Recommender system for ubiquitous learning based on decision tree

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***Abstract* — In recent years, the fast development of mobile, wireless communication and sensor technologies has provided new possibilities for supporting learning activities. Ubiquitous learning, which is learning that can take place anywhere and anytime, is the best example.In order to provide learners with adequate learning experience, factors such learner's characteristics and context should be considered. Managing the learner context can help delivering the best resource adaptation services. Learning object proposed to the learner is obtained from contexual informations using the decision tree model. On the present paper, a recommender system for ubiquitous learning using context information of the learner and a decision tree model is presented, and k-fold cross validation is used in the experiment for estimating and validating the performance of our recommender system for ubiquitous learning.**

***Keywords*—Ubiquitous learning; Recommender system; Decision tree; Context; Context awareness**

I. INTRODUCTION

The emergence of new types of interactive systems like ubiquitous computing in education helps consider new approaches and new learning environments. However, the quality of the educational service depends on the ability of these new learning approaches to provide learners, on one hand, educational content tailored to the learner profile and context, and on the other hand, processes that guide them truly in their learning process. Adaptive education systems are designed to meet this need. Ubiquitous learning is a way to use new technologies to improve the quality of learning, providing learners the right resource at the right time and in the best way.

Adaptation in traditional learning systems often focuses on the learner profile; it does not always take into account the context in which learning takes place explicitly. Adaptation in a ubiquitous system of learning is therefore regarded as an extension of it. It essentially consists of selecting relevant resources not only to the learner profile (e.g. the knowledge, skills, preferences, interests, etc.) but also to his current context (e.g. the physical environment, technologies, mobility, tools, time, location, noise, luminosity, etc.).

One of the most accurate definitions of the context is given by Dey and Abowd (2000) [1] These authors refer to context as: "Context is any information that can be used to characterize the situation of entities (i.e. whether a person, place or object) that are considered relevant to the interaction between a user and an application, including the user and the application themselves. Context is typically the location, identity and state of people, groups and computational and physical objects".

Context-aware systems are able to adapt their operations to the current context without explicit user intervention and thus aim at increasing usability and effectiveness by taking environmental context into account [2]. According to Henricksen, Indulska and Rakotonirainy [3], the acquisition contextual information is made using physical sensors that can be integrated directly into other tools, virtual sensors for extracting contextual information from virtual spaces such as programs, systems operation, network, etc., or logical sensors that use the information of the physical and virtual sensors to deduce other information.

The main purpose of this paper is to provide a recommender system for ubiquitous learning based on decision tree, and use it to extract the adaptation rules from a variety of contexual information. For estimating and performance validation for our recommender system, we will use the k-fold cross validation.

This paper is structured as follows. Section 2 concentrates on settings and basic definitions, the decision tree, context and context awareness, and recommender system. Section 3 describes a context-aware recommendation using context information and a decision tree. Section 4 presents the experimental result. Finally, Section 5 displays the main conclusions and future research.

II. SETTINGS AND BASIC DEFINITIONS

In this section we will discuss the three main concepts to achieve our approach, these concepts are: Firstly the decision tree to classify a population of individuals into homogeneous groups according to discriminating attributes, secondly the context to describe the situation of a person (e.g. location, time, noise level, luminosity, orientation, system properties, navigation history, etc.), in our case the person is the learner, and finally the recommendation system to produce personalized search results by performing analysis of user actions.

A. decision tree

The decision tree [7] is a set of classification rules based their decision on the tests associated to the attributes, organized in a tree structure, in which leaves (i.e. the terminal nodes) , represent class labels and branches correspond to features with associated values leading to the nodes.

Big advantages of decision trees are: Decisions easily interpreted, and rapid classification, Many different algorithms have been proposed for decision tree learning, among which ID3 [9], CHAID [11], C4.5 [10], and CART [8] are the most common ones; all the approaches follow the paradigm divide -and-conquer.

