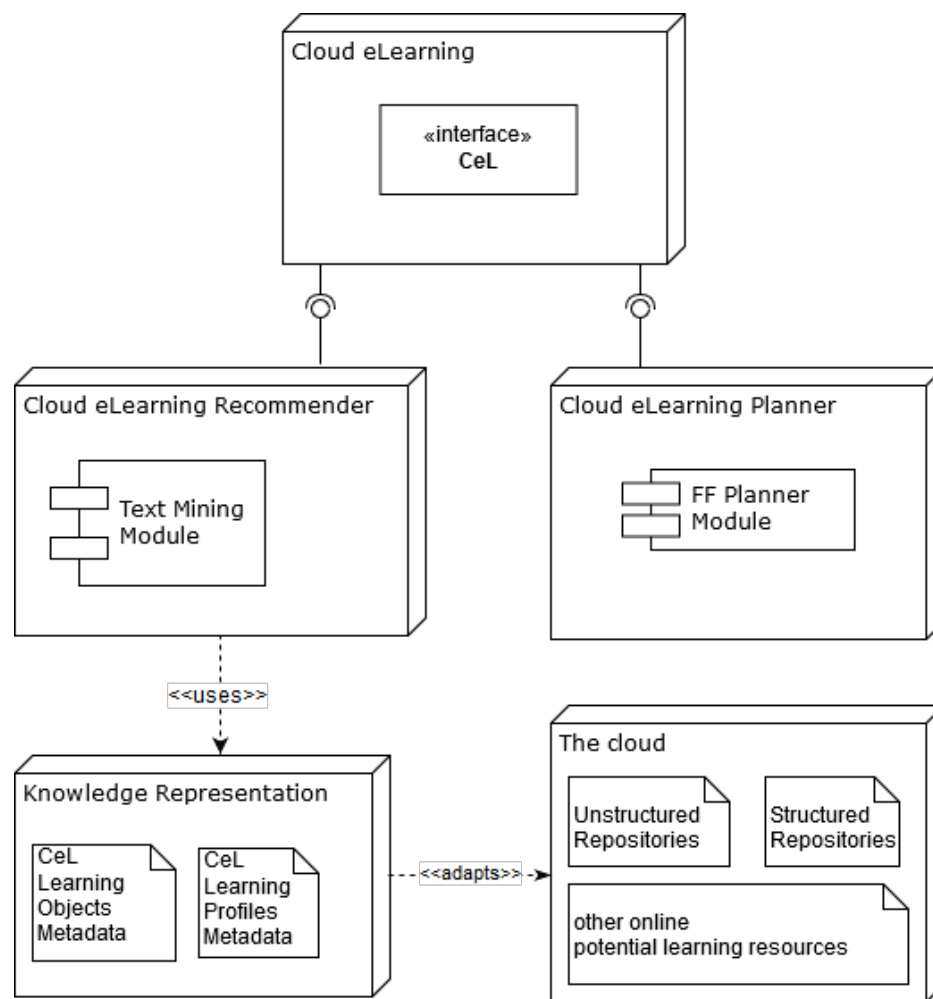Fig. 9.3 The Cloud eLearning prototype architectural components

So, the main Cloud eLearning interface interacts with the Cloud eLearning Recommender system and the Cloud eLearning Planner. Each of the modules depicted as part of the Cloud eLearning prototype architecture is explained in a detail from Chapter 6 to Chapter 8, starting from the knowledge representation of learners and Cloud eLearning Learning Objects, up to

the text mining process of the Cloud eLearning Recommender System and the final process
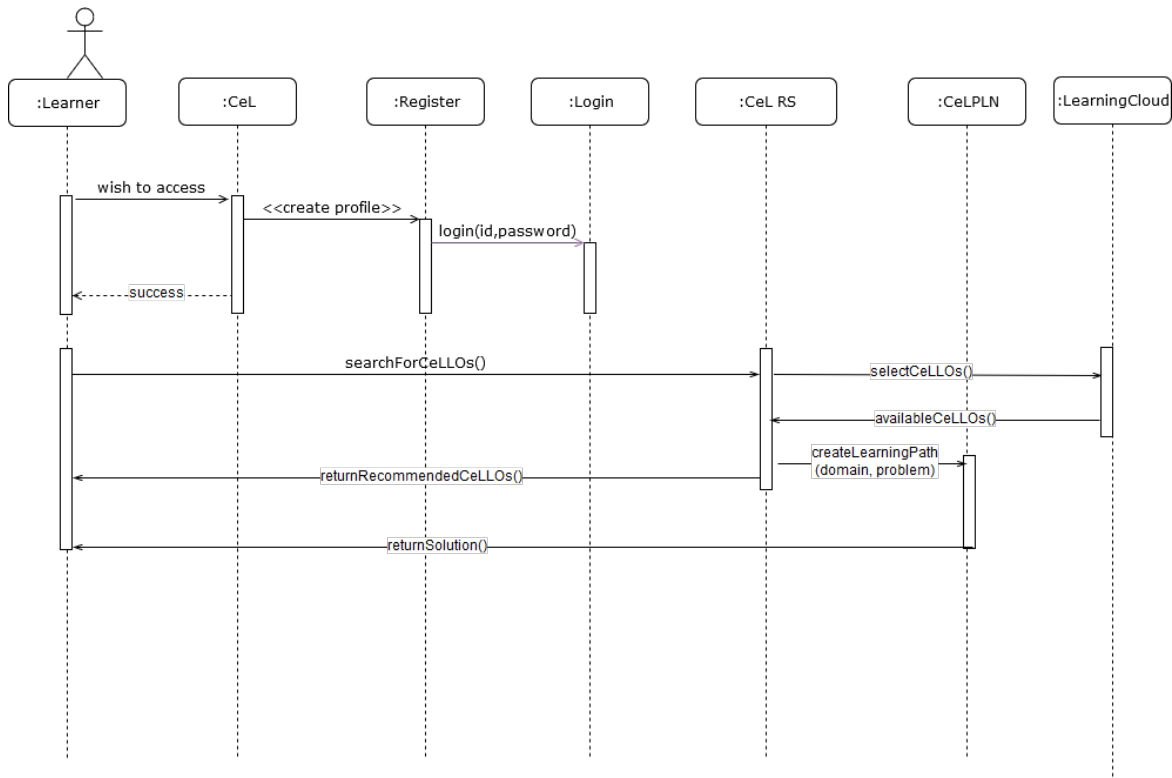of the Cloud eLearning planner.

Fig. 9.4 The Cloud eLearning prototype sequence diagram

In Figure 9.4 and 9.5 are depicted the Cloud eLearning sequence and activity diagrams
expressing the interaction of the learner with the Cloud eLearning prototype, specifically
the process of being registered, login into the Cloud eLearning, searching for a specific
topic/subtopic up to the CeL recommender system response list of CeLLOs, and furthermore
the generation of plan (learning path) from the Cloud eLearning Planner. So, the learner
initially wishes to access the Cloud eLearning prototype, which then requires the learner to
be registered and create a profile. After creating the learner profile, the learner is provided
with username and password in order to be able to login to the CeL prototype. So, after
entering the credentials from the learner, the systems notifies the learner for successfull login
process.

The second phase of the sequence, mainly the interaction of the learner with the CeL
prototype after login is as follows: the learners searches for a particular topic/subtopic, the
CeL RS selects the relevant CeLLOs after a matching process between the learner, desire
and exiting CeLLOs and it returns a list of ranked CeLLOs to the learners, and parallel to
that it creates a file (planning problem) which is used from Cloud eLearning Planner in order

to automatically generate a plan/solution. The plan contains the personalised learning path suggesting the learner which CeLLOs to studies in order to acquire the desired knowledge.

The same scenario is depicted also in Figure 9.5 as part of Cloud eLearning prototype activity diagram following all the explained processes from the entering of Cloud eLearning Prototype, up to the proposed CeLLOs for study.
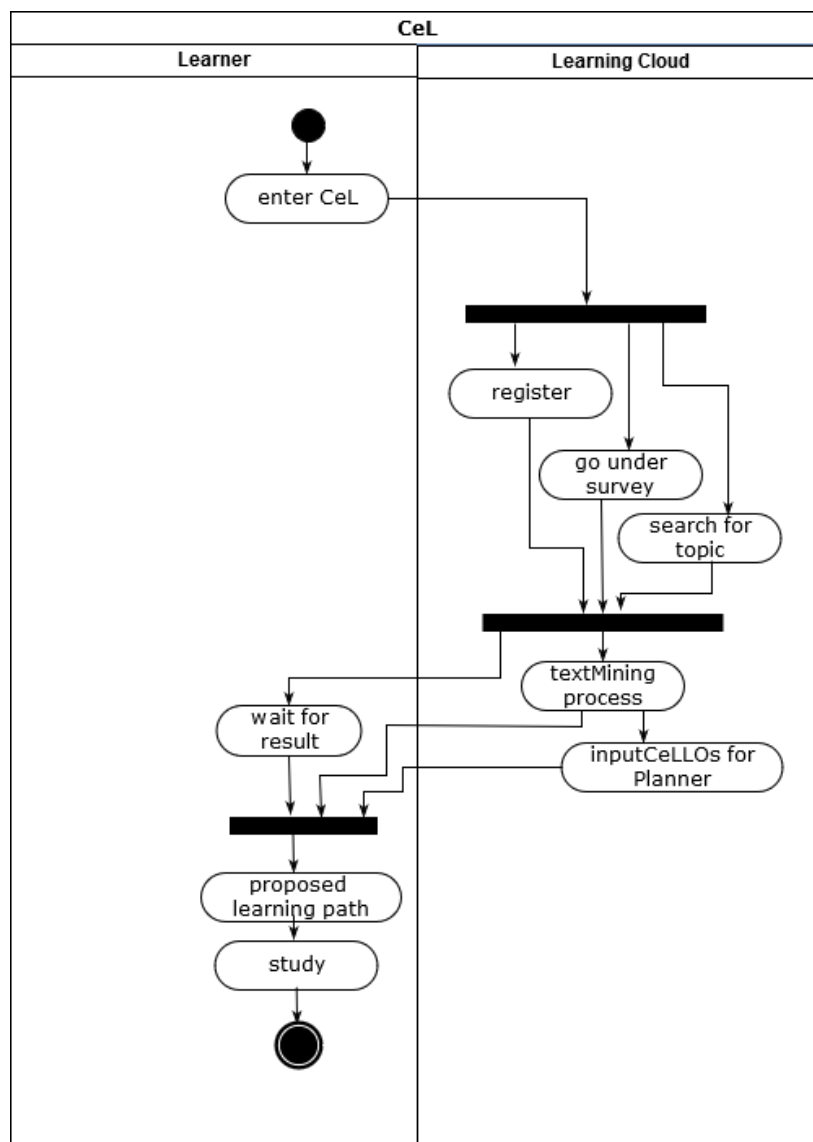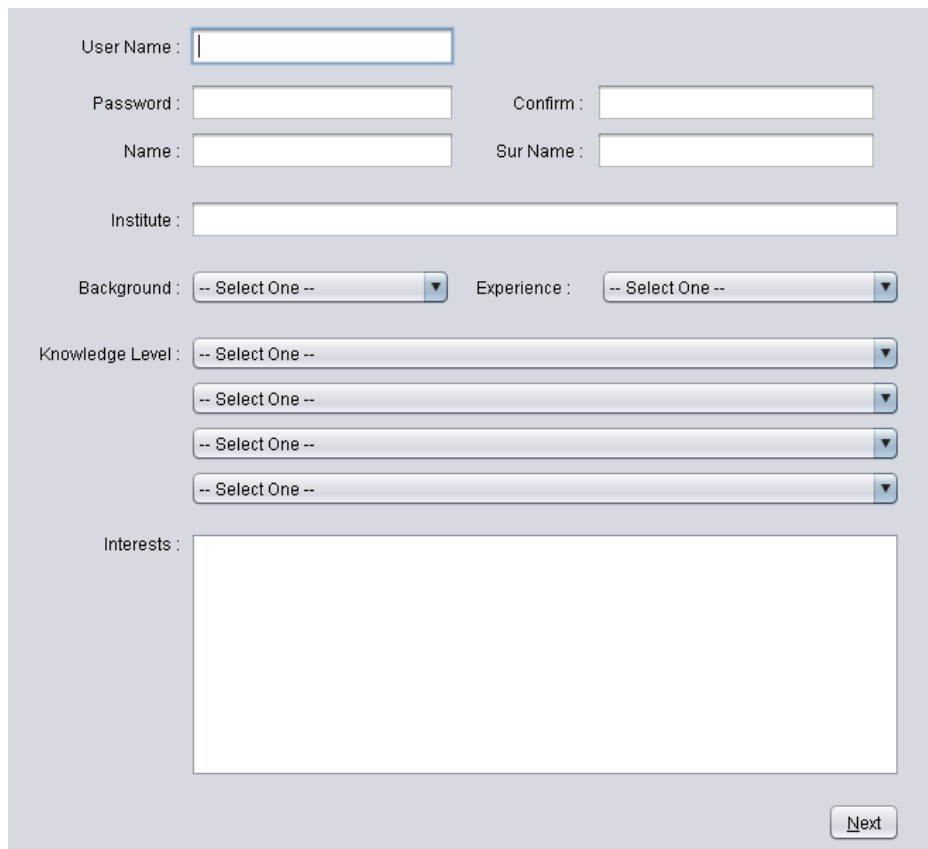

