International Journal of Engineering Education Vol. 28, No. 6, pp. 1373–1379, 2012
Printed in Great Britain
0949-149X/91 $3.00+0.00


# Learning Goals Recommendation for Self Regulated Learning*

NICOLA CAPUANO,[1] GIUSEPPINA RITA MANGIONE,[2] ANNA PIERRI[2] and SAVERIO SALERNO[1]
[1] University of Salerno, Dept. of Electronic Engineering and Information Engineering, 84084 Fisciano, SA, Italy.
[2] Centre of Research in Pure and Applied Mathematics, c/o DIIEI, University of Salerno, 84084 Fisciano, SA, Italy.
E-mail: {ncapuano, salerno}@unisa.it, {mangione, pierri}@crmpa.unisa.it

In the knowledge society the ultimate goal of education is not only to make learners learn but mostly to grow a correct learning behaviour that creates the best conditions for them to reach learning goals in a controlled and directed way. In many cases, a lack of self-regulatory skills is the main obstacle to adequate regulation and a new class of learning tools, named metacognitive tools, is needed. In this work we present a novel solution for self-regulated learning that tries to solve this issue by recommending feasible learning goals covering explicit and implicit learning needs and by generating individualized learning experiences based on recommended goals.

**Keywords:** recommender systems; self regulated e-learning; intelligent tutoring systems

## 1. Introduction

The learning process, especially when linked to *conceptually-rich domains* [1], requires suitable learning environments that support self-regulation of goals, personalisation of paths and elicitation of needs to develop a learning experience that may strictly match the individual's learning needs, and be controlled and revised in a participated manner. A significant educational action able to guide the learner in a comprehensive learning process is not only focused on learning (cognition level) but also on fostering a correct learning behavior that empowers learners to achieve their learning goals in a controlled and directed way (metacognition level) [2].

The *self regulated approach* has especially been adopted in the field of technology-enhanced learning: successful learning with advanced learning technologies is based on the premise that learners adaptively regulate their cognitive and metacognitive behaviours during the learning experience [3].

However, there is abundant empirical evidence that suggests that learners typically do not adaptively modify their learning behaviour, thus suggesting that they engage themselves in what is called *dysregulated learning* [1]. Dysregulated learning is a new term that is used to describe a class of behaviours that learners use, leading to minimal learning. A lack of self-regulatory skills is the main obstacle to adequate regulation and so implies deficient learning gains and conceptual understanding.

Modern e-learning systems present a set of services and tools supporting several activities and didactic procedures but they remain often linked to object oriented strategies and are characterised by a weak relationship between processes belonging to self-regulated learning and functionalities based on a technological-driven approach [4].

This study presents a system for self-regulated learning that uses an ontological interpretative approach to knowledge and combines its architecture with a goal-oriented learning strategy as that adopted by self-regulated learning. In such system a personalised learning experience can be generated starting from both an explicit request made by the learner in natural language or from an implicit one based on the analysis of a learner' profile and on the comparison of this profile with profiles of similar learners.

The proposed methodology upholds the social presence while supporting the development of self-regulated learning. Educational recommendations serve as pedagogical advance organizer for the learners, as they anticipate and spread needs, knowledge and learning paths. Furthermore they also improve the students' control over learning.

This paper is organized in this way: the section 2 introduces some background about recommender systems and self regulated e-learning and presents some existing application of such systems; the section 3 introduces the starting point of our research while section 4 focuses on the proposed methodology that defines a course building process starting from explicit and implicit requests made by learners; the section 5 describes two real applications of the proposed methodology; eventually, the section 6 describes conclusions and planned future work.

* Accepted 27 July 2012.

## 2. Background and related work

This paper mainly deals with *Self Regulated e-Learning* (SLR) that refers to the learners' ability to make adjustments of their own learning processes in response to their perception of feedback regarding their current status of learning. A self-regulated learner should be knowledgeable about his or her cognitive strategies and be willing to apply them in order to achieve his or her learning goals.

The scientific research highlights how the learner in a situation of no self-regulation could experience problems of inefficacy learning from a cognitive perspective, as well as, from a motivational standpoint, could tend to drop out of his/her learning path [5]. The development of a learner' self-regulation requires a new conceptualization of learning environments [6] and should enable learners to control the essential aspects of learning.

