A Mobile Recommender Methodology of Learning Paths with Automatic Planning

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Abstract— Despite the growing coverage of mobiles devices and its versatility, at present, is not sufficiently exploited this medium as an alternative for education. This is mainly due to the absence of a platform that allows teachers easy and intuitive creation of educational content, specifically designed to be consumed by students through mobile devices without requiring teacher´s technical knowledge. This proposal sets out how to use planning techniques so that a teacher can develop and recommend automatically (based on student´s learning profile), educational content as learning paths, to be viewed by students on their mobile devices.

Keyword - mobile devices, recommender, planning techniques, learning path and learning profile.

I. INTRODUCTION

The general training model, ranks as a top priority: "To enhance the quality of education for students to improve their educational achievements level; as well as expanding the educational opportunities to reduce inequalities; fostering research and the development of social innovations" [14, 28]. These events suggest the search for better learning methods in the students, and the improvement of the skills of teachers. The growing and fast development of technologies associated to the mobile devices has leaded to the creation of new forms of educational training (m-learning [1]), which make the learning possible from various global locations, and through different means. The incorporation of new technologies to the teaching field provides multiple advantages to education by facilitating the means and the ways of accessing the learning. But, in order for the process of learning to be fully effective, it is required to be developed in an environment that offers the necessary flexibility in this training modality, allowing a successful learning [21]. Particularly, both characteristics can be achieved through the construction of mobile applications that to recommend the sequence of the educational contents (or learning path), based on what is commonly known as learning profile [16], which deals with the fact of learning something using our own preferences or certain ways to learn [3, 7]. However, considering the amount of students who are often registered in a class, it becomes a complicated topic for the teacher when he is the one who is in charge of constructing the sequence of educational contents manually. Being aware of this limitation, the present proposal shows a way to automate the process of building learning paths customized to the students, by incorporating a planning algorithm in artificial intelligence, allowing to ease the work of teachers without requiring complex technical knowledge; and that the resulting sequence of educational contents can not only be generated by the teacher from any mobile device, but can also be visualized by the students in the same means.

II. REFERENCIAL FRAMEWORK

Recommender Systems were developed to overcome the problem of information overload by aiding users in the search for relevant information and helping them identify which items (e.g. media, product, or service) are worth viewing in detail. This task is also known as information filtering. Recommender systems do the information filtering by predicting whether a user will like or dislike an item. This prediction is based on the user's explicit and implicit ratings/preferences, other users' ratings, and user and item attributes.

Recommender systems generally fall into three categories: i) Collaborative Filtering Systems which compute recommendations by examining users' preferences on items based on similarities of other users of the same group [2]. ii) Content-Based Systems which compute recommendations from the semantic content of items [19] and Knowledge-Based Systems where recommendations rely on the knowledge about the domain, the users and pre-established heuristics [5]. The Table I summarizes the key aspects of each category.

TABLE I. Comparison of recommender systems, source: [15]

Recommender System	Advantage	Disadvantages	Requirements	Technical Aspects
Collaborative Filtering	No domain knowledge is required	Cold-start problem. Sparsity problem. Insensitive to preference change	Need to a set of users. Need to large of historical data set	Easy to create and use. Makes recommend actions based on the past interests of that user.
Content-Based Filtering	No domain knowledge is required	Overspecialization problem	Need to knowledge about user's presences.	Considers the preferences of a single learner
Knowledge-Based	Sensitive to preference change. Does not need to be initialized with a database of user preferences	Knowledge acquisition	Well understanding from the product domain	Need to knowledge engineering

Mobile devices, such as phones and PDAs, are evolving in to a major source of information [4]. In the past, many recommender systems have been developed for the desktop computer. However, these systems cannot be applied directly as an aid for mobile users since mobile recommender systems need to overcome many of the challenges generally present in the domain of mobile devices. The Table II, shows some related existing systems, they are studied as reference and inspiration. This was done to acquire knowledge on the strengths and drawbacks of other solutions and to establish a ground to base design decisions of the Mobile Application Recommender on.

TABLE II. Literature review

Application	Type	Use to LO in Mobiles
Appazaar [4]	A context-aware system for recommending mobile applications	The novelty of mobile applications as items in context-aware recommender systems is highlighted due to the importance of context within the mobile domain and the possibilities to continuously capture application usage along with contextual information.
AppAware [10]	Recommendations are solely based on the user's location	aims at aiding users in making fortunate discoveries of mobile applications by making use of context (location) to produce recommendations
Personalized Multimedia contents [18]	For the recommendation based on user's personal characteristic and preference, adopts and applies the DISC model which is verified in psychology field for classifying user's behavior pattern	This System, given users the ability to use multimedia content such as music and movie on personal mobile devices, anytime and anywhere. Through the implementation and evaluation of a prototype system, shows that the proposed method has an acceptable performance for multimedia content recommendation.
Review of Personalized Recommendation for Learners in E-Learning Systems [22]	The knowledge-based recommendation system is proposed	In this review discussions and elaborations are given on how the rapid increase of learning materials and learning resources, either offline or online is making it quite difficult for learners to find suitable materials based on their needs. Recommender Systems help learners find the appropriate learning materials in which they need to learn.
Technology in Physical		This work presents a discussion, about how to provide students with personalized Physical Education (PE) course to conform to