Fig. 9.5 The Cloud eLearning prototype activity diagram

9.2   The concrete Cloud eLearning Prototype

In Figure 9.6, is the screenshot of the registration process (first use case in Table 9.3). After the successful registration process, the learner searches for the subtopic of interest through unstructured queries within the CeL repository and the CeL responds with a list of CeLLOs that match the learners' background and interest. So, the results are listed after the text mining process, as described in Chapter 7, which maps the learner desire with the topics/subtopics represented in the ACM Computing Classification System, and then ranks the list of CeLLOs classified under the topic/subtopic according to the cosine similarity calculation explained in subsection 7.2. Hereafter, the whole process is supported also with screenshots from the CeL prototype, starting with Figure 9.6, which shows the required parameters when the learner starts to be registered.
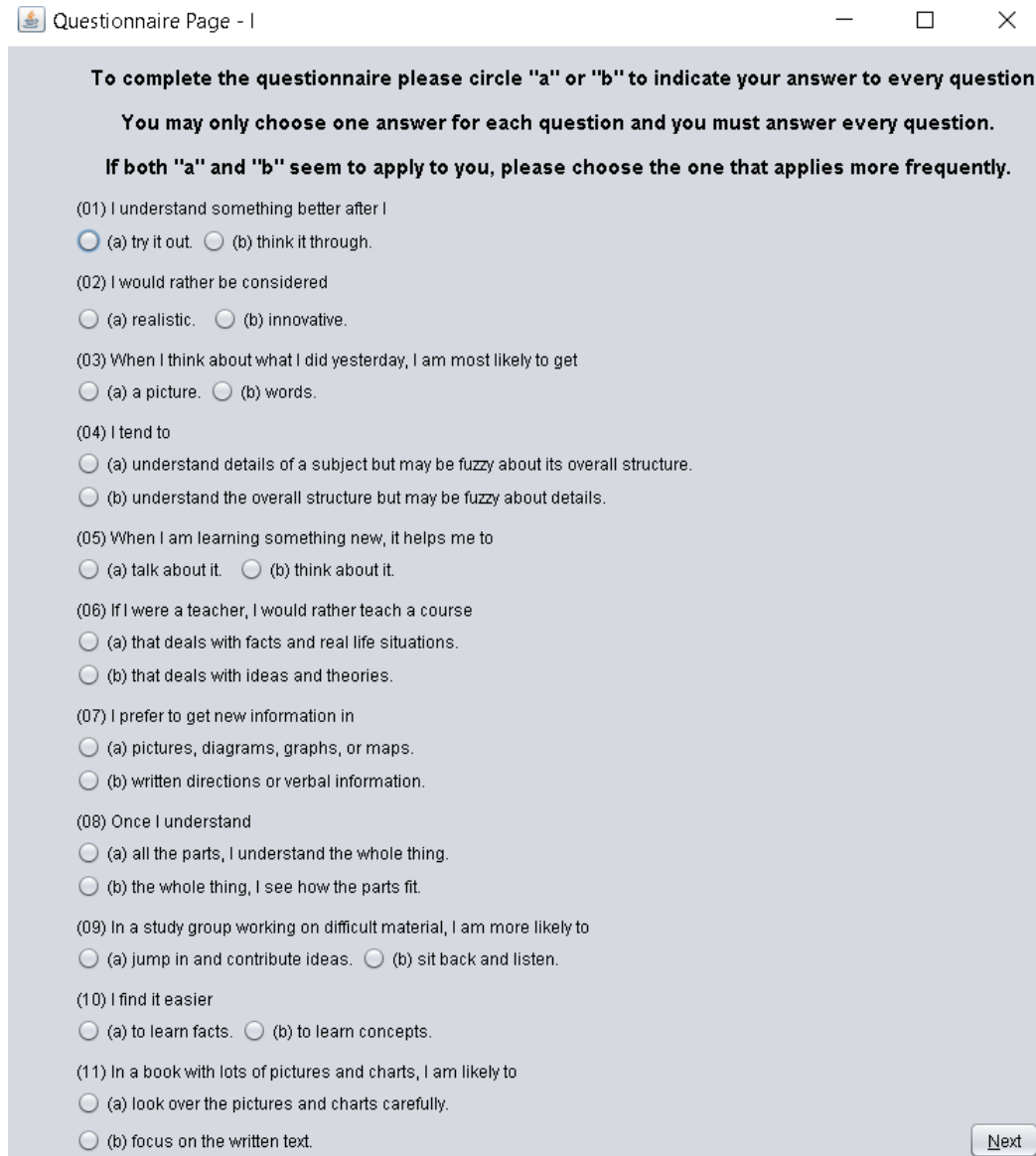
Fig. 9.6 The registration of the user in Cloud eLearning prototype

As part of the registration phase, the learner provides information on educational background, level of experience in the particular field, and knowledge level in Java, algorithms and relevant courses. Furthermore, for CeL purposes, each subject completes the selected

index of learning styles (Figure 9.7), which is proposed by Felder and Soloman [55, 56] for categorising individuals into one of the four categories, described in section 3.1.

Fig. 9.7 The Felder and Soloman index of learning styles

After completing this process, the learner authenticates using username and password credentials which were specified while registering in CeL. After successful authentication, the learner will see the user interface as shown in Figure 9.8. Through this interface (Figure 9.8) the learner will be able to search the particular topic/subtopic of their interests.

Fig. 9.8 Cloud eLearning Recommender

In the case shown in Figure 9.9, the learner searched for information related to "data types", and after the text mining process described in Chapter 7, the result is ranked as shown in Figure 9.9. Furthermore, the CeLLOs as entities, or the set of CeLLOs could be rated depending whether the learner thinks that the list of CeLLOs or the CeLLOs as standalone learning material is appropriately ranked in the resulted list.

Fig. 9.9 A ranked list of the CeLLOs listed as an output of learner's interest for "data types"

Furthermore, the list of CeLLOs displayed in Figure 9.9 can be rated individually or rated as a whole list at the bottom of the application screen.

In the context of this thesis, we feel that it does not have any added value to generate an evolutionary prototype, which could offer the possibility to study the materials, while reading and/or watching and then go through a testing process. Therefore, we developed a throwaway prototype, which explicitly requested that learners specify whether they have studied (while checking the titles and/or metadata associated with that) the recommended materials or not (just to check the functionality of CeL approach). If the learner expresses a positive answer and clicks "I have studied the whole Materials", then the system will list the CeLLOs with higher complexity compared to the previous search (difficult level defined using Bloom Taxonomy as explained in section 3.3) if the learner searches for the same topic

a second time in the CeLRS The system thereby assumes that the learner has passed the very first level and is making progress (Figure 9.10).
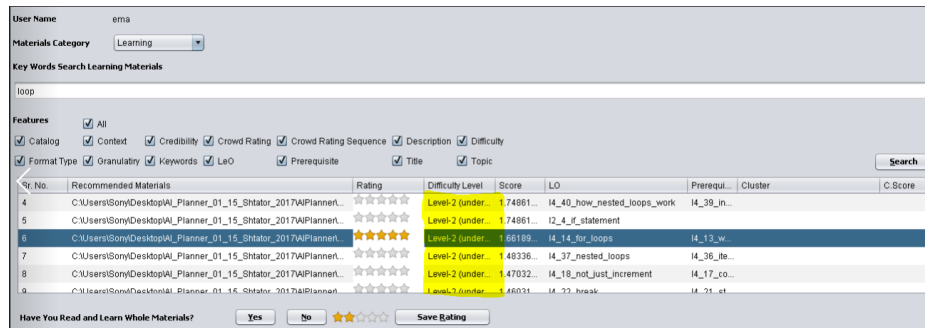
Fig. 9.10 A ranked list of the CeLLOs listed as an output of users' interest "loop"

And, finally, the personalised learning path, specifically the automated plan generated from the CeLPLN (described in Chapter 8), is shown in Figure 9.11. So in CeL, the CeLLOs (which have a fixed duration) are treated as reusable resources and can be used in various contexts. The validity of the approach was demonstrated through the example shown in the subsection 9.1. We managed to implement the problem using linear planning, i.e., STRIPS notation, through PDDL, and used the CeLPLanner.

```
(createlearningplan while_loops plan683)
(addstudycello studycello1 l1_1_introducing_control_flow plan683)
(addtestcello testcello1 l1_1_introducing_control_flow plan683)
(addstudycello studycello2 l1_2_decision_making plan683)
(addtestcello testcello2 l1_2_decision_making plan683)
(addstudycello studycello41 l1_41_if_statement plan683)
(addtestcello testcello41 l1_41_if_statement plan683)
(addstudycello studycello23 l1_23_logical_operators plan683)
(addtestcello testcello23 l1_23_logical_operators plan683)
(addstudycello studycello27 l1_27_nested_if_statements plan683)
(addtestcello testcello27 l1_27_nested_if_statements plan683)
(addstudycello studycello14 l1_14_while_loops plan683)
(addtestcello testcello14 l1_14_while_loops plan683)
```

Fig. 9.11 The generated personalise learning path

To conclude, these activities, beginning with CeL prototype design followed by learning resources curation prepared the online environment for learners' evaluation research, which are presented and analyzed in the next chapter.

Summary

This chapter presented the experimental show case of Cloud eLearning prototype. We started with the design and implementation of Cloud eLearning prototype, which represents the core

layer of the Cloud eLearning proposal discussed in Chapter 5. Further, we discussed the requirements, use cases, sequence and activity diagrams in order to give a detailed explanation of the Cloud eLearning prototype functionality whose architecture is presented in Figure 9.3. As can be understood from this chapter the Cloud eLearning prototype has followed the modular approach, starting from the CeL Recommender System which represents one module, the CeL Planner representing the next module, and all these use the knowledge representation module which has the adequate data, respectively the CeL learners and the CeL Learning Objects. Finally, we concluded the chapter with a number of screenshots taken from each of the modules created as part of the Cloud eLearning prototype.

Chapter 10

Experimental show case evaluation

Recalling the first chapter, the aim and research questions of this thesis are defined in section 1.2. At that stage it would have been premature to try to formulate the hypotheses that should be explored, but these emerged as the work developed through the stages described in the subsequent chapters.

The evaluation of the showcase in this chapter therefore starts by drawing out explicitly the hypotheses that are to be evaluated, the design of the evaluation activity and emphasizing the constrains that are faced when dealing with the evaluation of learning activities, the evaluation sample is described and the activities that were carried out in order to evaluate the CeL prototype, and the results are presented with descriptive statistics, the analysis of the evaluation data and comparing the results with the stated hypotheses.

10.1   Investigated Hypotheses

Throughout this thesis a number of hypotheses have emerged and by drawing them out here will lead us to the analysis of evaluation data and elaborate how far they are verified.

These hypotheses are as follows:

H1: The background and experience of the learner, the learning style and the current interest, influence the result of personalised learning path, and it should provide sets of resources for individual learners that match these attributes than conventional eL systems can.

