

Construction of Deduction System of Learning Profile from Performance Indicators

Fatima-Zahra Ammor, Driss Bouzidi, and Amina Elomri

Abstract—When leaning, be it a face to face or online, students favor a customized learning that meets their needs and preferences. Learners are more motivated and their evaluation results are satisfactory. Indeed, the adaptation of interventions according to the learning profiles of student is one of the best ways to improve learning. However, a learning profile is easier to detect in a face to face learning situation rather than in an online learning situation, especially when the defining rules the different profiles are imprecise and difficult to formulate in a digital language. In our contribution, we aim to solve this problem by proposing a profile deduction system allowing to translate the performance rules provided by the expert into numerical rules manipulated by the machine, which will facilitate the deduction of learning profiles from interactions made by learners face to training. For this, we will use the algorithm classification ANTClust. An experiment part is proposed to verify the accuracy of the classification performed and the obtained results.

Index Terms—E-Learning, deduction system of learning profiles, performance indicators, classification, ANTClust algorithm.

I. INTRODUCTION

The e-learning systems aimed to revolutionize the world of training, provide pedagogical training available at any time for all types of people aimed to better support face-to-face training. Unfortunately, this has not been the case and e-learning systems are still experiencing significant dropout rate, which is due to several reasons including the lack of support and sense of isolation that the learner may feel facing the machine. Several solutions have been proposed, ranging from suggestions on working group integration [1] to the analysis of facial expressions to deduce learners emotions [2], [3]. Also, among the proposed solutions and approved for their satisfactory results, we find the adaptation and customization of training by learning profiles of learners. Indeed, learners are more motivated and prepared to advance when provided training is tailored to their needs and preferences. To infer patterns of student learning, there are two ways to do this:

- 1) Gather information explicitly through questionnaires [4], [5]. This method gives satisfactory results, but can, on the one hand, bring the learner to be quickly bored. On the other hand, may include risks of disrupting the progress of the learning activity.

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- 2) Implicit understanding of learner's behavior following his/her interaction with the environment [6], [7]. Recorded traces by the system can be extracted and analyzed to deduce his/her profile. It is this second approach that we have adopted in our work.

However, determining the learning profile of the learner, in an online learning situation, is a difficult task especially when profiling rules are imprecise and difficult to formulate in a digital language and be manipulated by the machine (the learner is stirred in a learning situation, he speaks little, he likes to be alone when working ... etc.). It is therefore necessary to consider a system that transforms the superficial rules defined by the expert teacher in numerical rules facilitating the deduction of learning profiles from learner's interactions face to training. We propose to build a fuzzy system of deduction of learning profiles to:

- Manually gather, by an expert, performance profiling rules defining the different learning profiles.
- Modeling performance rules through behavioral indicators.
- Automatically deduce numerical values representing the characteristics that define the different learning profiles.
- Decide on the learning profile of each student.

Our paper is divided into four main parts. The first part presents some existing learning styles and the tool of the seven profiles that we have adopted. The second part presents the behavior indicators created to facilitate the modeling of profiling rules provided by the expert pedagogue. The third part presents our deduction system of learning profiles (DSLPP) based primarily on profiling explicit rules of the expert and profiling implicit rules derived by the classification algorithm ANTClust. The last section presents the experimental results of the algorithm classification and an illustrative example of our system. We conclude our work with a conclusion and perspectives.

II. LEARNING PROFILES

Several studies have focused on learning profiles and how to set them. We find for example the learning styles of Kolb [8], the work of Felder and Silverman [9] or the VAK model was used to develop the tool of the seven learning profiles [10]. These works are widely used for the improvement and adaptation of on-learning systems [11]-[14]. Our choice is placed on the tool of seven learning profiles because it allows to:

- Explain the behavior of learners facing a learning situation.
- Guide tutors on the best way to interact with learners and the expressions to use or avoid in order to increase

their motivation. The very interesting thing to provide personalized accompanying [15].

The seven learning profiles tool consists, among others, of seven identity profiles that define the needs and preferences of an individual in a learning situation and represents the characteristics that each individual possesses and influence on his way of learning. The following Table shows the information that we have for each profile based on three criteria: the level of interest, the time necessary learning and levels of collaboration during learning [10]:

TABLE I: CHARACTERISTICS OF THE SEVEN LEARNING PROFILES IN A FACE TO FACE LEARNING SITUATION

Learning profile	Level Of interest	Learning time	Collaboration level
intellectual	1) loves to learn new things 2) curious by nature and loves to lean for leaning sake 3) involves in his learnings	1) takes his time 2) needs more information to have the feeling that he understood the question	1) prefers to be alone while working 2) talks a little and rarely asks 3) prefers to listen and analyze speeches 4) talkative if the topic is interesting
perfectionist	1) needs lots of information 2) everything must be understood and well done	1) dissect the information to understand everything	1) honest, disciplined and pleasant
Kind	1) learns to please teachers 2) gives up when in difficulty	1) slow learner compared with others	1) kind 2) pleasant 3) helpful
Emotional	1) when depressed his motivation goes down and no longer learns	1) slow learners	1) warm 2) when not happy he shows it 3) unfolds easily
rebellious	1) conventional and boring process .needs activities to do things	1) needs to expand in his learning	1) boisterous 2) can be verbally nasty as it can be extremely nice
enthusiastic	1) learn best if the subject gives him pleasure 2) being obliged to learn under constraint increase demotivation	1) is struggling to finish what he started	1) is in a good mood 2) love the humor and jokes regularly 3) quite agitated in a group situation 4) nice and very friendly, is honored to entertain a group
Dynamic	1) it crashes when it thinks it is too complicated 2) prefer the practical side of things 3) can be very average in learning situation but be very good to get along in life	1) Loves have multiple activities at the same time	1) like to show his success and highlight 2) like to talk, which is a problem in learning situations 3) has easy contact with other

In order to model the characteristics of learning profiles in e-learning context, it is necessary to create behavioral indicators to represent the criteria presented in the Table above.