Education (PE) [13]		increasing personalized demands of contemporary college students
Recommendation System based on a Multi-Expert Knowledge Acquisition Approach [11]	The study developed the expert system for ESL English reading recommendation by the opinions and domain knowledge from the English teaching experts.	This work presents a discussion importance of assigning proper articles to individual students for training their reading ability in English courses. This study in proposes an innovative approach for developing reading material recommendation systems by eliciting domain knowledge from multiple experts.
Review of Recommender Systems for Learners in Mobile Social/Collaborative Learning [24]	This work uses the feature vector of learning resources and a learner's rating value on each resource, firstly defines the learning interest feature vector to model the learner's behavior. Experimental results show that their proposed algorithm exhibits good community organizing efficiency and scalability	In this work a presentation is made on how finding similar e-learners in a distributed and open e- learning environment and helping them to learn collaboratively is becoming one of the urgent challenges of personalized e-learning services. Literature shows that current e-learner community building approaches are generated from qualitative studies of small-sized learner-centered classrooms which may need the teacher's participation.
AHArquitectures [25]	It´s is an extension of content based recommender system	This system made of three levels architecture: i) a domain model describing the knowledge of teaching, ii) a user model defining learner’s profile and learning’s context, iii) an adaptation model containing rules and metaheuristics, which aims at combining learning modules. Our system takes into account the spatio-temporal context of the learners, the evolution of learner’

It is important to remember what the purpose of producing recommendations when building a recommender system. What it all comes down to is helping human beings make decisions and discover new items with less effort than by manually searching for items. In this case, the idea is recommender-learning paths, the next section present the proposed recommender.

III. SINTAXYS RECOMMENDER

The recommender system of learning paths is oriented to help teachers with the generation of educational applications recommended to the learning profile of the student; however, it is expected that the recommender of paths acts in a transparent way to the user without requiring previous knowledge from both teachers and students. So, the system will include a planner based on states which will allow the automation of the process of construction of learning paths that for this case constitutes a (plan) sequence of learning activities associated to knowledge domain, and recommended for a student who must follow to fulfill that student’s objectives. The resulting educational content from the process must be visualized through a mobile device [6], aiming to motivate the action of learning by the student. In this case, the recommender analyses features of the educational content and match them to the features of the user (e.g. preferences based on learning theory model [3, 7]), the Fig. 1, presents the M-learning recommender system architecture.

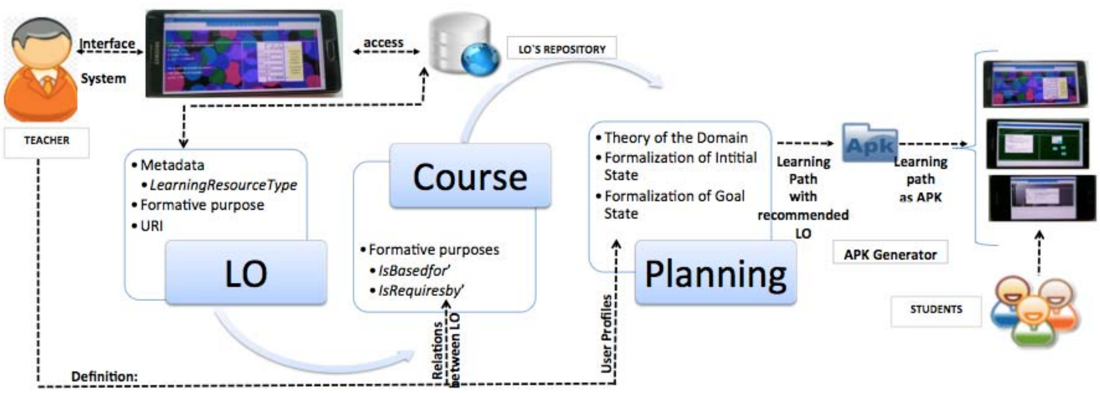

Fig. 1. M-learning recommender system architecture

This architecture shows that teacher user, can built you educational application, from device mobile, for this stage, the recommender model represents a tool program that provides an environment which facilitates the realization and treatment of the information: writing, organizing, transmitting and presenting. Regarding the educational applications to be modeled in this work, they belong to the type of the presentation. he proposal of [16], following the principle of an application developed in power point, where each page looks like a slide, and one or more slides, can be converted to a learning object (LO). This way, the repository of the LO (LO´s Repository) i all the LOs are stored under taxonomy of concepts; the concepts represent the formative purposes (topics and bub-topics) of a course. Since for storing a LO, it is necessary to indicate the field that defines the formative purpose among the metadata. Subsequently, the teacher must fill out the metadata field *LearningResourceType*, which has been extended, from the LOM standard [12], aiming to identify the percentage of contents in each resource – remember that in device mobile the LO may be composed by a different proportions multimedia content image, video, text-. Subsequently, the teacher (if wanted), may order the sequence of concepts (formative purposes), assimilating the prerequisites of knowledge of a course, from experience. For instance, before reading about “Methods” in a programming course, the student must have certain knowledge about “variables”. This restriction establishes an order of dependence on the formative purposes. So, in order to model these restrictions, four types of causal relations are proposed: *’IsBasedfor’* and *’IsRequiresby’* (and their inverses *IsBasedOn* and Requires) [17]. These relations are interpreted as hard requirements; this is to say, necessary elements where they have to be completed before starting another LO. Example, suppose that B, A and C are LOs aiming at different formative purpose, besides, “B *IsRequireby* A” and “C *IsRequiereby* B”. In this case, B and C must be covered before doing A. Supposing now that “B *IsBasedfor* A” and “C *IsBasedfor* A”, only one of the LOs, “B or C”, must be completed before starting A. This level also has a search engine which looks for the LOs whose formative purpose is associated with the concepts selected by the teacher, as the ones he wants to teach. Then is necessary that the teacher sets the learning profile for which he wants to build the learning path. So the recommender system automatically generates two files are built with this process, one specifying the domain and the other specifying the planning problem. The planning mechanism which notifies the repository the concepts that the LO wants to look for. These concepts represent the formative purpose the teacher wants to teach. This process also allows considering some restrictions of convenience such as the pedagogical one, defining the objects that can be better adapted to “X” or “Y” learning profiles. The final process provides a plan in PDDL, which describes the sequence of the LO, in the proper order to be viewed, known as learning path. However, for this stage, a path for each learning profile is generated, making sure that each path teaches the same concepts the teacher wants to teach (formative purpose). Then is necessary allows the conversion of each learning object of the plan (described in PDDL) to the corresponding sequence of the previously created pages in the first level by the teacher, but this time they are described in XML. This content is deals with the construction of APK, taking up the XML and interpreting them by their content to generate an APK file containing texts, images, audio and videos. Finally, the content can be visualized by the students on their mobile devices. As it was created by the teacher, but keeping the rules and standards required for this devices.