H2: The satisfaction of learners is increased when learning occurs through personalised learning paths.

H3: Because CeL can draw on a large set of resources from the cloud, it should provide sets of resources for individual learners that are more appropriate to their needs than conventional eL systems can.

H4: Because CeL considers the potential impact of crowd feedback, it should provide sets of resources that are ranked more appropriately for individual learners than conventional eL systems can.

10.2 Evaluation Methodology

In various phases of this thesis, different research method approaches were used to increase capacity to accomplish the Cloud eLearning research aim. The project started with a literature review in these areas: information retrieval and processing data, data mining, recommender systems, automated planning and cloud computing. The aim of the literature review was to identify what has been accomplished so far in these areas and then identify the most promising approaches and associated gaps which the prototype should address. The main focus of this work was to develop a new concept of eLearning, namely Cloud eLearning which offers personalised learning paths for the Cloud learners.

Evaluating any kind of learning activities such as this, there are three constraints that commonly arise when dealing with the evaluation. Such as:

- There could not be realised any direct comparison between different learning approaches when followed by any individual subject, as they can only learn a particular topic/subtopic once. Consequently, the only way in which a direct comparison of two different approaches that could be realised is by trying them out with different groups of subjects, and this immediately makes the comparison more complicated, since we need to compute averages of statistics over the different groups.

- The need for groups of subjects means that ideally we need a high number of subjects (enough that any statistics will be fairly reliable, for example above 100), and this makes any evaluation method complicated to manage.

- Learning something non-trivial takes time, and the more time is required the more difficult it becomes to recruit subjects, which creates pressure to keep the evaluation method simple.

All three of these constraints applied to the evaluation of CeL as well. Ideally we would have liked to evaluate CeL by creating two different groups of learners that have equivalent

levels of abilities (such as: background level, learning styles to name a few) and to one group offering a new material using an established eLearning platform, and the other one using CeL showcase, and measuring how effectively each group learned the material. In practice, though, this would have ended up evaluating two completely different approaches that rely under different conditions, which would have affected the final results.

Furthermore, the definition of a "group" requires certain attributes. Such as, how many learners are enough for one group? For how long should we monitor the progress of the learners? As stated above the number of learners within the groups and the time constrains of learning a particular material may complicate the evaluation process.

In order to get as near as practical to an ideal study, we designed an evaluation methodology by aiming to evaluate, firstly the functionality of CeL prototype which was created after we have defined the CeL, and secondly offering the CeL prototype for user evaluation. So, the evaluation of the an experiment show case was implemented in three consecutive stages: 1) an experiment of using Cloud eLearning, 2) a questionnaire regarding the personalised learning path, and 3) an analysis of the mixed methods' results (correlation of quantitative and qualitattive data).

The questionnaire does not aim to evaluate the whole approach or the learning process associated with Cloud eLearning but it aimed only to demonstrate the functionalities of the prototype to the users' and be able to offer the opportunity to the users to value the approach of personalisation in CeL.

The experimental show case engaged students and professors in five courses within Computer Science and Information System faculties at a Kosovo university [1]. The study focused on Java programming competencies. The inspiration for the selection of this particular course for the very beginning was because the 'pass rate' in this course at this particular university is significantly low: only 10% of students typically pass this required course. So, it made good sense to investigate CeL as an added value to facilitate the learners with new approaches to learn this subject in a personalised manner, specifically through personalised learning paths beside the eLearning platforms that the university offers in order to reduce or avoid the challenges that they are facing currently. So, at this stage, the Cloud eLearning has adapted only the Java course, but in the next five years the number of adapte courses for Cloud eLearning will increase gradually.

So, in response to this problem, the research proposal first secured human subjects review permission from University of Sheffield, which is attached in the Appendices. Students read the consent form before starting to complete the online questionnaire which produced qualitative and quantitative results presented in the following sections.

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[1]UBT, www.ubt-uni.net/

Throughout the prototype development and evaluation process, the aim remained facilitating the learning process through personalised learning paths. Within the context of significant diversity of knowledge backgrounds and experiences, they explored and evaluated the functionality of the automated planning approach directing construction of the CeL prototype, which incorporated selected elements identified through an extensive literature review. Then they analyzed the generated personalised learning paths and assessed whether the prototype satisfied their overall learning process aims.

For being able to offer the prototype for the evaluation, firstly it required the adaption of a resource collection of learning objects. The learning objects were gathered from various sources, some with standard descriptions and others without any descriptions. Learning objects were collected from:

- online open CourseWare (such as: MIT OCW, Udacity)

- learning object repositories (example: https://cnx.org/)

- and even from webpages that provided open examples in Java domain (example: javapoint.com, tutorialspoint.com, etc.)

Based on the descriptions that the learning objects were associated with, we ended up with learning objects that were associated with

- structured,

- un-structured and

- semi-structured descriptions.

This situation was foreseen in Chapter 6. Therefore, we anticipated a transformation process (shown in Figure 6.7) which transformed the learning objects into Cloud eLearning objects, which required creation of structured learning objects according to the ACM Computing Classification System. This was mandatory in order to be able to generate a validated plan/solution, which coupled various Cloud eLearning Learning Objects to produce a personalised learning path.

We emphasize that this transformation process was mandatory because the AI planning process tends to work better when dealing with structured objects. All gathered CeLLOs are part of the "Object Oriented Programming Language" domain, of which a "Java" course is a part. More than 300 learning objects were gathered and adapted into CeLLOs. This process checked whether the collected learning objects supported any of metadata standards and, if not, the CeL metadata was applied to these learning objects as described in subsection 6.5.

10.3 Data Collection

In Phase 1, in order to ensure subjects with different backgrounds and various perspectives, undergraduate and graduate students were recruited. Subjects constituted sample of individuals from 5 courses at a Kosovo university who volunteered to participate in the research study. The student participants included 17 users, 3 post graduate students and 14 undergraduate students. In phase 1, after students used the prototype, they evaluated its efficacy using an online questionnaire. Phase 2, consisted of unstructured interviews to collect 2 teachers' perceptions of the Cloud eLearning proposal and observations on students' "learning experiences" using CeLLOs.

Phase 1 consisted of a 60-minute session, the script for which is presented in Table 10.1.

Table 10.1 A list of activities during the experimental phase

Instruction of using and evaluating the CeL	
Open CeL	Run the CeL application on the desktop.
Register as a new user and create a profile	Follow the steps to be registered as a new user for CeL. Complete a questionnaire for the system to categorize user learning style.
Search for a specific topic in Java	Search for the topic or subtopic within the Java and algorithm domain, in the CeLRS.
Go through the generated path	Analyse the list of CeLLOs responses from the CeLRS, the ranking of the CeLLOs, including required prerequisites.
Rate the proposed list of CeLLOs	Check the ranked and recommended CeLLOs from the CeLRS to the user and rate it.
Rate CeL learning objects	Rate the CeLLOs as a standalone object.
Complete the survey process	Complete the online questionnaire to assess CeL activities.

During the first 20 minutes of the session, subjects registered as users and created a profile. Then they conducted searches and reviewed results.

In order for the learners to evaluate the system, they followed the defined script (in Table 10.1), starting from the registration phase and concluding with the online survey. The first step required registration so that the system could develop a learner profile including the knowledge level, learning styles and other relevant characteristics explained in chapter 6, particularly in subsection 6.6.

For the system to become familiarised with the learner (i.e., develop a learner profile), an explicit approach was used to learn to know learners by asking questions which must be answered directly by them (example: knowledge level in specific topic, current interest, to name a few). An explicit approach – rather than an implicit approach which requires considerable time within the system in order to generate a learner profile, was chosen, for reasons of simplicity and because of time constraints.
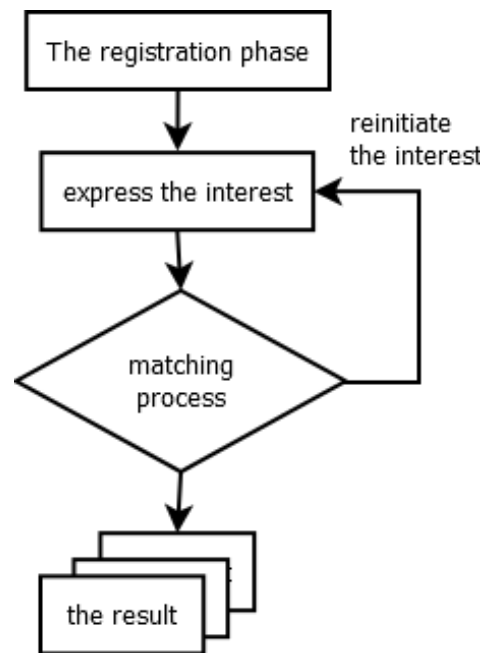
Fig. 10.1 The flow process of the user activities with the system

As depicted in Figure 10.1, the learner first completes the registration process. Then the learner searches for the subtopic of interest through unstructured queries within the CeL repository and the CeL responds with a list of CeLLOs that match the users' background and interest. So, the results are listed after the text mining process, as described in Chapter 7, which maps the learner desire with the topics/subtopics represented in the ACM Computing Classification System, and then ranks the list of CeLLOs classified under the topic/subtopic according to the cosine similarity calculation explained in subsection 7.2. As described above, the 17 samples conducted searches and reviewed results, they evaluated the prototype using the questionnaire shown in Tables 10.2, 10.3 and 10.4.

Table 10.2 The questionnaire for evaluation process - Part 2 and 3

Part 2: Experiment Setup and General Questions						
1	Prior to participating in this experiment, I was aware of personalised features used in CeL, the learning styles, the recommendation process, the learning path.	Yes	No			
2	Prior knowledge to Java course content (e.g. Java)?	Poor	Average	Good	Very Good	Excellent
Part 3: Personalisation in learning process						
3	Do you think that personalised e-Learning activities would assist learners in achieving their full potential	Yes	No			
4	Do you think personalization of learning path can improve students learning progress?	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
5	If a software for personalising e-Learning activities was available would you use it?	Yes	No			
6	Do the personalised services provided by CeL satisfy your requirement?	Very Unsatisfactory	Unsatisfactory	Moderate	Satisfactory	Very Satisfactory
7	The learning style questionnaire has correctly categorized my preferences on learning.	Yes	No			

Table 10.3 The questionnaire for evaluation process - Part 4

Part 4: CeL Recommender System						
8	How do you feel that the top three learning materials recommended by CeLRS are appropriate	Very unsuitable	Unsuitable	Moderate	Suitable	Very Suitable
9	How do you feel that our system gives lower ranking order for inappropriate learning materials (check the result in CeLRS)?	Very unsuitable	Unsuitable	Moderate	Suitable	Very Suitable
10	The content of the course was appropriate for me (e.g. Java level of difficulty)	Very unsatisfactory	Unsatisfactory	Moderate	Satisfactory	Very satisfactory
11	In CeL there exists learning objects related to these topics: introduction to OOP, statements, arrays, inheritance, data types, primitive types, character and integer, float, etc. Which learning objects are appropriate to be recommended when searching for data types?	Intro to OOP, arrays, float, character and integer	Data types, primitive types, character and integer, float	Intro to OOP, statements, arrays, inheritance	Arrays, inheritance, data types, primitive types	

Table 10.4 The questionnaire for evaluation process - Part 5 and 6

Part 5: CeL Personalised Learning Path					
12	My knowledge is increased of possible personalised features as a result of completing this experiment.	Yes		No	
13	Do the learning process provided by CeL satisfy your requirement?	Very unsatisfactory	Unsatisfactory	Moderate	Satisfactory / Very satisfactory
14	Overall generated learning path satisfaction	Poor	Average	Good	Very Good / Excellent
15	When a new course path was created, my goal reflected in the final learning path.	Very unsatisfactory	Unsatisfactory	Moderate	Satisfactory / Very satisfactory
16	Which of the following learning paths sequence is appropriate to acquire the desired knowledge on: java statements if your background knowledge in Java is advanced beginner?	Comments → data types → operators → control flow→ conditional statements → loop statements → branching statements	Operators → control flow→ conditional statements → loop statements → branching statements → arrays → methods	Control flow→ conditional statements → loop statements → branching statements	Data types→ operators → control flow→ conditional statements → class → interface
Part 6: Open-ended comments and suggestions					

The questionnaire was divided into six parts, as follows:

Part 1: Consent Form - Conditions and Stipulations

Part 2: Experiment Setup and General Questions

Part 3: Personalisation in learning process

Part 4: CeL Recommender System

Part 5: CeL Personalised Learning Path

Part 6: Open-ended comments and suggestions

Before completing the questionnaire, participants were asked to use the Cloud eLearning prototype, based on the script defined in Table 10.1, and after that they continued on with the questionnaire.