The basic algorithm for inducing a decision tree from the learning or training sample set is as follows:

- Decide if a node is terminal, will decide if a node must be labeled as a leave. (e.g. all the examples are in the same class, there are less errors, etc.).
- Select a test to be associated with a node. (e.g. randomly, using statistical criteria, etc.).
- Affect a class to a terminal node. All classes are attributed, except those which are used with the cost or risk functions.
- Validate the tree using a cross-validation or other techniques.

A perfect decision tree is a decision tree such that all the examples of the training set are correctly classified.

B. context and conext awareness

Recently, many discussions took place about the meaning and definition of context and context-awareness. Dey and Abowd [12] define context as a piece of information that can be usedto characterize the situation of a participant in an interaction. Context awareness [13] means that the system is able to explore the environment to determine the current context and conduct learning activities in a particular context. In other terms, the system first detects its can detect and react to his environment in relation to the latter by following these three phases the detection, acquisition and interpretation of the context elements and its changes.

The various layers are described as follows:

- **Sensors**: the collection of physical and virtual sensors
- **Acquisition**: Recovery by components
- **Treatment**: At this level we find the implementation of methods to interpret contextual information and making information from multiple sensors compositions
- **Storage**: The recovered contextual data is structured, stored and made available to the client through a public interface.
- **Application**: Clients methods that exploit contextual information

The figure 1 shows the layered architecture of the context (Principle and example)

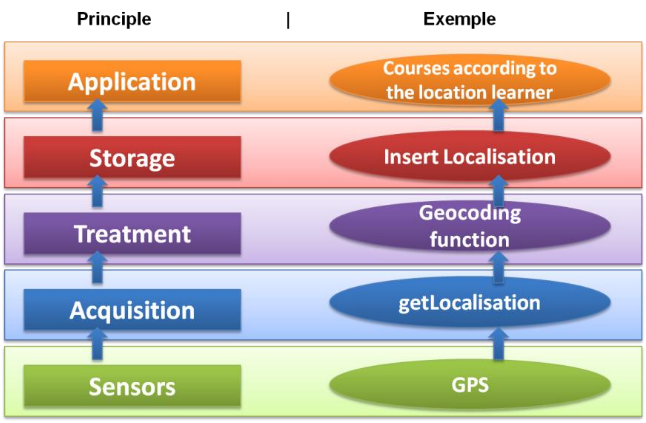

Fig. 1. Layered architecture of the context

C. recommender system

Recommender Systems introduces the concepts inherent in the recommendation, based, inter alia, on information research, filtering, machine learning, and collaborative approaches. It also treats the assessment of such systems and presents various applications.

Recommender System is a way to propose to the user the products that are likely to interest, The approaches in existing studies of recommending techniques can be generally divided into Content-Based Filtering [14] [15] [4], Collaborative Filtering [5], and Knowledge-based systems [6]. Content-Based Filtering, recommends items based on a comparison between the items content and a user profile. Collaborative Filtering, also referred to as social filtering, filters information by using the recommendations of other people.Knowledge-based systems, recommends items by using the knowledge on the user.

III. CONTEXT-AWARE RECOMMENDATION

Most of the common recommendation systems are only targetting online shopping platforms, restaurants and tourist targets, We aim to design a system that is more important and more general, because our application domain is the ubiquitous learning, which have became achievable thanks to technologies enabling context-awareness.

The main purpose of this article is to describe a recommender system for ubiquitous learning based on decision trees, in fact, the decision tree is used to extract the adaptation rules from a variety of contexual information.

Now, the first question that arises is: What are the learners contexual informations on which our decision tree will be based? This later will help us to extract the adaptions rules. At that point, additional questions will arise for example: what are the decisions taken for each rule?

According to the basic principle of decision tree building, the three essential components of a decision tree are:

- Attributes that represent a variable with multiple values constituting the tree nodes, in our case, the attributes are the contexual informations of the learner (e.g. connectivity, technologies, mobility, tools, time, location, noise, luminosity, battery level, Memory, Activity, etc.).

- Classes representing the adaptation based on the decisions, in our case, the classes are the format of the Learning objects offered to our learners (e.g. text, audio or video).
- Data samples that represent all possible combinations of different values of Attributes and classes.