A. Learning Path Syntax

A learning path is made up of a set of learning objects (LO). Basically, the LOs are units of study which can be consumed in a simple section representing reusable granules that can be created no matter the delivery means to be used [30]. Ideally, the LOs can be reused and connected together in order to build applications aiming at serving certain purpose or goal. Consequently, the LOs need to be free of the environment, which means that they need to carry useful information describing the type and context where they can be used [23]. Under this perspective, the standardization becomes a key topic to continue operating and even to continue growing the current applications. Among these initiatives, it is important to highlight: (i) LOM (Learning Object Model [12), this standard specifies the syntax of a minimum set of metadata needed to, completely and properly, identify, manage, locate and evaluate a LO.

Each LO is represented by: i) a URI where the LO is available as a digital resource; ii) metadata associated to a standard by which it is identified and described as the popular LOM (Learning Object Model) and finally, iii) a formative purpose represented in the educative domain by a theme or subtheme. Although, in the process of building paths, the three elements are relevant, the LOM metadata become vital when constructing recommended paths because they contain the *LearningResourceType* attribute, which define the type of resource - image, text, video, exercise, questionnaire, etc, - that represent the LO. With the identification of the resource and the theories of learning profiles [3], it is possible to affirm that a resource can be appropriate to the process of learning of the students or not, depending on their profile. Fig. 1 shows the association. For example, a questionnaire may be more convenient for a type of active learning while a text may be more appropriate for a student whose profile is based on theory. However, the LO in the field of mobile devices can be represented by more than one type of resource at the same time, for this reason, the *LearningResourceType* field has been extended, from the LOM standard, aiming to identify the percentage of contents in each resource, without exceeding the 100 percent (as shown in Fig. 2).

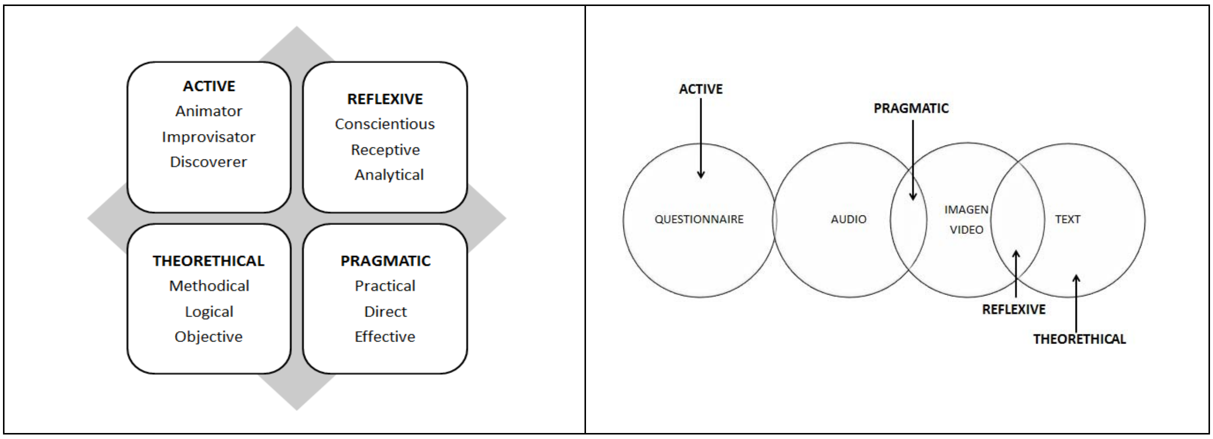

Fig. 1. Learning profiles

The recommender system is based on planning in artificial intelligence and sequencing are focused on the automatic generation of a plan, involving resource allocation and temporary restrictions in order to solve a problem within a particular domain. In general, a planning problem has the following components: a description of the actions in a formal language which constitutes what have been called the Domain Theory [8], a description of the initial state of the world and the specification of the desired state.