The questionnaire started with general questions, then continued with various parts, starting from personalisation learning process questions, continuing with CeL Recommender System questions, then CeL personsalised Learning Path questions, and concluding with Part 6, which invited open ended comments and suggestions from participants. The research instrument thereby collected both quantitative and qualitative data which will be presented and interpreted in this chapter.

In the very beginning, the participants were informed about the research process with a consent form, included in the questionnaire in the appendix. After this, they proceeded to answer the questions related to their prior knowledge of the topic, Java, and their use of the Cloud eLearning prototype in the session.

10.4   Results

A short explanation regarding the personalisation services in general, and specifically the personalisation services offered in CeL has been introduced to all the participants. This has been given to a group of students within a specific course as part of the classes in Computer Science and Information Systems Faculties. At the end we asked for two to three volunteers because of the time constrains. As volunteers have been introduced, they were advised related to all the processes and steps that needs to follow, also listed in Table 10.1. And finally, after going through all the steps listed in Table 10.1, the participants have gone through the survey.

The results will be elaborated in the same line, firstly will give three selected case explanation how the CeL prototype has interacted with three different learners and after that

we will continue with the elaboration of survey results from the user evaluation perspective. In our case, the three selected cases are used as representatives of three different groups as a whole.

10.4.1 CeL Prototype results

As discussed in the previous subsection the structure of our set of subjects is as follows: 17 users, 3 out of 17 are graduate and the rest are undergraduate students, further a group of students were in Information Systems and the rest in Computer Science. So, a number of groups were created which had learners with different background, different learning experiences, different learning styles and different interests. And, finally two teachers opinion were gathered using unstructured interviews.

To start using the Cloud eLearning Prototype, the user firstly needs to be registered. As explained in Figure 9.6 the user needs to give details regarding her/his background, his education level, interests and also his current knowledge level in specific topics.

Table 10.5 The selected cases for explanation of three different users

	Representative 1	Representative 2	Representative 3
Faculty	Computer Science	Information System	Computer Science
Level of study	Bachelor	Bachelor	Master
Knowledge Level in programming using scripting language	2	0	4
Knowledge Level in programing using object-oriented programming	2	0	3
Knowledge Level in Java language	2	1	4
Knowledge Level in Algorithms	2	0	2
Learning style	strong visual	moderate verbal	strong visual

So, the data of three selected representatives of various groups of students are presented in Table 10.5, which shows that all of them have different education background, they

have various knowledge level in programming using scripting languages, programming using object oriented programming languages, particularly in Java programming knowledge and also in algorithms. We encountered their knowledge level in these specific courses because as explained in the previous section the experiment has Cloud eLearning Learning Objects related to Java course, and we think that these courses will influence the flow of the experiment.

So, representative 1 is studying Computer Science in bachelor level, his knowledge level in programming using scripting language is defined as level 2 (out of 4), programming using object oriented programming languages is defined as level 2 as well, and the same are defined the knowledge level in Java specifically and also in algorithms. Continuing with representative 2, which currently is studying Information System in bachelor level and she has selected that she has novice knowledge only in Java. The analysis of data from representative 3, shows that he is more mature user, who currently is a master student of Computer Science and has knowledge of level 4 in programming using scripting language and also in java language, whereas in programming using object oriented programming languages he declared to have knowledge of level 3, in algorithms of level 2 respectively.

	11	9	7	5	3	1	1	3	5	7	9	11	
Active	11	9	7	**[5]**	3	1	1	3	5	7	9	11	Reflective
Sensing	11	9	**[7]**	5	3	1	1	3	5	7	9	11	Intuitive
Visual	11	**[9]**	7	5	3	1	1	3	5	7	9	11	Verbal
Sequential	11	9	**[7]**	5	3	1	1	3	5	7	9	11	Global

Fig. 10.2 Results of Felder and Soloman - Index of learning styles questionnaire for User 1

	11	9	7	5	3	1	1	3	5	7	9	11	
Active	11	9	7	5	**[3]**	1	1	3	5	7	9	11	Reflective
Sensing	11	9	7	**[5]**	3	1	1	3	5	7	9	11	Intuitive
Visual	11	9	7	5	3	1	1	3	5	**[7]**	9	11	Verbal
Sequential	11	9	7	**[5]**	3	1	1	3	5	7	9	11	Global

Fig. 10.3 Results of Felder and Soloman - Index of learning styles questionnaire for User 2

Active	11	9	7	5	3	1	1	3	5	7	9	11	Reflective
Sensing	11	9	7	5	3	1	1	3	5	7	9	11	Intuitive
Visual	11	9	7	5	3	1	1	3	5	7	9	11	Verbal
Sequential	11	9	7	5	3	1	1	3	5	7	9	11	Global

Fig. 10.4 Results of Felder and Soloman - Index of learning styles questionnaire for User 3

Whereas, in order to define the learning style of the users, each of them has gone through the Felder and Soloman[56] index of learning styles shown in Figure 9.7. As shown in Figure 10.2, the Felder and Soloman model has four dimensions of learning style. Each of the dimensions has two poles, such as active and reflective, sensing and intuitive, visual and verbal, sequential and global. The result of the index learning style of Felder and Soloman indicates the user preferences for one of these poles for all the categories. If the result remains 1 or 3, the user are balanced between two poles within that dimension, whereas if the users result remain 5 or 7, they preferences for the particular pole is moderated. And finally, if the users result remain 9 or 11, the user has a strong preference for the specific pole within that dimension and he or she may face problems or difficulties while learning within an environment that does not reflect these preferences. We have analysed the results of all three users and they have shown various learning style preferences, and for the simplicity reasons we have concluded to position the user preference based on the highest score of one of the dimensions that has shown. So, based on this idea, the user 1 and 3 has been categorised as strong visualiser whereas user 2 as moderate verbal.

So, based on these user data background explained briefly above and also listed in Table 10.5, the CeL prototype has produced various learning path when they show interests on learning in specific topic/subtopic of Java programming language. So, for example when users showed interest to learn "while loops in java programming", based on their specific search, the Cloud eLearning Prototype proposed the learning path as shown in Figure 9.11.

So, the Cloud eLearning generates the following paths for each of the users:

- **Representative 1:**

  1. Watch the video *c24* on "if statement";

  2. Take the test *t4*;

  3. Watch the video *c12* on "else statement";

  4. Take the test *t12*;

  5. Watch the video *c14* on "while loops";

  6. Take the test *t14*;

- **Representative 2:**

  1. Study text *c1* on "introducing control flow" ;

  2. Take the test *t1*;

  3. Study text *c2* on "decision making";

  4. Take the test *t2*;

  5. Listen podcast *c41* on "if statement";

  6. Take the test *t4*;

  7. Listen podcast *c23* on "logical operators";

  8. Take the test *t23*;

  9. Study text *c27* on "nested if statements";

  10. Take the test *t27*;

  11. Watch the video *c14* on "while loops";

  12. Take the test *t14*.

- **Representative 3:**

  1. Watch the video *c14* on "multiple ifs";

  2. Take the test *t14*;

  3. Watch the video *c15* on "loop counters";

  4. Take the test *t15*;

  5. Watch the video *c30* on "switch statement";

  6. Take the test *t30*;

  7. Watch the video *c14* on "while loops";

  8. Take the test *t14*;

Additionally, if the learner is a visual learner but Cloud eLearning does not have appropriate video CeLLOs in a specific subtopic, then Cloud eLearning will suggest the text and/or audio CeLLOs.

10.4.2   User evaluation results

Throughout this section the statistical results of the questionnaire are presented in Table 10.2, 10.3 and 10.4. So as specified in question 1, we wanted to show that all the participants' have used the prototype, prior to participating in the questionnaire. So, all the participants (100%) have claimed that before participating in this experiment, they have become aware of personalised features used in CeL, the learning style categorisation, the recommendation process, the learning path.

Continuing with question 2, we wanted to know whether the students have prior knowledge of the Java programming language, and if so, at what level. The reason for asking this question was that the Cloud eLearning Learning Objects have a predefined level of difficulty as shown in Figure 9.10, using the Bloom Taxonomy explained in section 3.3. So, based on the students' background, the CeL proposed also the CeLLO's level difficulty. In this respect, participants' self-reports produced data that, when analyzed, revealed that subjects had prior knowledge from a Java course, starting from novice up to proficient levels. Participant data shows that 29% of them were in the novice level, 29% in the advanced beginner level, 18% in competent level, and the remaining in the proficient level (Figure 10.5).
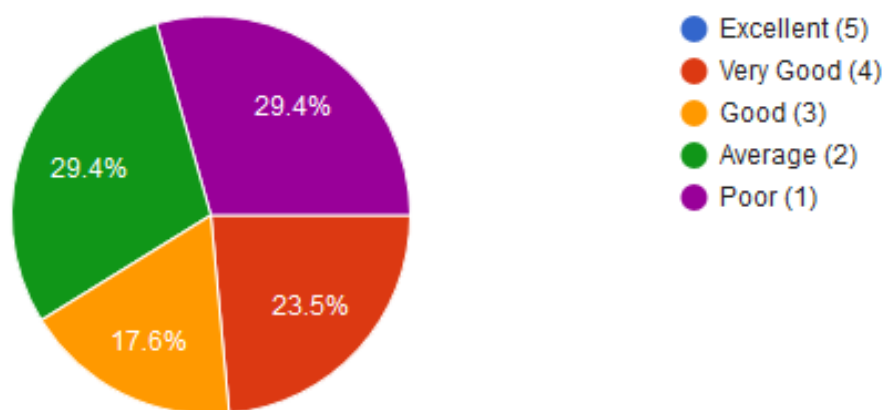
Fig. 10.5 Prior knowledge of Java course content

As per questions 3, the main concern was whether they are aware that personalised eLearning activities would assist learners in achieving their full potential, where 16 participants agreed positively.

In question 4, we asked the participants whether they think that personalisation of the learning path can improve the student learning process, 58% of them strongly agreed, 24% agreed, and 12% were neutral. One (6 %) said *"no, I don't think that this might influence the learning process"*, noting that *"the flexibility that is offered as part of the learning path*

may frustrate me while omitting me to go directly to the learning material that I am interest to learn" (Figure 10.6).
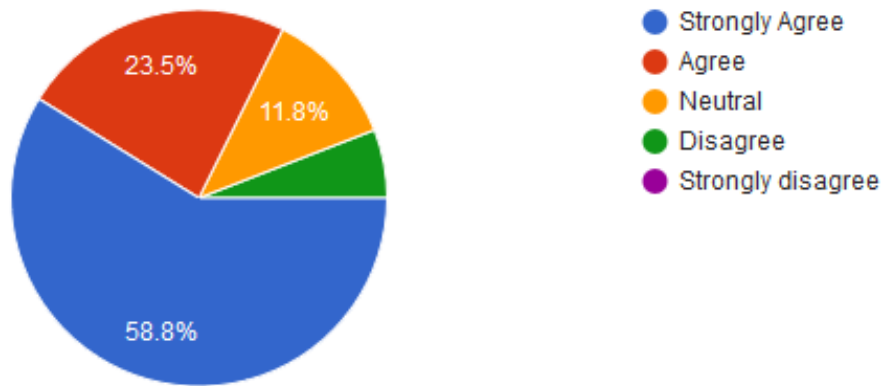
Fig. 10.6 The improvement of students' learning process as a result of personalised learning path