The learners should be given the possibility of accurately expressing and setting their goals, mainly who demonstrates to possess good self-regulation ability, autonomously controlling the elicitation of their needs.

In traditional e-learning systems, learners can decide about specific outcomes to be expected from their paths but they rarely can identify appropriate strategies to adopt for the achievement of the indicated goals [7]. The nurturing of self-regulation skills can occur through solutions submitted to learners as a knowledge advance organizer and that allow to navigate through the concepts of a given learning domain and then to select those concepts that may be of interest for his/her action.

Recently, authors refers that, in the development of e-learning systems the focus should be the detection, tracking, modelling, and fostering of the cognitive and self regulatory processes. This is exactly the aim of the system described in this paper that, to obtain these results, propose the adoption of models and methodologies coming from the research field on recommender systems.

*Recommender Systems* (RSs) are aimed at providing recommendations on the utility of a set of objects belonging to a given domain, starting from the information available about users and objects [8]. Several applications of RSs for e-Learning have been introduced till now as summarized in [9].

One of the first systems, based on a collaborative approach, has been *Altered Vista*. Its goal was to explore how to collect user-made evaluations of learning resources and to propagate them to other users. A similar system is *RACOFI* that integrates a collaborative RS with a rule-based inference engine. *QSIA* is another RS for learning resources sharing, assessing and recommendation in online communities.

*CYCLADES* uses a collaborative approach with user-based ratings, but does apply the technique to several communities at the same time. A related system is *CoFind*: it uses digital resources that are freely available and also uses folksonomies for recommendations. In *ReMashed* learners can rate information from an emerging amount of Web 2.0 information and train a recommender system for their particular needs. *CourseRank* uses a hybrid recommendation approach and is used as an unofficial course guide by several universities.

In [10] authors developed a recommender system for learning objects based on sequencing rules that help users be guided through the concepts of an ontology of topics. A similar sequencing system is described in [11] and analyses group-learning experiences to predict and provide a personal list for each learner by tracking others' learning patterns regarding certain topics.

## 3. The starting point

In this section we introduce a learning system named **IWT** (Intelligent Web Teacher) [21] that we adopted as a basis to apply models and methodologies hereafter defined. As described in [12] IWT allows generating personalized learning experiences and relies on four interacting models as described below.

The *domain model* describes the knowledge that is object of teaching through a set of concepts (representing topics to be taught) and a set of relations between concepts. A set of *teaching preferences* can be added to the domain model to define feasible teaching strategies that may be applied for each available concept. The domain model can be specified by the teacher or semi-automatically learnt by the system through knowledge extraction approaches [22].

The *learner model* represents a learner and is composed by a *cognitive state* that measures the knowledge reached by him at a given time and by a set of *learning preferences* that provide an evaluation of which learning strategies are more feasible for him. Both components are automatically assessed by IWT by analysing results of testing activities and the learner behaviour during the learning experience.

The *learning resource model* is a metadata representing a learning resource and is based on the application of the IEEE LOM standard [13]. It includes the set of concepts that are covered by the learning resource and an additional set of didactical properties representing learning strategies applied by the learning resource.

The *unit of learning model* represents a sequence of learning resources needed for a learner in order to understand a set of target concepts in a given domain [23].

In [12] we have described the process to generate a unit of learning starting from a set of target concepts and from a learner model. The process generates a feasible sequence of domain concepts able to teach the target concepts. Then it removes domain concepts already known by the target learner by looking at his/her cognitive state. Eventually it associates to each remaining concept the best matching learning resources taking into account teaching and learning preferences.

In order to support **self regulated e-learning**, IWT implements an alternative method for the expression of a learning need through Upper Level Learning Goals (ULLGs) [14]. An ULLG is a meaningful set of target concepts on a given domain model with a connected textual description *d*. ULLGs can be built both by teachers and by learners and are accessed through a search engine.

The learner can so specify a learning need *n* in natural language and let the system find the list of best matching ULLGs basing on the similarity between *n* and the textual descriptions di connected to available ULLGs. To do that both *n* and each $d_i$ are transformed into vectors of terms pre-processed with stemming and stop-word lists. Terms coming from *n* are enriched with synonyms coming from domain dictionaries automatically extracted from Wikipedia. For all ULLGs, the similarity between $d_i$ and *n* is then calculated using the Cosine Distance and the Levensthein Distance.