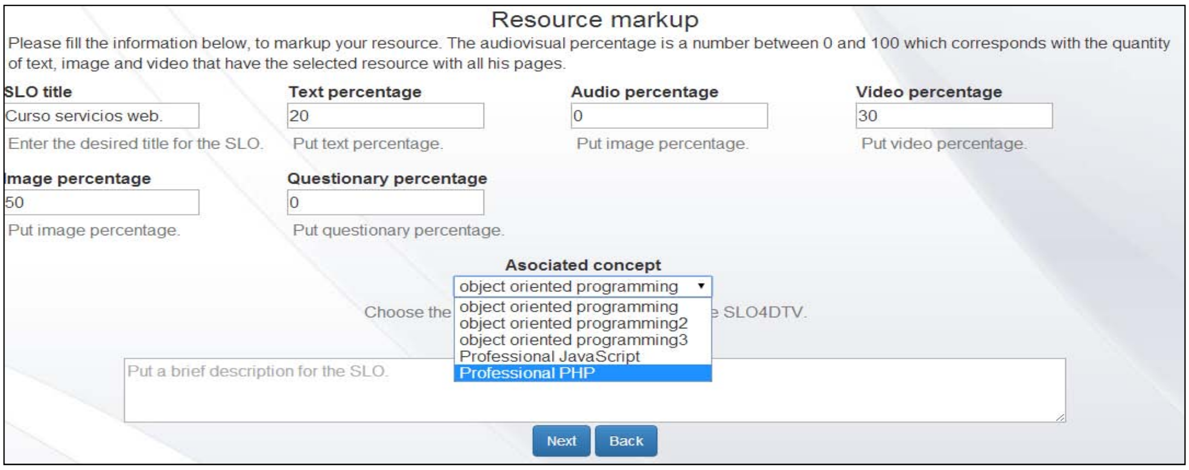

Fig. 2. *LearningResourceType* Attribute

The Domain Theory [15] must allow judgments that represent the relevant aspects such as the conditions of the operations and their effects throughout the world. Generally, the theories of domain follow some type of model of transition of states, that is, they introduce a notion of state (or situation), which is a description of the world in a certain point of time. Such a state connects the actions that generate the transitions among the states. Formally, a planning problem is defined by means of the tuple: (S,So,G,A,R), where S is the group of all the possible states of the world, $So \varepsilon S$ denotes the initial state of the world, $G \varepsilon S$ denotes the target state of the world that the planning system will try to get, *A* is the group of actions that the planner could carry out in order to change from one state to another in the world, and the movement relationship $R \varepsilon S x A x S$ defines the precondition and its effects to implement every action. Simultaneously, the problem of learning paths composition can be extended as a sequential interconnection, subordinating but not anticipating learning objects, which satisfies a specific objective of knowledge of a user [9, 26, 27]. The formal definition of planning can be compared to the problem of composition of learning paths, in which, *So* and *G* are the initial state and the objective state specified on the learning requirements of a user, *A* is a group of available learning objects, and *R* denotes the switching function of the state of knowledge of the user; if the requirements of each learning object are fulfilled. As a result of the previous analogy, this paper has considered to apply, for the process of composition of learning paths, a planning algorithm that incorporating some metrics which allow the evaluation of the accuracy of a learning object with regard to several, based on the learning theories.

B. *Syntax of the planner*

Artificial Intelligence has been focused, for a long time, on reasoning of actions to face real problems through one of its most important subdisciplines: Planning [20]. Its objective is the construction of computing programs which allow to get plans to reach a goal in an automatic way. These programs are known as planners. The first approximations, according to [8], formulate a planning problem based on the following components: i) a description of all the possible actions (*A*) that can be done, indicating the way they affect the objects of the world, their characteristics, and their relations. The last description is also known as the theory of domain which is constructed, for this purpose, using a repository of LO, in which each LO is focused on covering only one formative purpose described in a course, but where every purpose can be provided by several LOs. The relations of dependence, as well as the percentages of resources, are also part of this domain; being represented by the preconditions and effects: ii) A description of the world around us, the objects that make part of it, its characteristics, and the relations among them. This description is also known as Initial State (So). In the learning context, the initial state is taken from the learning objectives that the student knows about the course; ii) a description of the objective to be reached, also known as Goal (*G*), a description of the relations and the characteristics to be changed in the objects contained in the initial state.

1) *Theory of the domain of planning*

The objective of this formalization is to provide a theory of specification of the domain, this is to say, a formal description of the semantics of the available operations for the model of composition of learning paths. A theory of domain must basically allow sentences that represent relevant aspects such as the conditions of the operations and their effects in the world. Generally, the theories of domain follow a type of model of transition of states, that is to say, they introduce a notion of state (or situation), which is an instantaneous description of the world in a certain point in time. Such state relates actions that generate transitions among the states. Most approaches, including the proposed one, define a state S, extensionally as a set of atomic instances (facts). Each atomic instance can vary, or not, its value over time, for the first case, they are called fluents and those that do not change (second case) are called invariants.

Based on these components, the expected result of a planner is a performance, this is, an ordered sequence of actions that when it is carried out on the world described in the initial state *So*, of a student knowledge, allows to achieve a goal which will satisfy the description given in the Goal State *G*, that is, it allows to achieve the learning objectives of all the students in the course. This sequence of actions is known as plan, which, in this case, represents a learning path.

The syntax used in each element belonging to a domain and a planning problem will be explained in detail.

Definition 1. State. A state is an abstract representation of the world at any given time. A state can be modeled as assigning values to the literals and the numeric variables. The following definition shows this concept formally. A state, for the domain of learning, is defined as assigning values, not only to the set of literals (*L*), but also to the numeric variables (*F*). Using a trivaluated logic which defines that, a literal can be true (*V*), false (*F*) or unknown (*D*) in a state. The values of the numeric variables are rational numbers (*Q*).

$$\begin{gathered} S = \langle SL, SF \rangle \\ SL = \{ (l_i, v_i) \} : li \in L, v_i \in \{ V, F, D \} \\ SF = \{ (f_i, w_j) \} : f_i \in F, w_j \in Q \end{gathered} \tag{1}$$

Definition 2. A numeric problem of planning is defined through the tuple:

$$\langle F, L, A, I, G, m \rangle \tag{2}$$

Where: *F* represents the numeric functions, *L* represents a set of literals (or facts), *A* corresponds to a set of actions, *I* is the initial state, *G* represents a set of goals (also known as final state) and *m* represents the criterion of optimization, this means the metric of the problem.