In questions 5, the intention was to ask the participants whether they would use any software that will contribute toward personalisation of learning activities. So, 94.1% answered positively. The one student who answered negatively reasoned that he/she will persist with or without personalised eLearning – but this individual did not say that this approach was not helpful.
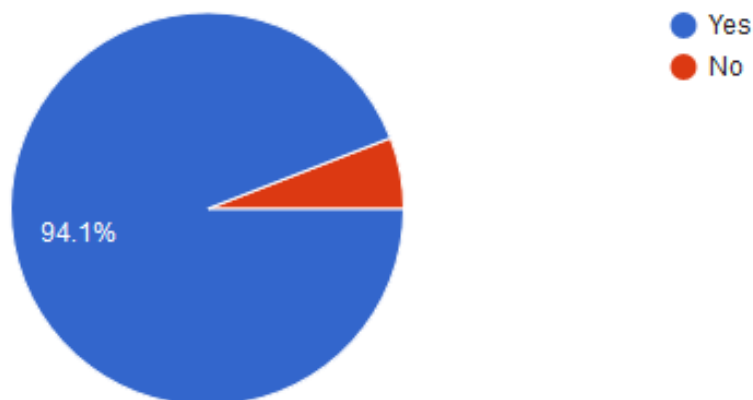
Fig. 10.7 The use of a software for personalising eLearning activities

In the 6 question the intention was to ask the participants whether the personalised services which were demonstrated in the very beginning were reasonable, and whether they

satisfy their current requirements or not. From the total of participants, 94.1% were very satisfied (35%) and satisfied (59%), and the rest moderately satisfied (Figure 10.8).
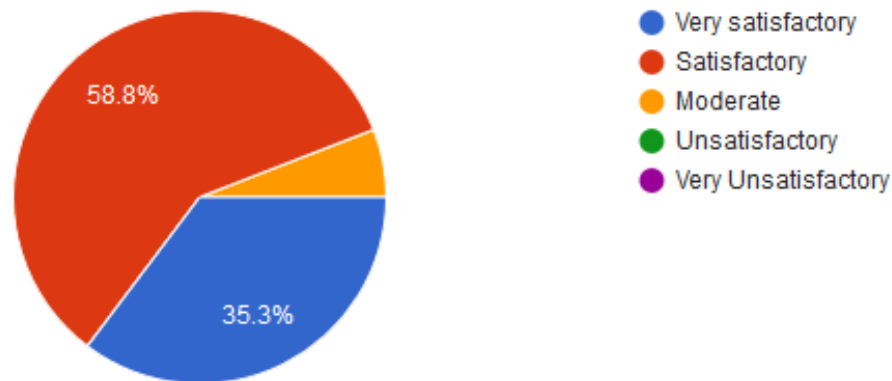
Fig. 10.8 The satisfaction of students' requirements based on the personalisation services of CeL

During the registration phase, participants entered data as required from the tool provided in Figure 9.7, which used the Felder and Solomon index of learning styles to classify participants based on their learning styles.
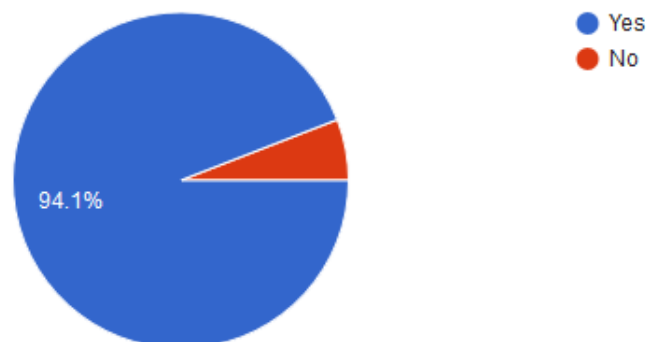
Fig. 10.9 The categorisation of students based on their learning style

So, in question 7, the participants were asked whether this tool provided during the registration phase has correctly categorised their preferences on the learning process as explained in subsection 3.2. 94% of the subjects reported that satisfaction with the classification of their learning styles in the Cloud eLearning prototype. One participant (6%) was not satisfied. The one that was not satisfied said that "my learning styles do vary depending on my mood, so sometimes I am part of tactical category and sometimes part of visual category", which

is consistent in learning theory literature because learning styles are not exclusive (Figure 10.9).

In question 8, the participants were asked to go to the list of the CeLLOs that were ranked by the Cloud eLearning Recommender System and to analyse whether they were ranked appropriately or not. 47% of the students said that the listed CeLLOs were very suitable, 47% responded that the CeLLOs were suitable, which in total is 94%. The remaining student responded "moderate". Among the students who found it suitable, one argued that he/she would like only CeLLOs that are directly connected to the search goal. Another replied that the CeL Recommender System should avoid providing the CeLLOs with prerequisites, preferring instead that the CeLLOs matched their topical interest, without regard for prerequisites. This comment suggests that in future work, in order to advance the prototype development, the next CeL could asses participants and based on their result it will suggest the upcoming CeLLOs(Figure 10.10).
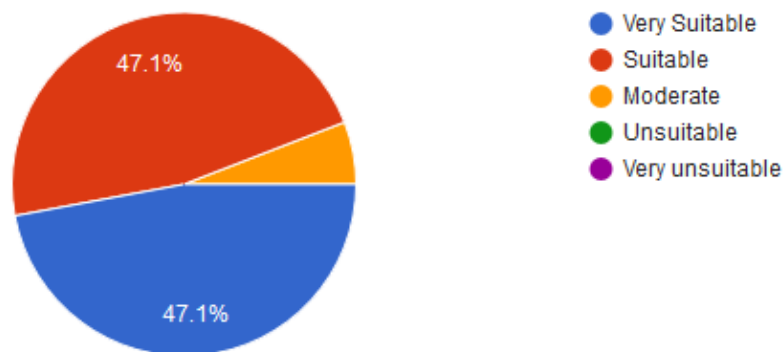
Fig. 10.10 The higher ranking of CeLLOs in CeL Recommender System

In contrast to question 8, in question 9 the participants were asked to check the lower ranking of the CeLLOs that are listed in CeLRS, and whether this was appropriate or not. 41% of participants found it very suitable, 41% of them suitable, one did not respond, one said moderate and the other one found it unsuitable (Figure 10.11).
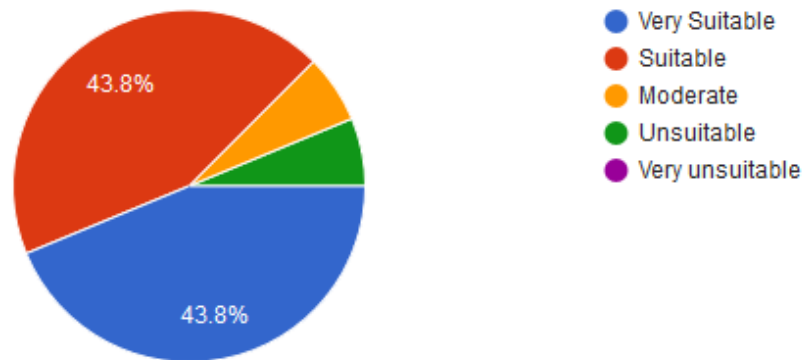
Fig. 10.11 The lower ranking of CeLLOs in CeL Recommender System

In question 10, the participants were asked to check the level difficulty of CeLLOs (as shown in Figure 10.12), and whether it was appropriate with their current knowledge level. This is important for the system, in order to suggest only CeLLOs that are in the same level of difficulties in order to avoid gaps that might be created when the student is forced to learn learning materials which are not appropriate to the their level of understanding (Figure 10.12).
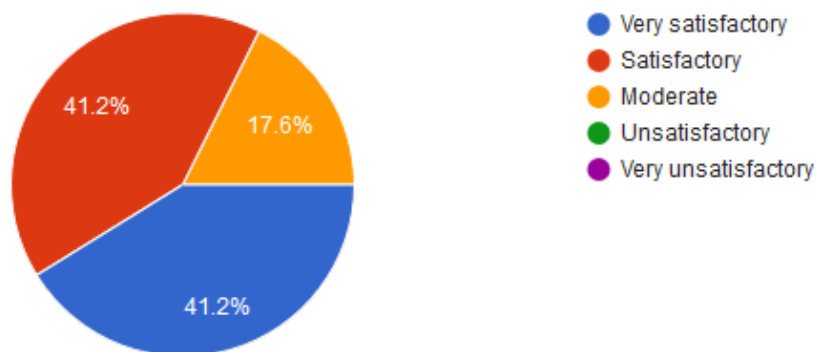
Fig. 10.12 The level difficulty of CeLLOs were appropriate to my prior knowledge in Java

Continuing with question 11, the participants were asked to predict what the system should recommend when their intended desire is to search for "data types". The success ("hit") rate of the CeL recommended list of CeLLOs is 82% (Figure 10.13). This means that only 3 users have said that they would select another learning path then the one CeL suggested, the rest had the same proposal with CeL.
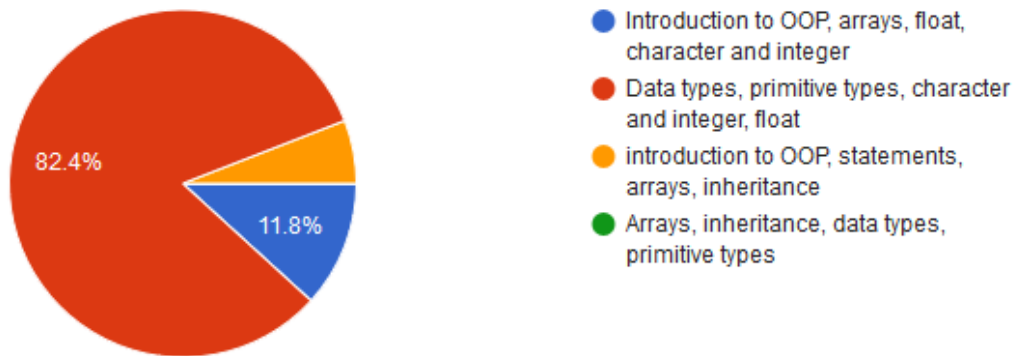
Fig. 10.13 The selection of CeLLOs manually from students

In Figure 10.14, we depicted the comparison between what the participants have selected and what CeL proposes. As can be analysed only three participants selected different option rather the one that CeL proposes, which mean that 82% of participants have selected the same option that CeL proposes.
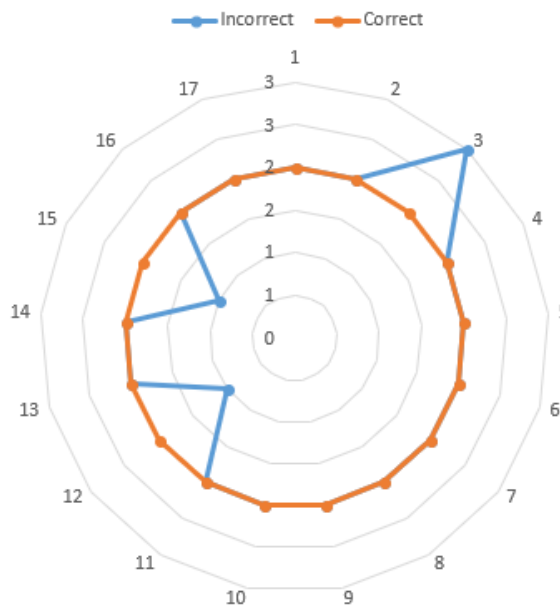
Fig. 10.14 The proposal of CeL recommended CeLLOs versus manually student selection path

Question 12 explored students' increase in knowledge based on participation in this study. All the participants said that as part of this experimental show case, they now have better understanding of using the personalised services in the learning domain. Furthermore, some were amazed at how much this influenced personal motivation in their overall learning

process. This could be counted also as a contribution, which increased the awareness of personalised learning paths.

Question 13 asked the students whether the learning process provided by Cloud eLearning satisfy their requirements. 59 % of participants declared as very satisfied, 35 % satisfied and 6 % moderated.