After building our decision tree, we can then extract the adaptation rules, on which our recommendation system will be based.

A. system description

In this paper, we propose a recommender system using contextual informations and decision trees for efficient recommendation for ubiquitous learning, one of the main objectives of ubiquitous learning is to provide learners the right resource at the right time and in the best way, It essentially consists of selecting relevant resources not only to the learner profile (e.g. the knowledge, skills, preferences, interests, etc.), but also to his current context (e.g. the physical environment, technologies, mobility, tools, time, location, noise, luminosity, etc.)

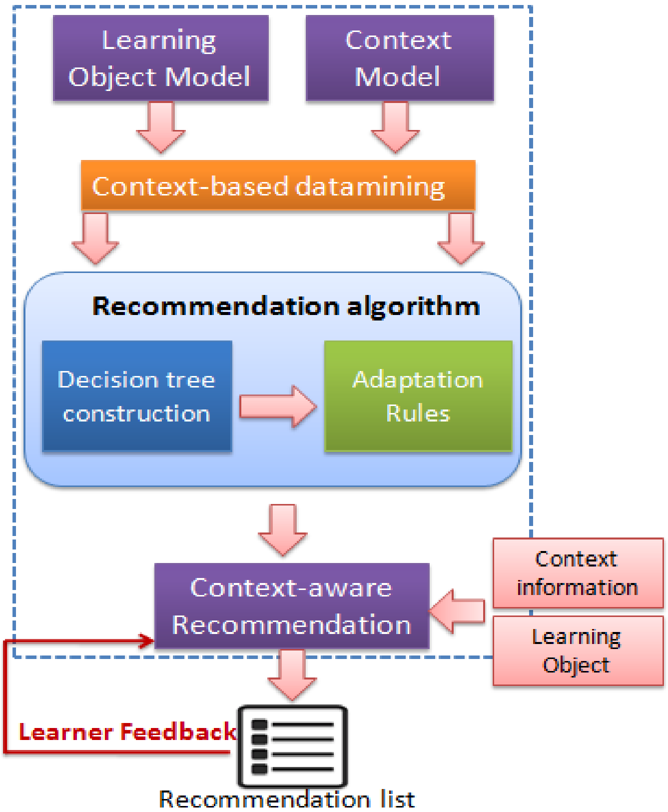

Fig. 2. Our recommender system for ubiquitous learning based on decision tree

The recommender system proposed in this paper is articulated in two parts (figure 2).The first part is Context-based Data Mining, which presents all possible combinations of different values of Learning Object choices (i.e. text, audio or video), and context information (i.e. mobility, noise, luminosity, and connectivity). The second part focuses on recommendation algorithm generation, based on the decision tree, i.e. we will be converting the samples to a tree, from which we will construct the adaptation rules.

Finally, after presenting the recommendation list to our learner, considering his feedback is very important in order to reduce the probability of learning objects that he is not interested in.

Now the question is: On what context model we will build in order to recommend Learning Objects to our learners? That represents a very essential component in our system.

B. context model

We construct our context model by answering the question: "What are the resources of my close environment?", this is why, our contextual elements are defined from the learner environmental adaptation points

Our context model is represented by the quadruplet $V=<N, L, M, C>$, where N represents the Noise level, L is the Luminosity, M represents the Mobility, and C is the connectivity.

The following is the definition of the various components of our context model:

- Noise: the noise level must be below a certain level of learner distraction , otherwiseadapting the Learning Objects to the noise level is obligatory, we note that the normal noise level must be : *70 dBA <B <75dBA*
- Luminosity: To ensure that each learning session can be correctly achieved -The studies on the subject have shown that non sufficient or high lighting had important consequences on eyestrain, and therefore the difficulty of learning, also we note that the normal luminosity level must be : *1000 Lux<L<1500 Lux*
- Mobility: If the learner is moving, we can not assign a text type for Learning Object, but it will be appropriate to offer him an audio type of Learning Object, the values for this attribute are: “yes” or “no”.
- Connectivity: If the learner has a very low connection, the system will offer him a text type for Learning Object, the values of this attribute are: “high” or “low”.