Definition 3. Action. An action is represented by the tuple:

$$\boldsymbol{a} = \langle L_{prec}, F_{prec}, L_{eff}, F_{eff}, ExecutionFailure \rangle \quad (3)$$

Where: L_{prec} is a set of propositional logics which represents the propositional preconditions of an action. L_{prec+} and L_{prec-} are called the subset of literals and negative literals of L_{prec} respectively. F_{prec} is a set of numeric restrictions which represents the numeric preconditions of the action. L_{eff} is a set of propositional logics and the propositional effects of the action. From now on, L_{eff+} and L_{eff-} will be denoted as the subset of literals of L_{eff} respectively. F_{eff} is the set of numeric effects of the action. *ExecutionFailed*, is a logic value which is only shown with a value of truth if the action fails. Such value corresponds to true.

To reference each component, the function notation will be used; indicating, in parenthesis, the action it belongs to. For example, to reference the propositional preconditions of an action a, the notation $L_{prec}(\boldsymbol{a})$ will be used. There are two concepts concerning the actions to be formalized. The first one is the applicability (or executability) of an action in a certain state. The second one refers to the changes that the execution of an action produces in the state on which it is applied. Both concepts are defined below.

Definition 4. Applicability (or executability) of an action. An action a is applicable in a state *S*, if its preconditions are satisfied:

$$exec\ (\boldsymbol{a}, S) = V \leftrightarrow satisfy\ (pi, S) = V,\ \forall pi \in L_{prec}\ (\boldsymbol{a}) \wedge\ r_{value}\ (r, S) = V,\ \forall r \in F_{prec}(\boldsymbol{a}) \quad (4)$$

On the other hand, an action a is not applicable in a state S when one of their preconditions is not satisfied:

$$exec\ (\boldsymbol{a}, S) = F \leftrightarrow\ \exists\ pi\ \in L_{prec}\ (a)\ /\ satisfy\ (pi, S) = F\ \ \vee$$
$$\exists\ r\ \in F_{prec}\ (\boldsymbol{a})\ /\ r_{value}\ (r, S) = F \quad (5)$$

Definition 5. Result of Applying an Action $\boldsymbol{a}$, $\boldsymbol{a}$ is a State *S*. The result of applying an action $\boldsymbol{a}$ on a state:

$S = \langle SL, SF \rangle$ is a new state $S' \in S$. In this way, the new state S' corresponds to: If a is applicable in *S* and there are not external factors δ which may block the correct execution of $\boldsymbol{a}$, so $S' = S$, except that the values of the propositional effects of a are replaced by true *V* if there are positive effects, or by false *F*, if there are negative effects. The numeric variables also change their value according to the numeric effects of $\boldsymbol{a}$:

$$esult\ (a\ ,S,\ \delta) = \langle SL', SF' \rangle$$

$$SL' = \quad (l_i, v_i) \in SL\ /\ l_i \quad L_{eff}\ (\boldsymbol{a}) \quad \cup \quad (l_j, F)\ /\ l_j \in\ L_{eff}\text{-}\ (\boldsymbol{a}) \quad \cup \quad (l_k, V)\ /\ l_K \in Leff+\ (\boldsymbol{a}) \quad (6)$$

$$SF' = SF \quad (f_l, W_l) \quad \cup \quad (f_l, n\ result\ (n_l, S))\ \ , n_l, = \langle f_l, ass_l, exp_l \rangle \in F_{eff}\ (\boldsymbol{a}), Si\ exec\ (_a, S) = V \wedge\ \delta = 0.$$

Fig. 3, shows an example of the syntax of the domain built to represent the knowledge of a course of Programming Oriented to Objects (POO). In this case, each formative purpose is an action (modeled as indicated in Definition 2) and the requirements represented by the four types of causal dependences '*IsBasedfor'* and *'IsRequiresby'* (and their inverses *IsBasedOn* and Requires), are translated as preconditions (once they have been established by the teacher); also, as it is shown in Fig. 3, it is required that the LO teach a unique formative purpose (and not a different one), the reason for the action to improve in its preconditions, when representing that the student does not know about it.

The effects correspond to the facts that must be fulfilled if the action is applicable (See Definition 4), which changes the state of the world (Definition 5). This implies that: i) the student already knows the formative purpose that was taught with that LO, and ii) the numeric variables increase their value;