Question 14 asked for participants' satisfaction with the generated plan and whether all CeLLOs that are part of the personalised learning path are reasonable there. 59% answered that they found the learning path (plan) "very satisfactory", 35% responded "satisfactory", and the remaining answered "moderate" (Figure 10.15).
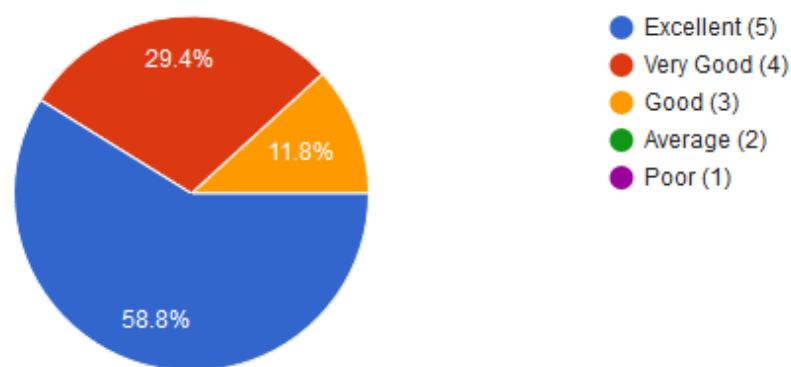
Fig. 10.15 Overall generated personalised learning path satisfaction

Question 15 asked the participants to check the plan that was generated from the CeL Planner, and see whether the CeLLOs which are part of the personalised learning path match to their interest or not. 41% found it very satisfied, 35% found it satisfied and the remaining it moderated (Figure 10.16).
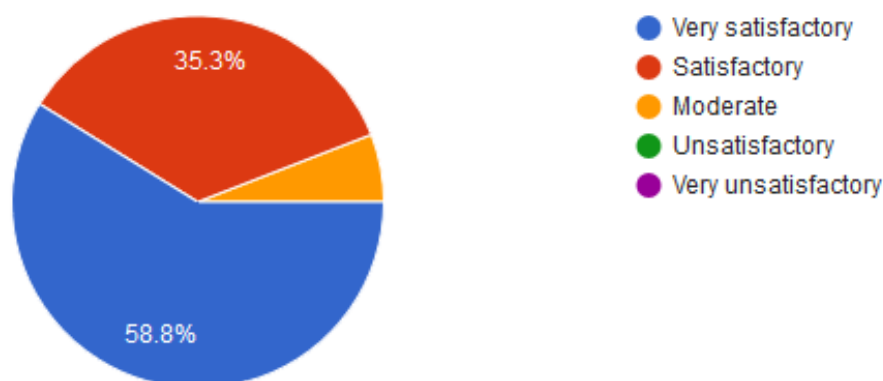
Fig. 10.16 The learning path reflected the participant goal

Question 16 asked the participants to manually select a learning path that they would like to follow, if their knowledge level is at the beginner level (blue line in Figure 10.17): Question 16: Which of the following learning paths sequence is appropriate to acquire the desired knowledge on "java statements" if your background knowledge in Java is advanced beginner? In contrast to that, we also analysed what the CeL suggested to the participants (orange line). When we analyse Figure 10.17, we can see that the participants' suggestions are not matching what the CeL suggested, as only 23% of participants' answers matched with CeL suggestions. We analysed this situation, and we saw that the question was not sufficiently clear when we directed the students to select a particular path if they are advanced beginner. They were not aware that this self-assessment is based on Bloom's Taxonomy, in which the lowest knowledge level is named novice. So, here perhaps we should have given more clarification in order to avoid the ambiguous terminology.
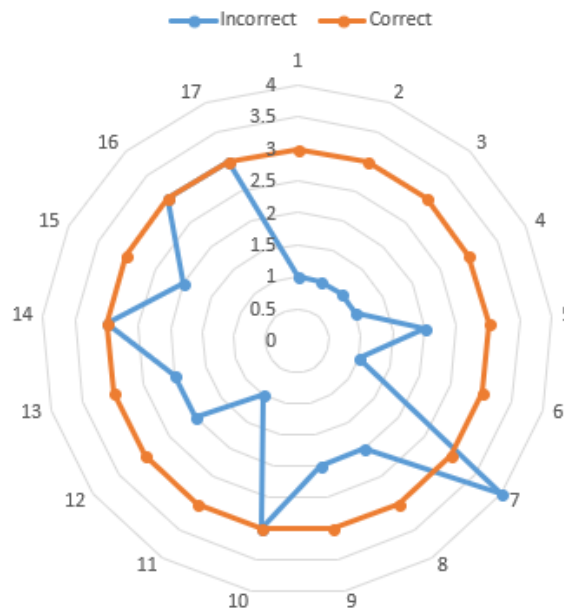
Fig. 10.17 The proposal of CeL recommended CeLLOs versus manually student selection path

And, now comes the open ended questions of the students which is the qualitative part of the questionnaire, and through these comments the participants expressed their overall reflections about being part of this study, and furthermore they have suggested new feature to the new version of CeL prototype. In order to summarise their comments, we can categorise their opinions in the following categories:

1. The CeL should be provided also as a web tool and not only as a desktop application.

2. The CeL introduction should offer some more lead text to make users more comfortable in making choices.

3. The CeL should supply an English auto-correction function when we type search queries with mistakes.

4. The future work should improve user interface to make it more visually attractive.

So, based on participants' comments, these 4 suggestions will guide the next version of CeL prototype. Also, further research will focus on how to increase the efficiency of the system response, and results will be built into system modifications. Also, the opinion of the two teachers supported the idea, but they curious to see the CeL after 5 years, when we have more data and the prediction accuracy starts to be increased.

To conclude, the results are very promising and will inform the next iteration of the development life cycle, as explained further in Chapter 11. Clearly, this study also contributed to participants' increased awareness of the influence of a personalised learning path in the learning process, as well as the use of artificial intelligence technologies in making the personalisation of learning paths possible.

Table 10.6 Correlation among Performance of the system, personalisation services, learner background and learner satisfaction

		CeL Perf.	Initial learner backg.	Personal. in learning process	Satisf. of learner
Pearson Correlation	CeL Performance	1.000	.321	.715	.516
	Initial learner background	.321	1.000	.383	.016
	Personalisation in learning process	.715	.383	1.000	.685
	Satisfaction of learner	.516	.016	.685	1.000
Sig. (1-tailed)	CeL Performance		.104	.001	.017
	Initial learner background	.104		.065	.476
	Personalisation in learning process	.001	.065		.001
	Satisfaction of learner	.017	.476	.001	

Coming back to the overall picture of evaluating the system, if we analyse the categorization of questions within the questionnaire we can conclude that the questionnaire targeted the learners background, the personsalisation services that could have been used or/and are used to facilitate the learning process, the Cloud eLearning Recommender System and its performance when interacting with the learners and finally the satisfaction of the learner when the Cloud eLearning Planner generated the personalised learning path. So, the questionnaire covered the learner background, the personalisation of the learning process, the CeL performance and learner satisfaction, and based on the collected data, we can conclude that the correlation between these variables is as shown in Table 10.6

So, analysing the above results and also Table 10.6, we can conclude that the significant correlation between "performance of the system" and "personalisation services" is 99%, between "performance of the system" and "learner satisfaction" is 99%, and between "performance of the system" and "learner initial background" is 90%. Further, between "initial learner background" and "personalisation services" is 95%, and between "learner satisfaction" with regard of using CeL and "personalisation services" is 99%.

So, the first hypothesis has been established, since the personalisation attributes (background of the learner, knowledge level, learning styles, to name a few) has between 90% - 99% influence in the performance of CeL, respectively in the personalisation of the learning path.

The same situation holds for the second hypothesis, which demonstrates that the satisfaction of the learners is increased 99%, when CeL provides personalised learning paths which encounters each learner individually. However, this demonstrates the ideal situation, thinking that CeL "knows" each learner and will be able to track their progress efficiently.

Further, in order to support the third hypothesis, the recommender system and automated planning has been developed as part of the CeL, which in our case from 300 CeL learning objects (CeLLO), is able to identify the most appropriate set of CeLLOs for individual learners.

And finally, the crowed feedback increases the ranking and the prediction of most appropriate CeLLOs to each of the learners as stated in the fourth hypothesis, however we think that in the next 3 to 5 years, when the system has large number of users feedback, the performance result, respectively the personalisation of learning path will be increased continually.

Summary

Since the evaluation of Cloud eLearning proposal has gone through two phases, the very first one was to validate the functionality of the proposed Cloud eLearning system through a throwaway prototype, the second phase covered the evaluation of Cloud eLearning from the perspective of the user evaluation approach. This chapter presented the experimental show case results and the whole procedures are explained in detailed, starting from the data collection up to the elaboration of final findings. Additionally, we selected three user cases, and explained them in detailed how they interacted with the Cloud eLearning prototype and furthermore we show also the perspective of Cloud eLearning prototype and how it automatically generated the personalised learning path to each of them. Furthermore, in the final section we elaborated each of the questions targeted in the survey and concluded the open comments.

Overall, CeL is an emerging process which requires time to be developed. The vision of CeL stated that the learners who use CeL will gradually develop a Learning Cloud which will include CeLLOs rated by them. In addition, CeL will become better in filtering and matching the learners profiles with the CeLLOs. This emergent behaviour is not existent in the startup phase in which we are currently at. Any attempt to claim that we evaluate CeL would be misplaced at this stage.

However, we can conclude that the performance of CeL will be increased if we provide personalised services (in our case personalised learning paths), further the system will suggest CeLLOs even if the learner has low background profile however update-in the learner background over time will have an impact to the CeL performance and in the overall learning process.

Chapter 11

Conclusions and Future Work

In this chapter, the conclusions and future work are presented and also the research questions are revisited in order to emphasize their completeness. Further a comparison between the Cloud eLearning vision, Cloud eLearning Core and Cloud eLearning prototype has been explained to crystallize the idea what we have proposed in the very beginning, what we are aiming to achieve in the forthcoming years and what we already have implemented. Also, the publications have been listed in Table 11.2 and mapped with contribution towards each chapter. Finally, we define some alternative research routes for future work.

11.1   Conclusions

In general, eLearning systems nowadays are inseparable systems from the learning process. The advancement of computing technology (cloud computing technology), especially the processing power of dynamic scalable service resources (such as: infrastructure, platform, software as a services), provides solutions to the challenges of dealing with massive amounts of data and processing it instantly.

Today, amidst continual growth of data and information on the Internet, online learning resources which can be used for learning purposes are of special interest, because these materials could be used as learning objects in various contexts. It is possible to use these learning objects when there are mechanisms that could annotate and describe the data in a structured manner. With the advancement of the knowledge representation technologies, the transformation of unstructured data into structured learning objects is possible using various techniques, such as: metadata, ontologies, to name a few.

The new trends in technologies reflected also in the evolution of eLearning systems (see Figure 2.1), especially the personalisation of eLearning services appeared from the year of 2008 [16].

The personalisation era, started with customisation of eLearning environment based on personalised characteristics of learners, and continued after 2014 with personalisation of learning paths. The main problem identified while investigating the eLearning learning management systems and massive open online courses with respect to personalisation of learning content (see Table 2.1), the personalisation of learning paths, the interaction among user and content and between users, are still faint. They still provide the services as one-size-fits-all approach, influenced by teacher-centered approach by offering fixed learning paths for all their learners.

Above this domain problem, we proposed an open approach of an advanced paradigm of eLearning, namely the Cloud eLearning, which offers the knowledge to the learners through these essential elements: (i) learner-centerd, (ii) openess, (iii) personalisation, (iv) self-motivation and (v) collaboration.

The learners can use a variety of tools to learn through learning materials that are developed by various institutions, so they are flexible to decide what, when and by whom to learn. From the teacher perspective, in CeL the teachers are open to collaborate and scrutiny from colleagues at other institutions, which will drive the teachers to achieve better quality and disseminate best practices and inspiration to others. And finally, from the institutions perspective, they will be forced to provide better service to learners and better policies for teachers. The open characteristics of Cloud eLearning (listed in Table 5.1) started with collective creation of syllabus, collection of learning materials through a variety of sources, selection of teachers, learners and providers, personalisation of learning paths and a customisable VLE. These are only few characteristics which will increase the engagment and the motivation of those learners that are knowledge-driven.

However, proposing the Cloud eLearning vision and conceptualising the overall proposal and its related activities of using Cloud eLearning as an advancement paradigm of eLearning faced a number of challenges. These challenges were of various nature, starting of the lower level approach of how we can identify the online resources that are usable for learning purposes. Further, problems arise when trying to link various learning objects as part of a sequence of a learning path, raising the wider question: could the learning path be personalised? If so, which are the techniques that could be used? Could the learning objects be loosely coupled, so that we have adequate flexibility for changing the coupling over the learners' progress? What techniques should we use in order to facilitate the aforementioned opportunities, especially those related with personalisation of learning paths? This thesis has categorised these challenges into four research questions as defined in Chapter 1. We recall them here to ensure that we have satisfactorily answered these questions throughout this thesis.

