Learning Goals Recommendation for Self Regulated Learning*

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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’s 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.

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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 approach 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 \( d \) connected to available ULLGs. To do that both \( n \) and each \( d \) 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 \( d \) 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’s 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 \( l \in L \) (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 \( CS_l: C \to [0, 10] \). 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 \( LPath = (c_1, \ldots, c_n) \): 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 \( CMF: L \times C \to \{0, 1\} \) that can be defined as follows:

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

(1)

So, given a learner \( l \), \( CMF(l, c) = 1 \) 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:

\[
u(l, c) = \frac{\sum_{l' \in L'} CMF(l', c) \cdot \text{sim}(l, l')}{\sum_{l' \in L'} \text{sim}(l, l')}
\]

(2)

where \( L' \) is the set of the \( n \) learners most similar to \( l \) while \( \text{sim}(l, l') \) is the similarity degree between \( l \) and \( l' \) obtained through 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 \( \text{sim}(l, l') \) 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 \( \text{ULLG}_i = (D_i, TC_1, \ldots, TC_{\alpha}) \) where \( D_i \) is a text describing the learning objective in natural language, while \( TC_1, \ldots, TC_{\alpha} \) 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 \( \text{ULLG}_i \), the corresponding learning path \( L_{Path_i} \) starting from the connected list of target concepts.

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

\[
au(l, \text{ULLG}) = \frac{\sum_{c \in L_{Path_i}} u(l, c)}{|L_{Path_i}|}
\]

(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** \( mu(l, \text{ULLG}_i) \) of \( \text{ULLG}_i \) for a learner \( l \) that can be obtained with the following formula:

\[
mu(l, \text{ULLG}_i) = \frac{\sum_{c \in L_{Path_i}} u(l, c)(1 - CMF(l, c))}{\sum_{c \in L_{Path_i}} (1 - CMF(l, c))}
\]

(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:

\[
u(l, \text{ULLG}_i) = \alpha au(l, \text{ULLG}_i) + (1 - \alpha)mu(l, \text{ULLG}_i)
\]

(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
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 MatematicaFacile 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.

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