Therefore the context i of a learner is defined as follows:

$$Vi=<N_i, L_i, M_i, C_i>$$

Each of these dimensions is important in our model, because they define the learner context necessary to provide himan adaptive learning suitable to his current context.

C. context-based data mining

The Data mining is a multidisciplinary domain, which can extract automatically or semi-automatically hidden, relevant and unknown informations from a very large quantity of data, our data samples represent all possible combinations of different values of Attributes (i.e. mobility, noise, luminosity, and connectivity) and classes (i.e. text, audio or video).

In our approach we construct a recursive decision tree by selecting the attribute that maximize Information Gain (2) according to the Entropy (1). This method works exclusively with categorical attributes and a node is created for each value of the selected attributes.

Where p (j) is the probability of having a characteristic element of j in the set S

$$E(s) = \sum_{j=1}^{|S|} p(j) log_2\, p(j) \quad (1)$$

$$Gain(S, A) = E(S) - \sum^{v} \left(\frac{|S_v|}{|S|} * E(S_v) \right) \quad (2)$$

Let S be a set consisting of s data samples, Let attribute A, the target attribute, contain v distinct values, *{a1, a2, ... a_v}*, S_v the subset elements where the attribute value is A_v, $| S_v |$ = Number of items of S_v and | S | = Number of elements of S.

Information Gain (2) is used to measure impurity separation, in fact a node is pure if all the individuals associated belong to the same class, there are other functions such as Gini (3) Index and Rule Towing (4).

$$gini(S) = 1 - \sum_{j=1}^{m} Pc^2 \quad (3)$$

$$T_{value} = \left(\frac{|T_L|}{n}\right) * \left(\frac{|T_R|}{n}\right) * \left(\sum_{i=1}^{k} \left| \frac{L_i}{|T_L|} - \frac{R_i}{|T_R|} \right| \right)^2 \quad (4)$$

Where p_c is the relative frequency of class c in the set S containing m classes. If S is pure, gini (S) = 0.

.

We look for the test case that maximizes the gain. Calculating the Entropy and the Information Gain is a repetitive procedure for constructing nodes of the tree,that's why, concerning the construction of our decision tree, any algorithm such as ID3 [9], CHAID [11], C4.5 [10], and CART [8] could be used and gets good results.

D. *decision tree construction*

In our approach we used decision trees because it can divide a population of individuals into homogeneous groups according to discriminating attributes based on a fixed and known target.Four contextual informations of the learner such as noise, luminosity, mobility, and connectivity are considered for analyzing the relationship between learner context and Learning Object choice. The decision tree construction using the CART (classification and regression tree) algorithm [8] represents an analysis result as shown in Figure 3.

The decision tree constructed is transformed into a set of rules. Each branch, coming from root to leaf, represents a rule, in the following the algorithm of figure 4 will deduce the learning objects that will be used according to the learner context.

E. *construction of the rules*

This algorithm (Figure 4) is generated from our decision tree as described in the previous section, the decision tree constructed is considered as a set of rules. Each branch represents a rule. For example, on the first right branch, if a learner is on the move and the noise level is low then only the audio type of Learning Object may be proposed to this learner. However in the first left branch, if the learner is not on the move, the connection is high, and the noise level is low, this learner may have only the audio type of Learning Object for learning.