Q1: Which artificial intelligence (AI) approaches could facilitate the personalisation of learning experience, based on learners' profiles, with the aim of creating a generalisable model for personal learning activities within Learning Cloud environments?

Q2: What features could influence the creation of personalised learning paths as a planning problem, taking into consideration the involvement of agents?

Q3: What are potential problems of linking a sequence of learning objects found on the Cloud and how can these be loosely coupled, so that there is adequate flexibility to change the coupling as the user progresses?

Q4: How can the Cloud eLearning approach be evaluated? Should a new prototype be created? Should the evaluation target only the functionality of this prototype or do we need a user evaluation also?

Based on the research questions, in earlier chapters, we have reviewed a number of existing research contributions and analysed how personalisation of online services has had a positive impact within online services (such as using Netflix, Amazon, to name a few). In these instances, personalisation approaches have increased interaction processes among users and between users and content. In further defining our original approach, we have reviewed the existing theory principles and applied techniques from Artificial Intelligence (such as: machine learning, automated planning, neural networks, fuzzy cognitive mapping to name a few) which have facilitated the personalisation of the online activities so far in various domains. We reasoned that these techniques could be applied also in a learning domain which is a more complex domain, because we need to provide a sequence of learning paths which involves a set of coherent learning objects, whereby potential learners will be able to learn and interact with learning objects that are relevant to learners characteristics, such as their learning backgrounds, learning knowledge levels, and learning styles, which then could contribute to the overall learning process.

Toward this conclusion, we proposed Cloud eLearning as an advancement of eLearning, aiming to provide personalised learning paths that match learners' preferences as shown in Figure 11.1.

For providing these personalised learning paths we used the Artificial Intelligence automated planning approach, which then had involved the knowledge representation in order to be able to derive and represent the learning resources within the Cloud. However, the main challenges of automated planning is the experience of exhaustiveness when dealing with the huge number of nodes in the search space. In our case, it is important that the pool of appropriate Cloud eLearning learning objects is relatively small so that we avoid
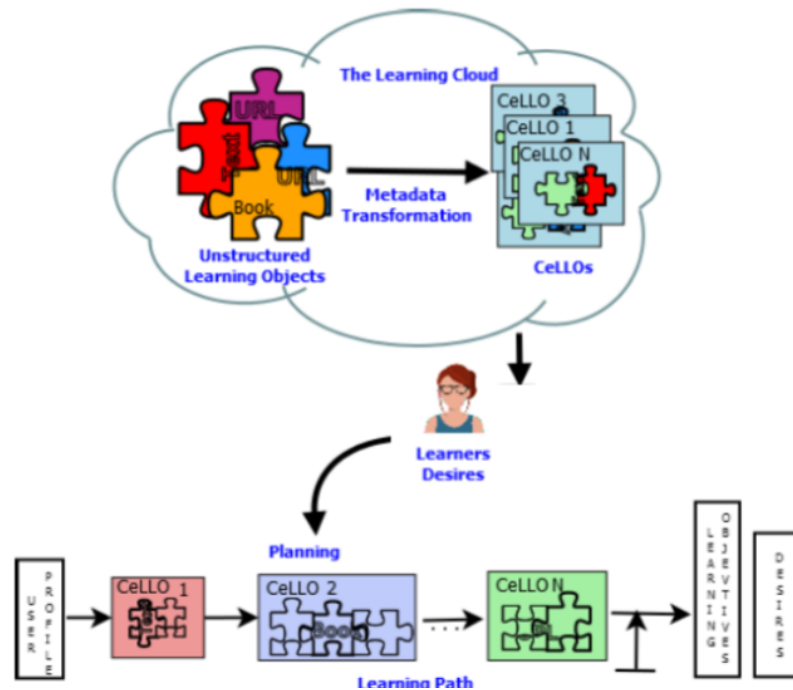
Fig. 11.1 Big picture of initial Cloud eLearning (CeL) proposal

combinatorial explosion which creates an inevitable computational problem, which is a common problem in any automated process. Therefore, our proposal shifted to the practical Cloud eLearning shown in Figure 11.2.

This approach (Figure 11.2) involved also the recommender system (text mining and K-Nearest Neighbour) as a middle layer technology, which aims to filter and rank a reasonable number of appropriate CeLLOs for particular learners interest and background. In this regards, the output of the recommender system will be offered as an input list to the AI automated planning, which automatically will generate a solution plan containing the personalised learning path, which is represented through a set of actions. The involvment of recommender system as a middle layer made the AI automated planning process run successfully.

So, in this context, explaining the whole CeL proposal, we start from the knowledge representation layer (the upper layer), where the knowledge representation technology is involved to provide structured representations of content (Cloud eLearning Learning Objects) and learners' profiles (Cloud eLearning Learning Profiles). Continuing with middle layer, the recommender system involved between the knowledge representation as upper layer and AI automated planning as bottom layer, which helps us to reduce the search space as explained above (which is a prerequisite for an AI planner in order to perform efficiently) and rank a number of Cloud eLearning Learning Objects which is then used as input data for the Cloud eLearning Planner for providing a validated personalised learning path (the generation
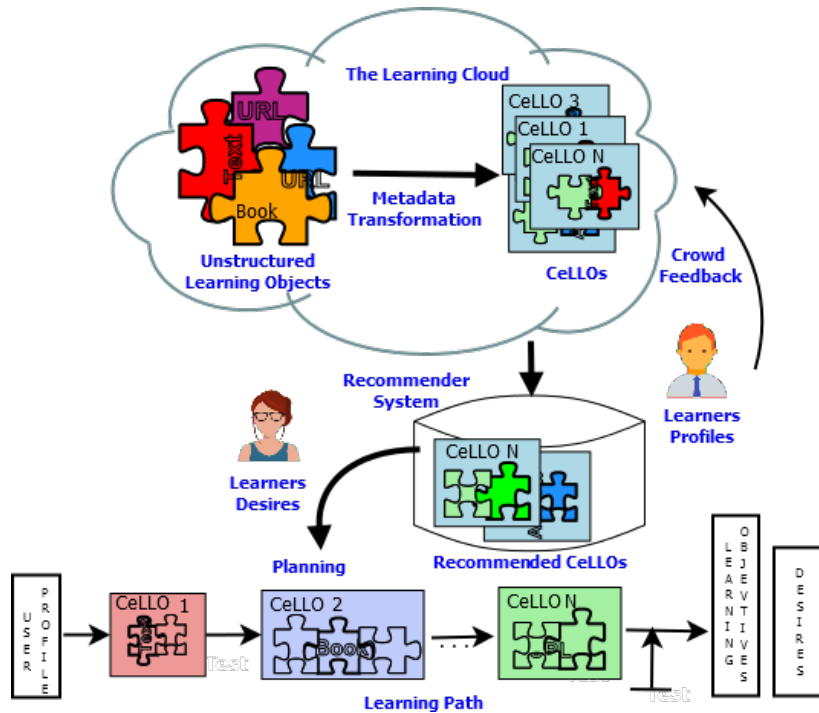
Fig. 11.2 Big picture of practical Cloud eLearning (CeL) proposal

of solution/plan). Coming back to each research question, for research question one that questions which artificial intelligence (AI) approaches could facilitate the personalisation of learning experience, based on learners' profiles, with the aim of creating a generalizable model for personal learning activities within Learning Cloud environments?
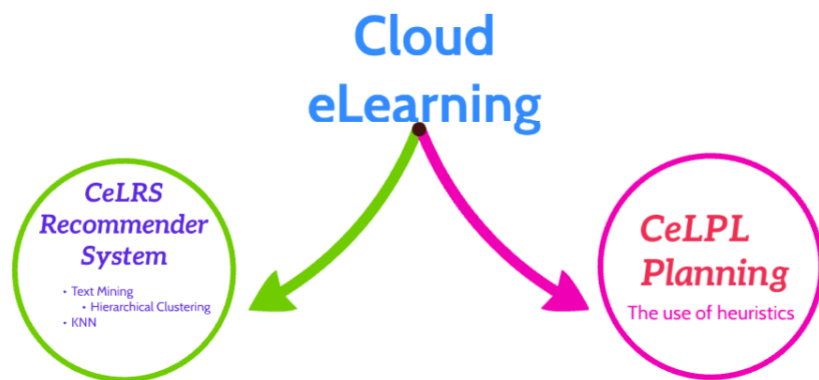
Fig. 11.3 The involvment of AI techniques in Cloud eLearning (CeL)

As shown in Figure 11.3, the Cloud eLearning initially has involved the use of Cloud eLearning recommender system, which uses the hierarchical clustering and K-Nearest Neighbour AI techniques for filtering and ranking the appropriate CeLLOs, and also the use of heuristics as part of Cloud eLearning Planner.

Continuing with research question two, questioning what features could influence the creation of personalised learning paths as a planning problem, taking into consideration the involvement of agents?

In this stage of Cloud eLearning, we can see the knowledge representation, the recommender systems and the automated planner as multi agent system which are able to work autonomously, communicate toward a specific standard with each-other to achieve a goal for generating personalised learning path, and proact and react independly. However, the multi agent systems in the near future can be involved also in the lower level of the CeL, considering in the learners module, course module and the intelligent control module as proposed in one of our research papers [140].

Continuing with research question three, questioning what are potential problems of linking a sequence of learning objects found on the Cloud and how can these be loosely coupled, so that there is adequate flexibility to change the coupling as the user progresses?

The analysis of current metadata standards , such as IEEE LOM and Dublin Core (part of Chapter 6) made us belive that there are still lack of flexibility in context of representing and tailoring the sequence of learning objects in a flexible manner, therefore we proposed the Cloud eLearning metadata which transformes the adapted learning objects into Cloud eLearning learning objects (CeLLO) and satisfies the possibility of coupling the CeLLOs in various context, as part of a personalised learning path, which is created by number of CeLLOs that are derived from various sources.

As shown in Figure 6.7 the elements of CeL Metadata are subsets of a number of elements of Dublin Core and IEEE LOM, and additionally of new elements (see Figure 11.4) that are required to achieve CeL aim.

The elements of Cloud eLearning Metadata are: (1) Title, (2) Description, (3) Keyword, (4) Content, (5) Meta-metada, (6) Catalog, (7) Pre/Post requisite, (8) Relationship, (9) Intended Learning Outcomes, (10) Format, (11) Granularity, (12) Cognitive Level, (13) Context, (14) Credibility, (15) Crowd rating CeLLO, (16) Crowd rating set of CeLLO, (17) Date, (18) Language. The extra added new elements are shown in Figure 11.4 as well as described in Table 6.1.
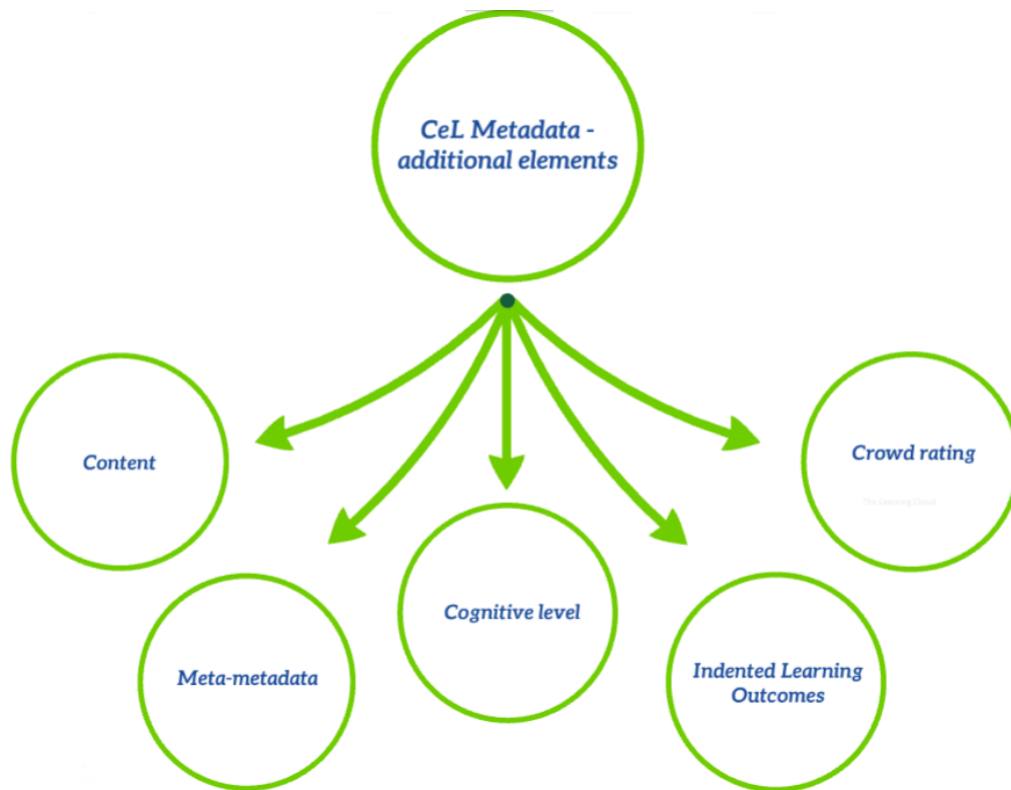
Fig. 11.4 The extra elements of Cloud eLearning Metadata

As per our evaluation process, which is part of research question 4, we have developed a throwaway prototype which has targeted only the core layer of Cloud eLearning (see Figure 5.3), accomplishing the open course layer functionality by tailoring the open Cloud eLearning Learning Objects adapted from various learning resources.