in this case, the level of difficulty is cited, and even if it is increased, it is done in inverse order over the metrics, since the aim in personalizing is that the difficulty always be less or equal to the one which the students can withstand; the content reward of the resource in the LO, along with the profile of the student; this way, if a learning path for an active profile student is desired (see Fig. 4), the planner will build his file of domain, including all the LOs fulfilling the sequence of the formative purpose established by the teacher, but incorporating only the ones that, whose description of *LearningResourceType* field, have a numeric value different to zero in "questionnaire". Once registered like this, the function will always be maximized, considering only the students most convenient LOs in the solution of the plan. However, the description of the way each function will act is formally described in the stage of formation of the Objective State.

```
(define (domain POO)
(:requirements :strips :typing :fluents :equality)
(:types application )
(:constants oa1 oa2 oa3 oa4 oa5 oa6 oa7 oa8 oa9 oa10 oa11 oa12 oa13
oa14 oa15 oa16 oa17 oa18 oa19 oa20 oa21 oa22 oa23 oa24 oa25 oa26
oa27 oa28 oa29 oa30 oa31 oa32 oa33 oa34 oa35 oa36 oa37 oa38 oa39
oa40 oa41 oa42 oa43 oa44 oa45 oa46 oa47 oa48 oa49 oa50 oa51 oa52
oa53 oa54 oa55 oa56 oa57 oa58 oa59 oa60 oa61 oa62 oa63 oa64 oa65
oa66 oa67 oa68 oa69 oa70 oa71 oa72 oa73 oa74 oa75 oa76 oa77 oa78
oa79 oa80 oa81 oa82 oa83 oa84 oa85 - application )(:functions
(contentReward ?a - application) (difficulty ?a - application)
(totalReward) (totalDifficulty))
(:predicates
(knowcpt9)
(teachcpt9 ?a - application)
(knowcpt8)
(teachcpt8 ?a - application)
(knowcpt7)
(teachcpt7 ?a - application)
(knowcpt10)
(teachcpt10 ?a - application)
(knowcpt1)
(teachcpt1 ?a - application)
(knowcpt2)
(teachcpt2 ?a - application)
(knowcpt5)
(teachcpt5 ?a - application)
(knowcpt6)
(teachcpt6 ?a - application)
(knowcpt3)
(teachcpt3 ?a - application)
(knowcpt4)
(teachcpt4 ?a - application)
)
(:action SeeConcept9
:parameters (?a - application)
:precondition (and (teachcpt9 ?a) (not(knowcpt9)) )
:effect (and (knowcpt9) (increase (totalDifficulty) (difficulty ?
a)) (increase (totalReward) (contentReward ?a))))

(:action SeeConcept8
:parameters (?a - application)
:precondition (and (teachcpt8 ?a) (not(knowcpt8)) )
:effect (and (knowcpt8) (increase (totalDifficulty) (difficulty ?
a)) (increase (totalReward) (contentReward ?a))))
```

Fig. 3. Syntax of the theory of domain in learning, “active profile”

2) Formalization of the Initial State

The planning module must consider the initial state of the world, since it must offer a plan that, when it is executed based on the initial world; it will lead to a specified goal. The initial world is just a state of the world (or situation), defined by the theory of domain. The core element, that constitutes a state in almost all the approaches, are the facts known as true in the initial state of the world. In the approaches of classic planning IA, it is supposed that the extensional definition of the initial state of the world provides a complete description. This allows to apply the close world assumption, which means that any fact that is not collected explicitly from the database of the state is considered false. Fig. 4, shows an example of the description of the initial state, as can be seen, the domain which is aimed is the contents of the POO course.

The numeric values of the functions will start from zero, and the next description corresponds to the state of knowledge of the student, which will indicate that the student does not have any type of knowledge on the ten educative concepts of the course. Immediately, the assigning values are registered to the *LearningResourceType* and Difficulty fields. In this case, it is considered that, as aimed in the domain, only those LOs whose description of *LearningResourceType* field, have a non-zero value in “image”, such value is assigned to the respective LO; the numeric value of the level of difficulty, is assigned according the value of the field.

```
(define (problem POO)
(:domain POO)
(:init

(= (totalReward) 0)
(= (totalDifficulty) 0)
(not(knowcpt9))
(not(knowcpt8))
(not(knowcpt7))
(not(knowcpt10))
(not(knowcpt1))
(not(knowcpt2))
(not(knowcpt5))
(not(knowcpt6))
(not(knowcpt3))
(not(knowcpt4))

(= (contentReward oa39) 0.6)
(= (difficulty oa39) 6.0)
(teachcpt4 oa39)

(= (contentReward oa35) 0.7)
(= (difficulty oa35) 9.0)
(teachcpt4 oa35)

(= (contentReward oa36) 0.7)
(= (difficulty oa36) 8.0)
(teachcpt4 oa36)

(= (contentReward oa37) 0.7)
(= (difficulty oa37) 7.0)
(teachcpt4 oa37)
```

Fig. 4. Syntax of the initial state of learning,"active profile"

1) Formalization of the Goal State

In the most classical approaches of planning, the goals are expressed as the properties that are needed to be kept in order to get the desired state of the world, generally in the form of conjunctions of literals (positive and negative facts). For this work, the goals of the problem are described as a set of propositional logics that:

$$G = \{g_i \,/\, g_i \in PL\} \tag{7}$$

The goal of the planner is to reach a state of the world in which all the objectives are satisfied. However, in dynamic and partly observable environments, it is not possible to be certain that all the goals have been achieved, this is to say, it is not possible to verify the fulfillment of all the goals, which requires that for the purpose of this work, be the beliefs about the world, the own planning module, to do so.

Consequently, the beliefs of the planning module will indicate that all the goals have been achieved, when a state in which all the goals are satisfied is reached, that is a goal state (*goalstate*).