The use of a lexical database enables to model human common sense knowledge and the incorporation of corpus statistics allows the method to be adaptable to different domains. An important aspect that this approach proposes is that it takes care not only of the semantic similarities between the single words existing in the short sentences but also of the order of words within the phrase.

ULLGs presenting higher similarities with the expressed learning need are provided to the learner. Then the learner can select a ULLG and let the system build a personalized unit of learning starting from the connected set of target concepts and from his/her learner model.

## 4. The proposed approach

In order to anticipate learning needs, we have defined and integrated in IWT a new process of course building based on ULLGs but starting from an implicit request rather than from an explicit one [9]. In other words, an algorithm to recommend ULLGs based on the analysis of a learner' cognitive state and on the comparison of this cognitive state with cognitive states of similar learners has been defined.

The algorithm consists of the following steps: concept mapping, concept utility estimation and ULLG utility estimation each described in one of the following sub-sections. Once the utility of each ULLG is estimated for a learner, the ULLGs with the greater utility are suggested to him.

### *4.1 Concept mapping*

Given a set of concepts *C* and a set of learners *L*, the *cognitive state* of a learner *l L* (as reported in section 3 and detailed in [12]), describes the knowledge reached by *l* at a given time and it is represented as an application $CS_l$: $C \rightarrow [0, 10]$. Given a concept *c*, with $CS_l(c)$ we indicate the degree of knowledge (or grade) reached by the learner *l* for *c*. If such grade is greater then a threshold $\theta$ then *c* is considered as known by *l*, otherwise it is considered as unknown.

At a given time a learner can be enrolled to one or more units of learning. As reported in 3 (and detailed in [12]), a unit of learning represents a sequence of learning resources needed by a learner in order to understand a set of target concepts in a given domain. Among the components of a unit of learning there is the learning path $LPath = (c1, \ldots, c_n)$: an ordered sequence of concepts that must be taught to a specific learner in order to let him/her complete the unit of learning.

Starting from that, we can define the set $COT_l$ of all concepts that are object of teaching for a given learner as the union of all learning paths *LPath* corresponding to the units of learning the learner is enrolled in.

Then we can define the **concept mapping function** that is a Boolean function $CMF: L \times C \rightarrow \{0, 1\}$ that can be defined as follows:

$$CMF(l, c) = \begin{cases} 1 \text{ if } CS_l(c) > \theta \text{ or } C \in COT_l \\ 0 \text{ otherwise} \end{cases} \quad (1)$$

So, given a leaner *l*, CMF(*l*,*c*) = 1 for all concepts *c* that are already known by *l* plus all concepts *c* that are currently object of teaching for him/her. It is equal to 0 for any other concepts.

### *4.2 Concept utility estimation*

The utility *u*(*l*,*c*) of a concept *c* for a learner *l* can be estimated starting from the concept mapping function. The utility of a known concept or of a concept that will be known soon is equal to 0. So $CMF(l,c) = 1 \rightarrow u(l,c) = 0$. Conversely, to estimate the utility of remaining concepts, a collaborative recommendation algorithm is used.

We can estimate the unknown utility of a given concept *c* for a learner *l* by aggregating, through a weighted sum, ratings for the concept *c*, included in the concept mapping function, coming for learners that are similar to $l$. The estimation can be done through the following formula:

$$u(l,c) = \frac{\sum_{l' \in L'} CMF(l',c) \cdot sim(l,l')}{\sum_{l' \in L'} |sim(l,l')|} \quad (2)$$

where $L'$ is the set of the $n$ learners most similar to $l$ while $sim(l,l')$ is the similarity degree between $l$ and $l'$ obtained though similarity measures like the *cosine similarity* or the *Pearson correlation coefficient* [15] calculated on *CMF*.

From the algorithmic point of view, to estimate the concept utility function, we start from the concept mapping matrix where each element $CMF(l,c)$ is defined with (1). This matrix is built the first time by considering every cognitive state and every course available on the system. Each time a learner starts, terminates or abandons a course then the row corresponding to this learner is updated, again, through (1).