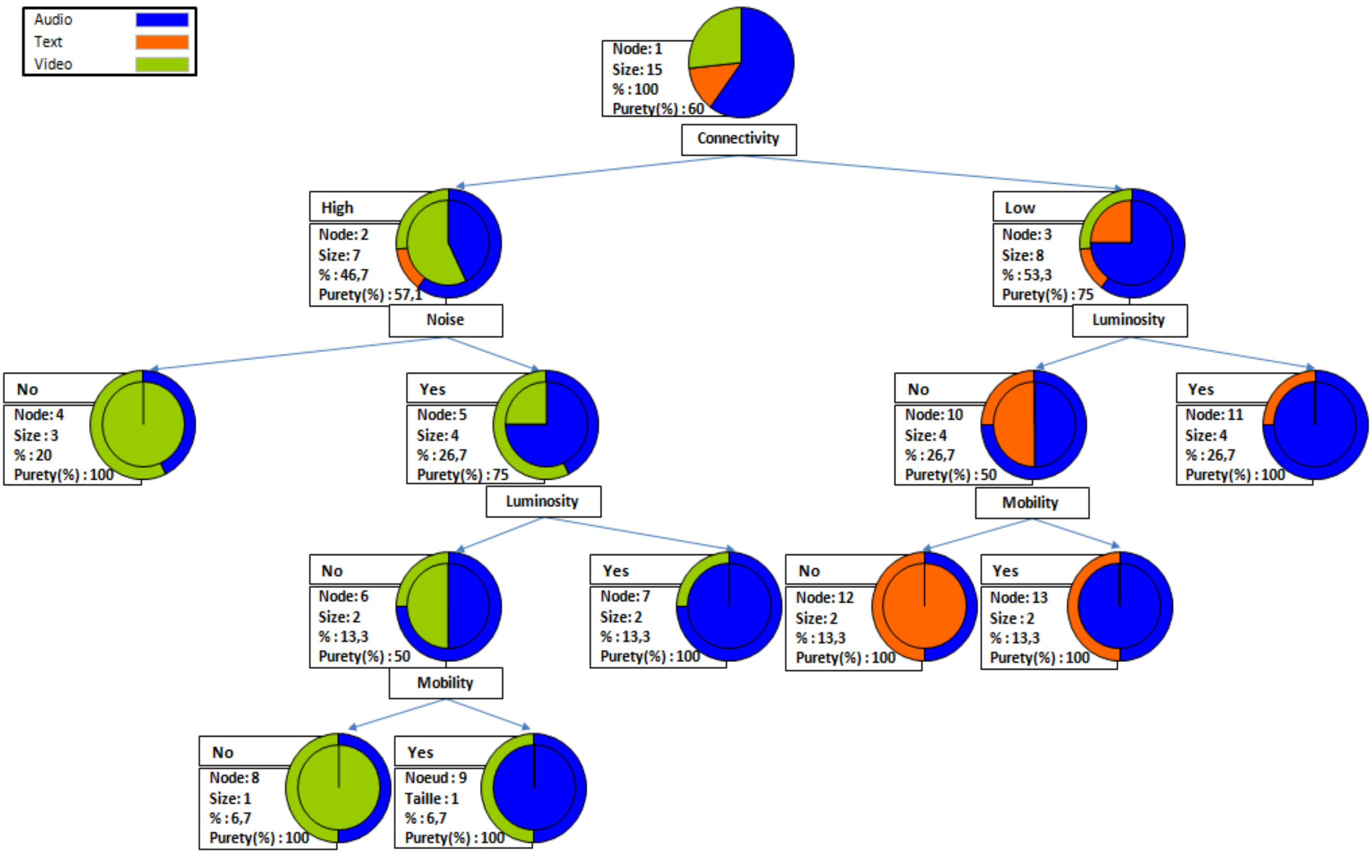

Fig. 3. Decision tree construction for Ubiquitous Learning

```
IF connectivity  == "High" THEN
    setLearningObject ("audio")
    setLearningObject ("video")
    IF noise== "no" THEN
            setLearningObject ("video")
    ELSE
            setLearningObject ("audio")
            setLearningObject ("video")
            IF luminosity == "yes" THEN
                    setLearningObject ("audio")
            ELSE
                    setLearningObject ("audio")
                    setLearningObject ("video")
                    IF mobility== "yes" THEN
                    setLearningObject ("audio")
                    ELSE
                    setLearningObject ("video")
                    END IF
            END IF
    END IF
ELSE
    setLearningObject ("audio")
    setLearningObject ("text")
    IF luminosity == "yes" THEN
            setLearningObject ("audio")
    ELSE
            setLearningObject ("audio")
            setLearningObject ("text")
            IF mobility== "yes" THEN
                    setLearningObject ("audio")
            ELSE
                    setLearningObject ("text")
            END IF
    END IF
END IF
```

IV. EXPERIMENT

The main purpose of this paper is to provide a recommender system using context information (i.e. Noise, Luminosity, Mobility, and connectivity) and a decision tree model for ubiquitous learning, In other words, the decision tree is used to extract the adaptation rules from a variety of contexual information. In this section, we used k-fold cross validation for estimating and validating the performance of our recommender system based on the decision tree.