Definition 6. Goal State. A state *S* is a goal state, if all the objectives of the problem *G* are satisfied in *S*.

$$goalstate\ (S, G) = \ V \leftrightarrow satisfy\ (g_i, S) = V \ \ \forall g_i \in G \tag{8}$$

The planner must identify a solution (a plan), that, when it is executed in the initial state of the world, it will result in a state of the world that satisfies the goal. For example, the goal (*knowcpt9*) described in Fig. 5, may specify a condition that requires that the formative purpose associated to topic 9, must be known after the execution of the plan.

```
(:goal
(and
(knowcpt9) (knowcpt8) (knowcpt7) (knowcpt10) (knowcpt1)
(knowcpt2) (knowcpt5) (knowcpt6) (knowcpt3) (knowcpt4) )
)
(:metric minimize (+ (* (totalReward) 81) (* (/
(totalDifficulty) 10) 19)))
)
```

Fig. 5. Syntax of the goal state in learning, "active profile"

2) Formalization of the plans

Definition 7. Plan. A plan is a sequence of actions $P = \{\boldsymbol{a}_0, \boldsymbol{a}_1,\ldots,\boldsymbol{a}_n\}$ that, applied on the initial state of the problem *I* is oriented to the achievement of the goals *G*. For convenience, the function result will also be he taken up again in order to calculate the resulting state from executing a sequence of actions *P*:

$$result(P, S, \{\delta_0, \delta_1, \ldots, \delta_n\}) = S' \leftrightarrow result(\boldsymbol{a}_0, I, \delta_0) = S_1, \tag{9}$$

$$result(\boldsymbol{a}_1, S_1, \delta_1) = S_2, \ldots result(an, S_n, \delta_n) = S'$$

Definition 8. Valid Plan. A valid plan *P (valid_plan (P, I, G, {δi}))*, is the one that is successful when it is executed on an initial state *I*, achieving a goal state *G*:

$$valid\_plan(P, I, G, \{\delta_i\}) = V \leftrightarrow result(P, I, \{\delta_i\}) = S' \wedge goalstate(S', G) = V \qquad (10)$$

Fig. 6, shows the learning path for an active style student¸ the plan defines the sequential order in which each LO must be covered, aiming to teach all the concepts that the teacher consider as the formative purpose of the course.

```
: --- Plan 0 ---
0: SeeConcept9 oa82
1: SeeConcept8 oa78
2: SeeConcept2 oa31
3: SeeConcept7 oa75
4: SeeConcept1 oa28
5: SeeConcept5 oa71
6: SeeConcept6 oa72
7: SeeConcept3 oa39
8: SeeConcept4 oa65
9: SeeConcept10 oa83
Best action: SeeConcept9 oa82
```

Fig. 6. Syntax of the plan in learning, “active profile”

IV. EVALUATION

In order to value the functionality of the system, several important tests were carried out. The first one is oriented to value the degree of adaptability of the learning path. For this case, the POO course was taken, and a teacher designed the sequence of formative purposes that he wanted to teach, the result can be seen in Fig. 7. Subsequently, the button “Path Building” was activated, and the paths for each learning profile were built.

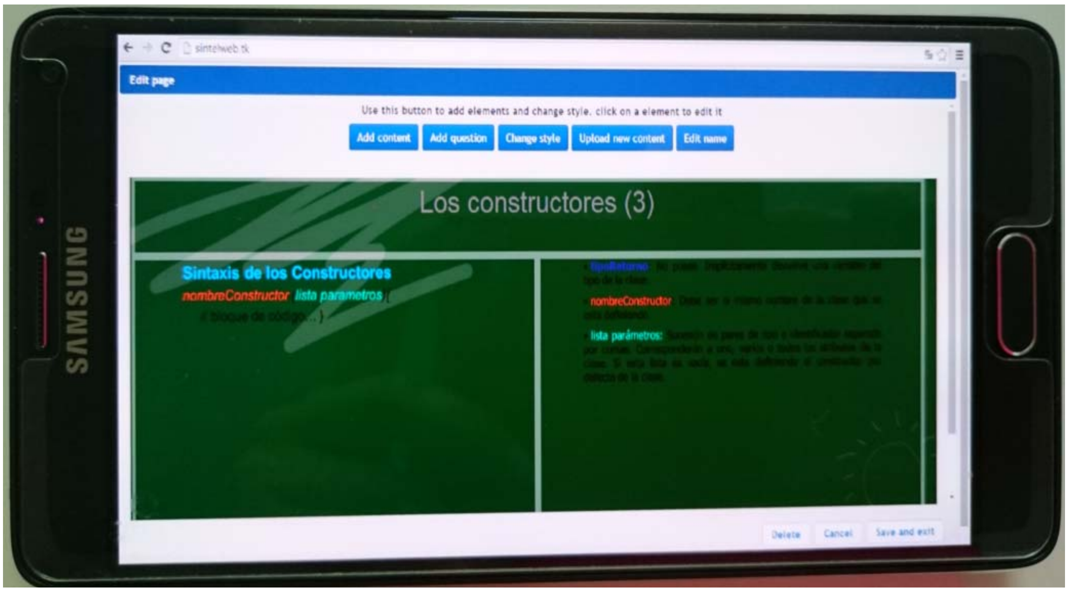

Fig. 7. Interface of formative purposes “constructores”

As can be seen in the Table III, the number of formative purposes was constant (9), however, the amount of LOs that intervene in the process vary due to the varied amount of the resource associated to the profile that was being built. For instance, learning objects were found for the active profile. These Los taught the topics that the teacher selected having greater than zero in the questionnaire in the *LearningResourceType* field.

Regarding the length of the plan, it remains constant due to the same number of topics to be taught (formative purposes), however, it is possible to observe that the LOs forming the learning path are different for every single case. Another aspect included into this test consisted of registering the time consumed in the planning and translation processes in order to generate the APK file.