Starting from the concept mapping matrix, the user-to-user similarity matrix is calculated. Each element $sim(l,l')$ of this matrix is obtained through a similarity measure between the rows of the concept mapping matrix corresponding to users $l$ and $l'$. Once the similarity matrix is calculated, to estimate an undefined $u(l,c)$ for a given learner $l$, it is necessary to isolate and combine, by applying (2), the utility expressed for $c$ by the $n$ learners more similar to $l$.

### 4.3 ULLG utility estimation

An *ULLG* can be formally defined as a tuple $ULLG_i = (D_i, TC_i1, \ldots, TC_{in})$ where $D_i$ is a text describing the learning objective in natural language, while $TC1, \ldots, TC_n$ is the list of target concepts that have to be mastered by a learner in order to reach such learning objective. A learning need *LN* is a textual sentence (like 'to learn Java programming' or 'how to repair a bicycle' etc.) expressed by a learner in order to start the unit of learning building process.

Through the unit of learning generation algorithm introduced in section 3 (and detailed in [2]) IWT is able to generate a learning path starting from a set of target concepts. By applying the algorithm described there, it is possible to determine, for each existing upper level learning goal $ULLG_i$, the corresponding learning path $LPath_i$ starting from the connected list of target concepts.

Once determined learning paths associated to available ULLGs, it is possible to estimate the **aggregated utility** $au(l,ULLG_i)$ of each of them for a learner $l$ with the following formula:

$$au(l, ULLG_i) = \sum_{c \in LPath_i} \frac{u(l,c)}{|LPath_i|}. \quad (3)$$

The calculus of the aggregated utility takes into account the utility of all concepts explained by the ULLG. This means that, if the learning path connected with the ULLG includes many concepts already known by the learner, its aggregate utility can be low even if the utility of remaining concepts is high. To take into account this information we introduce the concept of **marginal utility** $mu(l,ULLG_i)$ of $ULLG_i$ for a learner $l$ that can be obtained with the following formula:

$$mu(l, ULLG_i) = \frac{\sum\limits_{c \in LPath_i} u(l,c)(1 - CMF(l,c))}{\sum\limits_{c \in LPath_i} (1 - CMF(l,c))} \quad (4)$$

Thus the utility of an ULLG for a given learner can be obtained by combining aggregated and marginal utilities through a weighted sum with the following formula:

$$u(l, ULLG_i) = \alpha au(l, ULLG_i) + (1 - \alpha) mu(l, ULLG_i) \quad (5)$$

where $\alpha$ is the hybridization coefficient that is a real number between 0 (highest priority to the marginal utility) to 1 (highest priority to the aggregated utility). The choice for $\alpha$ will be done empirically basing on experimentation results. Low values for $\alpha$ privileges novelty while high values privilege accuracy of suggestions given by the recommender system.

## 5. Two concrete applications

In this section we present two concrete applications of the ULLG metaphor within two different initiatives. **ALICE** 'Adaptive Learning via an Intuitive, interactive, Collaborative, Emotional system' is a research project funded by the European Commission under the VII Framework Program [17]. In this project ULLGs have been used to teach Computer Science topics within a university context. After having accessed the system, a learner can search and use ULLGs created by different teachers by going in the 'personal learning goal section' (see Fig. 1).

In the first section, titled *my learning goals*, the learner can view and manage his ULLGs and study connected courses. The second section, titled *Recommended learning goals*, allows the learner to view a set of ULLGs the system suggests for him thanks to the application of the methodology defined in section 4.

The third section, titled *express your formative need*, allows the learner to indicate in natural