This prototype is developed in order to validate the proof of concept, and also to see the interoperability between the integration of Artificial Intelligence technologies as part of Cloud eLearning. In addition, the prototype was demonstrated to students and teachers who used and evaluated it through an online questionnaire and unstructured interviews.

Table 11.1 Comparison between CeL Vision, CeL Core and CeL Prototype

No.	CeL Vision	CeL Core	CeL Prototype
1.	Everything stored in the Cloud is a potential learning material	Validated materials from reputable institutions are provided as learning materials	Existing material from repositories
2.	All learning materials are transformed automatically into structured learning materials	Use only semi-structure and structure materials to transform automatically	Transformation of learning materials is done manually
3.	All learning materials are ranked dynamically based on crowd rating and the relevance of learner desire	Ranking through deep learning, advanced recommender systems	Ranking is based on text mining
4.	A learner profile is created gradually by tracking the learner behaviour	Profile is created by using the Cloud eLearning in an explicit way	Profile is generated from learners
5.	Personalised Learning Environment	Customised VLE including personal assistant agents	-
6.	Personalised Learning Path	Personalised Learning path through deep learning or relevant techniques	Artificial Intelligence automated planner
7.	Collaboration among learners, teachers and institutions	-	-
8.	Quality Assurance at local level, national and international level	-	-
9.	Accreditation at discipline or university level	-	-

To conclude, Table 11.1 presents a detailed comparison between the Cloud eLearning Vision, Cloud eLearning Core and Cloud eLearning Prototype, manifesting the limitations from Cloud eLearning vision up to Cloud eLearning prototypes. In Cloud eLearning Vision, we have proposed that everything stored in the Cloud is a potential learning material, all learning materials are automatically and instantly in the Cloud eLearning, the adapted learning materials are ranked and predicted with the help of crowd rating using advanced artificial intelligent techniques, the learner profiles are created in the fly by monitoring the user behaviour and network connection. Further, the vision of Cloud eLearning proposed a personalised learning environment, so the learners are able to adapt the environment by drag-and-drop user friendly interfaces and be able to decide by their own the user interface layout and structure so they can interact with CeL in a personalised way. Furthermore, CeL vision embraces the idea of increasing the collaboration among learners, learners and teachers and between institutions, so the learner will have the flexible education system which today has become part of our everyday activities. And besides, being educated on-campuses they also use CeL with personalised courses, personalised curriculums and offer the opportunity to the learners to decide what to learn, when to learn, where to learn, how to learn and by whom to learn.

Above this proposal we have created the Cloud eLearning prototype, which collected learning materials from various sources as explained in Chapter 9, adapted and transformed them to Cloud eLearning Learning Objects as described in Chapter 6, created learners profile by offering to use the prototype to the learners, matched the learning materials and learners background and desire as explained in Chapter 7 using the text mining approach, and finally generating personalised learning paths using automated planner.

11.2   Future work

In the next 3 to 5 years we encounter to deal with the Cloud eLearning core which has mainly similar attributes what Cloud eLearning prototype already has, however we think to advanced and automate the processes with new advancd techniques as specified in Table 11.1.

As shown in Table 11.1 there are a number of fields that we can continue our research in multiple area in order to fulfil our CeL vision.

Firstly, the current CeL prototype response time is not so efficient when it processes a large number of Cloud eLearning Learning Objects (example: 500 items). So, the **text mining** approach decreases the performance of Cloud eLearning when the number of CeL-LOs are increased, suggesting that we need to further investigate how we could increase

the efficiency of response time using various algorithms, without compromising retrieval effectiveness.

Secondly, we aim to automate the process of transforming the learning objects to the CeL Learning Objects and the creation of learner profiles while monitoring user behaviour and its network connections.

Thirdly, future work will include further work in regard to Automated Planning in order to consider the temporal planning techniques and to investigate more the benefits of **Planning and Scheduling techniques**, particularly the case of the job-shop problem. This a new technology which, besides the time constraints, deals also with resource constraints, as consumable or borrowable resources.

Fourthly, since the Cloud eLearning Learning Objects are comprised from various sources and everything stored in the Cloud can potentially be used for eLearning purposes, we will continue for future work to consider whether the services should be part of any of the Cloud service models that are described in Figure 4.2 (Chapter 4), and if there is any possibility to do research toward a new proposal of service models, namely the **Learning as a service (LaaS)**. In addition, we will analyse who might control progressing the layered activities defined in Figure 4.4 (the units, assessments, roles, database and data, framework, middleware and running, visualisation, servers, storages and networking).

Last but not least, as part of the collaboration between the University in Kosovo (UBT), University in Sweden (Linnaeus University) and University in USA (University of Pacific) there is an initial project created, namely Knowledge Center. As part of this project, a digital repository [1] is created and tending to offer digitalised learning materials to the community, firstly locally, then nationally and aiming to increase the reputation for international use. As part of second phase, is initiated the creation of learning materials from staff and students, and after this phase we want to enable to use the Cloud eLearning Recommender System and propose the learning materials to the users based on the users background and initial interests[174].

11.3   Research Publications

Large parts of this thesis has been compiled based on a number of peered review publications that have been published and presented since the official starting date of this PhD programme.

For further detail information toward publications and the mapping of chapters with respect to the publications is presented the Table 11.2.

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[1] Koha UBT, http://library.ubt-uni.net:9050/

Table 11.2 List of publications

No	Publications	Publisher	Peer Reviewed	Contribution wrt chapters
1	Pireva Krenare, Petros Kefalas, Dimitris Dranidis, Thanos Hatziapostolou, and Anthony Cowling. "Cloud e-Learning: A new challenge for multi-agent systems." In Agent and Multi-Agent Systems: Technologies and Applications, pp.277-287. Springer, Cham, 2014	Springer	Yes	4, 5
2	Pireva, Krenare and Petros Kefalas. "The use of multi agent systems in cloud eLearning." Doctoral Student Conference on ICT, Thessaloniki, SEERC, 2015	SEERC	Yes	4, 5
3	Pireva Krenare, Petros Kefalas, and Ioanna Stamatopoulou. "Representation of learning objects in cloud eLearning." In Information, Intelligence, Systems and Applications (IISA), 8th International Conference on, pp.1-6. IEEE, 2017	IEEE	Yes	6
4	Pireva, Krenare and Petros Kefalas. "A Recommender System Based on Hierarchical Clustering for Cloud e-Learning." In International Symposium on Intelligent and Distributed Computing, pp.235-245. Springer, Cham, 2017	Springer	Yes	7
5	Pireva, Krenare and Petros Kefalas. "A review of Automated Planning and its Application to Cloud e-Learning." Doctoral Student Conference on ICT, Thessaloniki, SEERC, 2017 (Best Paper Awarded)	SEERC	Yes	8
6	Imran, Ali Shariq, Krenare Pireva, Fisnik Dalipi, and Zenun Kastrati. "An analysis of social collaboration and networking tools in eLearning." In International Conference on Learning and Collaboration Technologies, pp.332-343. Springer, Cham 2016	Springer	Yes	2, 3
7	Pireva, Krenare, Ali Shariq Imran, and Fisnik Dalipi. "User behaviour analysis on LMS and MOOC." 2015 IEEE Conference on e-Learning, e-Management and e-Services (IC3e), pp.332-343. IEEE, Melaka, 2015	IEEE	Yes	2, 3

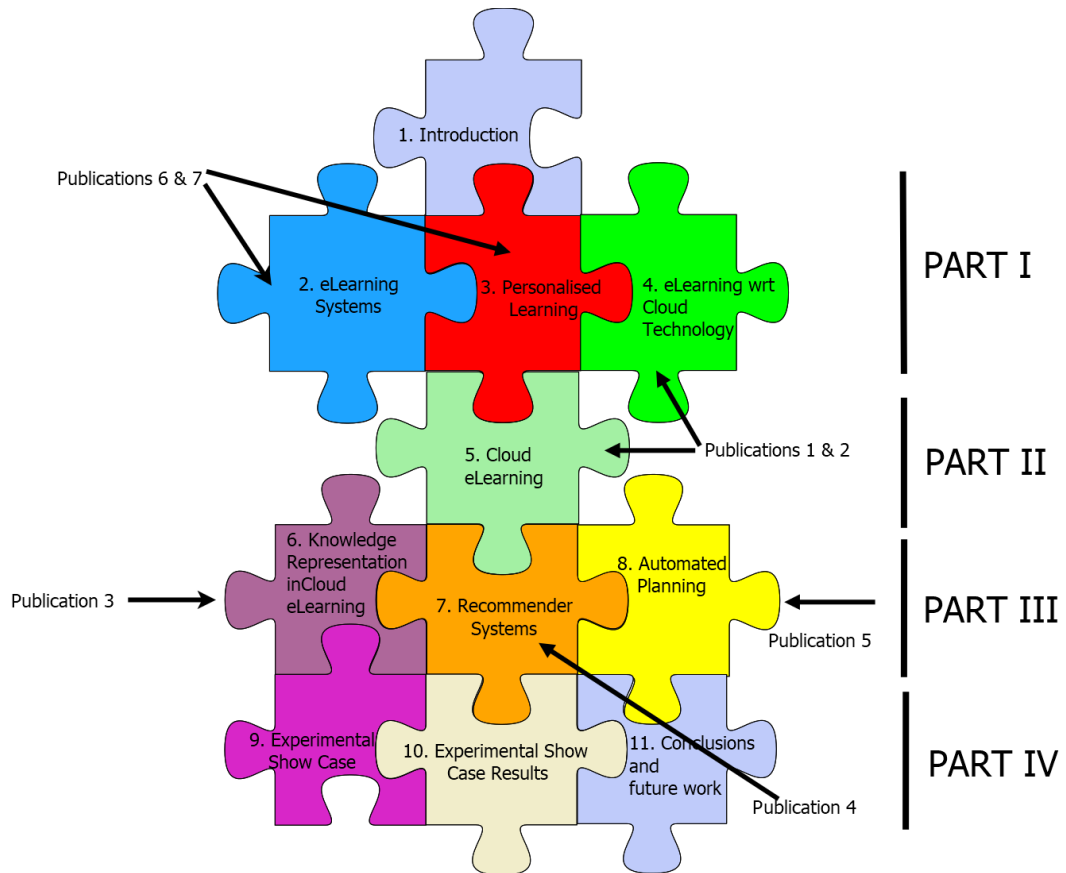Furthermore, the structure of the thesis mapped with the publication papers is depicted in Figure 11.5.

Fig. 11.5 The relation of contribution according to thesis structure

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