TABLE III. Plans for different profiles

Case N°	N° Formative Purposes	Profiles	No OA	Name of the actions	Lenght of the plan	Translation Time (milliseconds)	Planning Time (milliseconds)
1	10	Active	85	0: SeeConcept9 oa82 1: SeeConcept8 oa78 2: SeeConcept2 oa31 3: SeeConcept7 oa75 4: SeeConcept1 oa28 5: SeeConcept5 oa71 6: SeeConcept6 oa72 7: SeeConcept3 oa39 8: SeeConcept4 oa65 9: SeeConcept10 oa83	10	32	1690
2	10	Reflexive	73	0: SeeConcept8 oa65 1: SeeConcept7 oa64 2: SeeConcept2 oa26 3: SeeConcept5 oa61 4: SeeConcept6 oa63 5: SeeConcept9 oa68 6: SeeConcept1 oa1 7: SeeConcept3 oa39 8: SeeConcept4 oa53 9: SeeConcept10 oa72	10	38	1659
3	10	Pragmatic	66	0: SeeConcept8 oa59 1: SeeConcept7 oa58 2: SeeConcept2 oa24 3: SeeConcept5 oa55 4: SeeConcept6 oa57 5: SeeConcept9	10	39	1644

				oa61 6: SeeConcept10 oa65 7: SeeConcept1 oa1 8: SeeConcept3 oa36 9: SeeConcept4 oa45			
4	10	Theoretical	71	0: SeeConcept9 oa69 1: SeeConcept7 oa64 2: SeeConcept8 oa67 3: SeeConcept10 oa71 4: SeeConcept1 oa24 5: SeeConcept2 oa28 6: SeeConcept5 oa59 7: SeeConcept6 oa62 8: SeeConcept3 oa39 9: SeeConcept4 oa58	10	43	1635

The time shows the effectiveness of the system. As a result, it is possible to affirm that the cost of planning ends up being very high compared to the one of the construction of the APK (see Fig. 7); this is because the planning mechanism is connected to the search engine to check the ROA in order to identify the LOs to participate in the construction of the learning path for this profile. Each domain, initial state and goal state are built dynamically. Although the last two states are the same in every case, the cost of search and the flow of messages increase the time consumed in this stage.

The second evaluation also consisted of measuring the times consumed by the system, but this time, varying the number of concepts (formative purposes). The results were registered in Table IV.

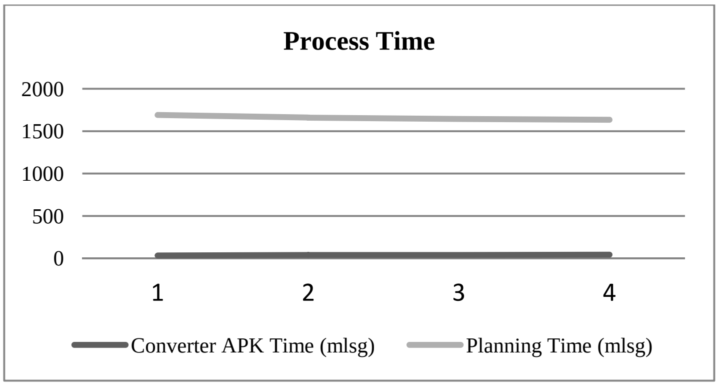

Fig. 7. Processing Times

TABLE IV. Plans with different numbers of formative purposes.

Case No.	No. Formative Purposes	No LO (by goal)	Plan Length	Translation Time (milliseconds)	Planning Time (milliseconds)	Total Time(milliseconds)
1	10	10	10	19	1393	1412
2	25	10	20	32	1524	1556
3	50	10	50	45	1732	1777

As expected, the time consumed by each process was proportionally to the number of purposes (see Fig. 8); even with the same high difference between the translation and the planning process, since the time of this process was registered as it was done in the first case, considering the time consumed by the searcher.

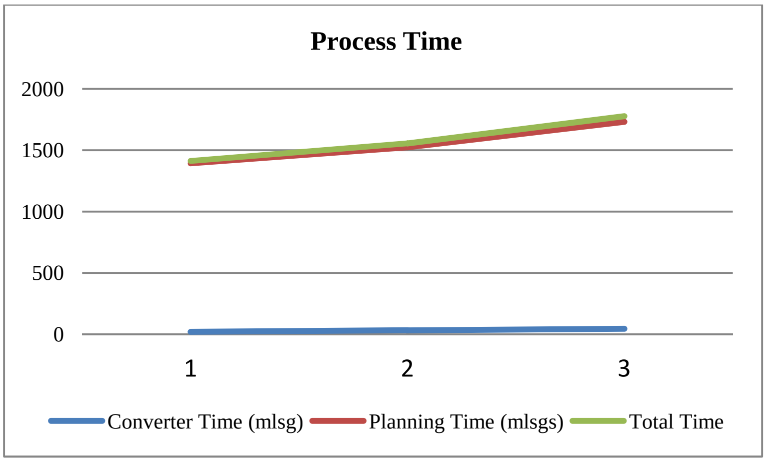

Fig. 8. Processing Times.

V. CONCLUSIONS

This work presents a mobile recommender system of learning paths which includes a planning mechanism to automate and adapt the paths to the learning profiles of the students, using a templates model similar to the one of the presenters aiming to be user friendly.

The syntax of the specification of the core of the planning algorithm, which works on the specifications of the LOs in the LOM standard and over some semantic specifications described in OWL, was presented in detail. The planning mechanism makes use of the numeric functions and it also includes metrics to optimize the degree of adaptability of the LOs to the profile of the student. Another advantage of the system is that the construction of the APK, resulting from the process, is carried out automatically; and it only requires its referral by the teacher who finally knows, from his experience, the profile of each one of the students.

As future work, we propose to articulate with an LMS as Moodle, aiming to maximize the generalization of this operator, fostering the multi-device education.

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