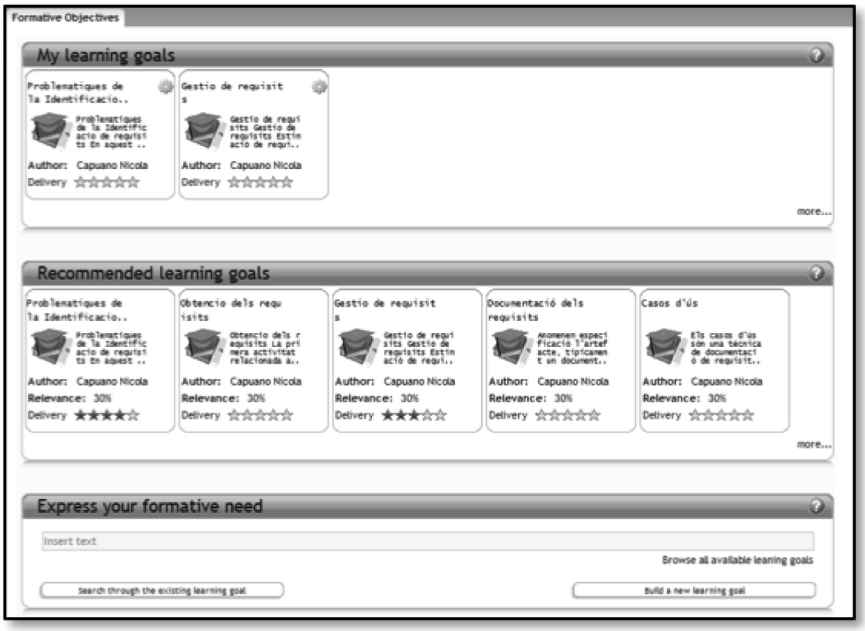


**Fig. 1.** the Personal Learning Goals panel of ALICE.

language the learning goals he/she wants to achieve and to verify which are the most suitable ULLGs to reach the fixed goals. If available ULLGs are not adequate then the learner can choose among all of the concepts belonging to ontologies created by the different teachers of the platform, those concepts that constitute his/her educational goal.

Another application of the same methodology is within the **MatematicaFacile** portal whose purpose is to modify shapes and modes of learning mathematics through a pedagogical driven solution which integrates advanced technologies and didactic models as well as principles, learning conditions and guidelines about metacognition and self-regulated learning.

MatematicaFacile is a solution able to support, in a gradual way, the learners in their transition from the secondary schools to the academic learning path and is oriented at the acquisition of mathematical skills. By applying the methodology described in section 4 MatematicFacile is able to valorise the development of self-regulated abilities. The main functions offered by the system are:

- *directed-learning*—learners can improve their mathematical achievements by accessing personalised and interactive learning experiences basing on entry tests that assess the knowledge background of each single learner;
- *self-regulation*—learners can develop individual skills through the formulation of learning needs in natural language and the generation of personalised sequences of learning resources; when learners do not formulate learning needs, the system proposes some feasible learning goals thanks to the supported recommendation facilities;
- *pedagogical guidance*–learners can benefit from didactic scaffolding sessions managed online by a domain tutor who makes his/her competency available for the students to be oriented and drawing attention to some real or apparent complexities that may have blocking effects on the learner.

The MatematicaFacile initiative is promoted under the patronage of the Regional School Office for the Campania Region, which has fostered its application in all regional secondary schools. Following the first year of experimentation and basing on a thorough analysis of obtained results, the initiative is progressively extending at a national level.

## 6. Conclusions and future works

We described in this paper a solution for self regulated learning defined and developed inside an already existing adaptive e-learning system and currently used in two teaching domains: mathematics and computer science. The self regulated learning component valorises the learner's capability of self-definition, navigation and direction of his/her path having full awareness of educational needs and the opportunity to express them in a natural way.

The possibility to use natural language allows the student to intervene, with no dispersion due to catalogue navigation, by suggesting possible paths to follow and reducing the delay between the moment of understanding of their needs and that in which they can exploit a path suitable for satisfying these needs.

An unsatisfactory response to the process of self setting of activities leads the student to develop a greater locus of control (using an autonomous map navigation of concepts) or to access a community for help seeking contributing, in this way, to self-reinforcement and self-reflection.

*Acknowledgments*—The research reported in this paper is partially supported by the European Commission under the Collaborative Project ALICE [17] 'Adaptive Learning via an Intuitive, interactive, collaborative, Emotional system', 7th Framework Program, Theme ICT-2009.4.2, Grant Agreement n. 257639.