In following the steps of k-fold cross validation:

1. the original sample is divided into k samples
2. For $i = 1,\dots, k$:
   a. Train the classifier using all the examples that do not belong to Fold i
   b. Test the classifier on all the examples in Fold i
   c. Compute n_i, that represent the number of examples in Fold I that where wrongly classified
3. Return the following to the classifier error (5) :

$$E = \frac{\sum_{i=1}^{K} n_i}{m} \quad (5)$$

K-fold cross validation is used in the experiment for estimating and validating the performance of our recommender system, the predictor selection plot suggests that inclusion of 3 predictors in the model is optimal.

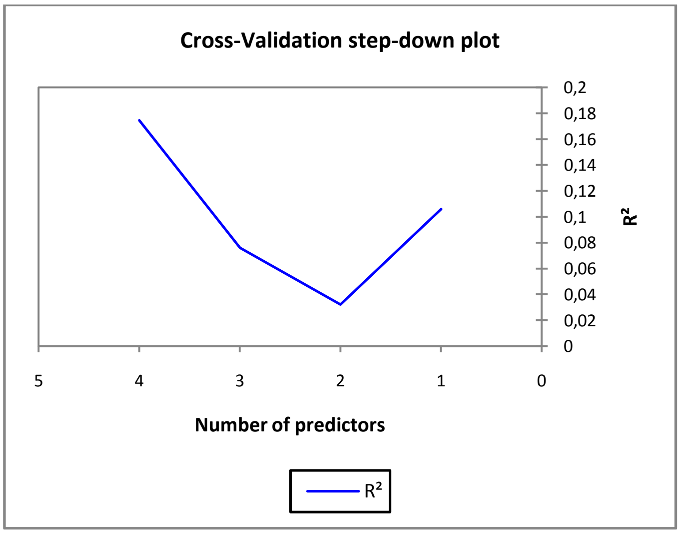

Fig. 5 . Cross-validation Step-down Plot

The Cross-validation Predictor Count table (Table 1) suggests that Mobility, Luminosity and Noise are the most important predictors, being included in 480, 463, and 451 of the 1806 cross-validated regressions.

Predictor	Round_1	Round_2	…	Round_100	Total
Mobility	6	2	...	6	480
Luminosity	6	2	…	6	463
Noise	6	2	…	6	451
Connectivity	6	0	…	6	412
Total	24	6	…	24	1806

Table 1: Cross-validation predictor count table

V. CONCLUSION AND FUTURE WORK

Ubiquitous learning is a set of methods using new technologies to enhance learning and expand the traditional perspective of the learning process itself. One of the main objectives of ubiquitous learning is to provide learners the right resource at the right time and in the best way. In this work, we presented an approach considering context information in providing adapted learning object with ubiquitous settings; in this paper, therefore, a recommender system for ubiquitous learning using context information of the learner and a decision tree model is presented. The presented approach contributes to a recommender system for ubiquitous learning in three ways: First, it aims to demonstrate how to use the decision tree to generate the rules adapation. Second it aims to demonstrate the architecture of arecommender system based on the decision trees considering the learner contextual informations. Third it aims to demonstrate how to use k-fold cross validation for estimating and validating the performance of a recommender system. The major directions for future work regarding the system feature include the following: Implementing and evaluating the proposed approach, implementing a recommender system that use the full context and produce the full adapted educational activity and infrastructure. Finally the sample size was an important limitation of this study. Data mining is also related to large amounts of data, which includes millions entries in general. Therfore the results can be more generalizable with larger sizes of datasets.

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