## References

1. R. E. Mayer, Advances in applying the science of learning and instruction to education, *Psychological Science in the Public Interest*, **9**(3), 2009.
2. G. R. Mangione, M. Gaeta, F. Orciuoli and S. Salerno, A Semantic Metacognitive Learning Environment. In: Cognitive and Metacognitive Educational Systems, AAAI Fall Symposium, 2010.
3. R. Azevedo and R. Feyzi, Dysregulated Learning with Advanced Learning Technologies, *Journal of e-Learning and Knowledge Society*, **7**(2), 2011, pp. 9–18.
4. P. Winne, A Perspective on State-of-the-art Research on Self-regulated Learning, *Instructional Science*, **33**(5–6), 2005, pp. 559–565.
5. B. J. Zimmerman, Theories of self-regulated learning and academic achievement: an overview and analysis, in B. J. Zimmerman and D. H. Schunk (eds.), Self-regulated learning and academic achievement, Mahwah, NJ, Lawrence Erlbaum Associates, pp. 1–37.
6. I. Lee, Searching for new meanings of self-regulated learning in e-learning environments. In Cantoni, L., and McLoughlin, C. (eds.), Proceedings of World Conference on Educational Multimedia, Hypermedia and Telecommunications, pp. 3929–3934, 2004.
7. B. J. Zimmerman, Attaining self-regulation: a social cognitive perspective, in M. Boekaerts, P. Pintrich, M. Zeidner (eds.), *Handbook of self-regulation*, New York, Academic Press, 2001, pp. 13–39.
8. G. Adomavicius and A. Tuzhilin, Toward the next generation of recommender systems: a survey of the state-of-the-art and possible extensions. *Knowledge and Data Engineering, IEEE Transactions on Knowledge and Data Engineering*, **17**(6), 2005, pp. 734–749.
9. N. Capuano, M. Gaeta, P. Ritrovato and S. Salerno, A Recommender System for Learning Goals. Lytras et al. (eds.) Information Systems, E-learning and Knowledge Management Research for the Knowledge Society: The era of Social Networks, Web 2.0 and Open Source Paradigms, CCISS, **278**, Springer-Verlag, 2012.
10. L. Shen and R. Shen, Learning content recommendation service based-on simple sequencing specification. In: Liu W et al. (eds), LNCS, pp. 363–370, Springer, 2004.
11. Y. M. Huang, T. C. Huang, K. T. Wang and W. Y. Hwang, A Markov-based Recommendation Model for Exploring the Transfer of Learning on the Web. *Educational Technology & Society*, **12**(2), 2009, pp. 144–162.
12. N. Capuano, M. Gaeta, A. Marengo, S. Miranda, F. Orciuoli and P. Ritrovato, LIA: an Intelligent Advisor for e-Learning. *Interactive Learning Environments*, Taylor & Francis **17**(3), 2009, pp. 221–239.
13. IMS Global Learning Consortium, IMS Meta-data Best Practice Guide for IEEE 1484.12.1-2002 Standard for Learning Object Metadata (2006).
14. N. Capuano, M. Gaeta, F. Orciuoli and P. Ritrovato, On-Demand Construction of Personalized Learning Experiences Using Semantic Web and Web 2.0 Techniques. In: 9th IEEE International Conference on Advanced Learning Technologies, 2009, pp. 484–488.
15. G. Adomavicius and A. Tuzhilin, Toward the next generation of recommender systems: a survey of the state-of-the-art and possible extensions. *Knowledge and Data Engineering, IEEE Transactions on Knowledge and Data Engineering*, **17**(6), 2005, pp. 734–749.
16. ALICE Adaptive Learning via an Intuitive, interactive, Collaborative, Emotional system. EU-project, www.alice-project.org
17. R. Azevedo, Using hypermedia as a metacognitive tool for enhancing student learning? The role of self-regulated learning. *Educational Psychologist*, **40**(4), 2005, pp. 199–209.
18. K. Steffens, Technology enhanced learning environments for self-regulated learning: a framework for research, *Technology, Pedagogy and Education*, **17**(3), 2008, pp. 221–232.
19. N. Capuano, M. Gaeta, S. Salerno and G. Mangione, An Ontology-Based Approach for Context-Aware e-Learning. F. Xhafa, L. Barolli, M. Koppen (eds.) Proceedings of the 3rd International Conference on Intelligent Networking and Collaborative Systems, Fukuoka, Japan, 789-794, IEEE Computer Society (2011).
20. G. Dettori and D. Persico, Detecting self-regulated learning in online communities by means of interaction analysis, *IEEE Transactions on Learning Technologies*, **1**(11–19), 2008.
21. G. Adorni, S. Battigelli, D. Brondo, N. Capuano, M. Coccoli, S. Miranda, F. Orciuoli, L. Stanganelli, A. Sugliano and G. Vivanet, CADDIE and IWT: Two Different Ontology-Based Approaches to Anytime, Anywhere and Anybody Learning, *Journal of e-Learning and Knowledge Society*, **6**(2), 2010, pp. 53–66.
22. M. Gaeta, F. Orciuoli, S. Paolozzi and S. Salerno. Ontology extraction for knowledge reuse: The e-learning perspective, *IEEE Transactions on Systems, Man, and Cybernetics Part A: Systems and Humans*, **41**(4), 2011, pp. 798–809.
23. G. R. Mangione, A. Pierri and S. Salerno, A model for generating personalised learning experiences, *International Journal of Technology Enhanced Learning*, **1**(4), 2009, pp. 314–326.

**Nicola Capuano** is research assistant at the Dept. of Electronic Engineering and Information Engineering of the University of Salerno. He's project manager and research consultant within the Italian Centre of Research in Pure and Applied Mathematics (CRMPA) and research and development consultant for MoMA Software and Research S.p.A. He coordinated and participated as researcher in several projects co-funded by the European Commission and by the Italian Ministry of University and Research. He's currently research and technology manager of the FP7 project ALICE 'Adaptive Learning via Intuitive/interactive Collaborative and Emotional systems'. He's author of about 50 scientific papers published on Journals, Conference Proceedings and Books about Artificial Intelligence, Intelligent Tutoring Systems, Knowledge Representation and Distributed Systems. He's scientific referee and member of editorial boards for International journals and conferences. He's a PMI certified Project Management Professional (PMP).

**Giuseppina Rita Mangione** is PhD in Telematics and Information Society by the University of Florence. In 2003 she was granted the post-graduate Master in 'e-Learning Project Management and Design' by the University of Florence. In 2004

she was granted the post-graduate Master in 'Multimediality for E-learning' by the University of Rome '3'. She's member of the scientific committee and editorial board of the Journal of e-Learning and Knowledge Society (Je-LKS). She is manager in 'Methods and Pedagogies' for CRMPA and collaborate for research projects taking the role of Responsible and Coordinator of the activity related to the Pedagogical and Didactical Models. She is contract professor in the course of Media Education—University of Salerno. She is mainly committed to the study and application of innovative methodologies for the design of active teaching and learning experiences able to satisfy lifelong and inclusive education's needs in different learning contexts (school, university, enterprise). She has participated as a Project Manager and WP leader into numerous research projects. Her main research interest's technology enhanced learning, adaptive instruction and adaptive learning system, Metacognitive and Self regulated learning, Collaborative learning semantic based. She published papers in international journals, conference proceedings and book chapters.

**Anna Pierri** is PhD in Mathematics by the University of Salerno. In 2003 she is graduated cum laude in Mathematics from University of Salerno. Contract Teacher of Computer Science at the University of Salerno from 2010 to 2012. Collaborator of the Department of Electronic Engineering and Information Engineering – DIEII- for the development of some learning research projects and of the CRMPA for research projects financed under the 7th FP of the European Commission. She is Project Manager of the ALICE 'Adaptive Learning via Intuitive/Interactive, Collaborative and Emotional systems' Project. She was Dissemination Manager in the framework of the EU funded project ELEGI, and Responsible and Coordinator of the activity related to the 'Pedagogical and Didactical References'. Author of more than 20 scientific papers. Her research activity is dealt with: Learning Platforms, adaptive learning system, semantic web and ontologies.

**Saverio Salerno** has obtained a Degree in Mathematics from 'Scuola Normale di Pisa' at 21 years of age and is currently a Professor at the 'University of Salerno' in the Department of Electronic Engineering and Informatic Engineering. He was the creator and Director until 2002 of the Consortium 'Centre for Research in Mathematics' and a member of the Technical-Scientific Committee for Industrial Research the Ministry of Education from 2002 to 2009. He is currently the coordinator for the Polo of Excellence on Knowledge and is responsible for numerous European and National research projects. His main research interest moves from mathematical modelling, simulation and optimization of complex systems to distributed service oriented software architecture and Technology Enhanced Learning. He has been author for more than 80 scientific publications including journal papers and several books.