III. BEHAVIORAL INDICATORS

In order to deduce the learners' learning profiles, and after studying the seven learning profiles tool [10], we created three behavioral indicators from the analysis of the behavior of learners:

A. Concentration Rate

The concentration ratio represents the level of interest of students in relation to the subjects studied, it is calculated by the study of semantic similarity between the courses and the web pages visited during the learner web surfing [16], [17].

$$R_{Concentration} = \frac{\sum_{i=1}^n \text{SimSem}(C, P_i)}{n} \quad (1)$$

With:

n represents the number of pages visited during the course learning C .

$\text{SimSem}(C, P_i)$ represents the semantic similarity between the current study and the page i visited. It is calculated using the following formula [18]:

$$\text{SimSem}(C, P) = \sum_{j=1}^m \frac{\sum_{i=1}^l C_i * P_j * \text{sim}(i, j)}{\sum_{i=1}^l C_i * P_j} \quad (2)$$

With:

i represents the concept of the course being studied

j represents the concept of the visited page

q_i the weight of concept i in the course

d_j the weight of concept j in the visited page

And $\text{sim}(i, j)$ represents the semantic similarity between two concepts i and j calculated by measuring *edge counting* [19]. It is a measure that calculates the semantic similarity based on the number of edges between the two concepts i and j in the shortest path in the hierarchy. Two concepts are more remote, the less they are similar:

$$\text{Sim}(i, j) = \frac{1}{1 + \text{dist}(i, j)} \quad (3)$$

So if $R_{Concentration} \approx 0$ (≈ 1), this means that the learner has zero (high) concentration.

B. Collaboration Rate

Collaboration rate is used to analyze the behavior of the learner in a group situation [20], [21]. We consider that the collaboration rate is equal to the percentage of student participation in working groups. Thus, a learner is considered preferring the collaborative situations when he participates often in working groups.

$$R_{Collaboration} = \frac{\sum_{i=1}^n \text{number of participation}(G_i)}{\text{total number of participation in } G_i} \quad (4)$$

With:

number of participation (G_i) represents the number of learner participation in the discussion group G_i

total number of participation in G_i represents the total participation of all learners in the group discussion G_i

So if $R_{Collaboration} \approx 0$ (≈ 1), this means that the learner prefers not to discuss (prefers to collaborate) in a learning situation.

C. Perseverance Rate

Perseverance is the time taken for the learner's learning (including study of current course, discussions in the working groups, the consultation pages related to the course, ... etc..) on the total time that learner spent on the platform. So:

$$R_{Perseverance} = \frac{T_{CC}}{T_{TA}} \quad (5)$$

With:

T_{CC} = time during consultation

T_{TA} = total learning time

If $R_{Perseverance} \approx 0$ (≈ 1), this means that the learner has a zero (high) perseverance.

IV. DEDUCTION SYSTEM OF LEARNING PROFILES (DSLIP)

Our system DSLIP allows exploiting explicitly the provided knowledge by expert teachers - knowledge to giving an overview on the different profiles - to build profiling rules understandable by the machine, and to decide on the learners' learning profiles. DSLIP is presented as follows:

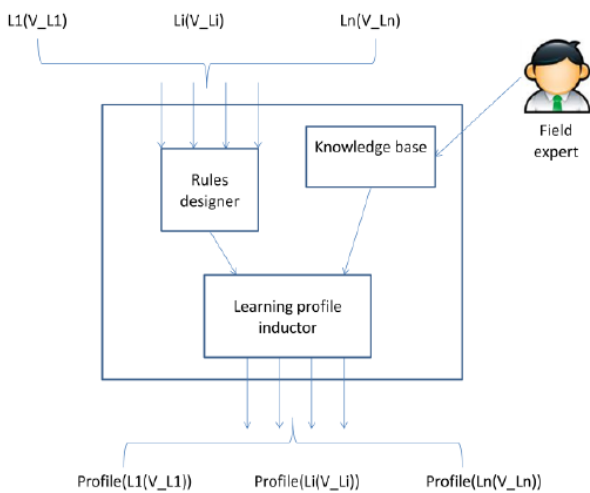


Fig. 1. Deduction system of learning profile.

The system retrieves in input learners' behavioral vectors - defined by three indicators seen a bit above - to give as output their learning profiles. Thus, each student is represented by the vector $L_i(R_{Concentration}_i, R_{Collaboration}_i, R_{Perseverance}_i)$ / $i = \{1, \dots, p\}$ where p is the number of learners enrolled in the learning platform.

Our system consists of three main components:

A. Knowledge Base

Knowledge Base gathers information collected from the work of Michel [10] according to behavioral indicators. This is a job that requires collaboration between a teacher and a computer expert. The following figure shows the resulting rules:

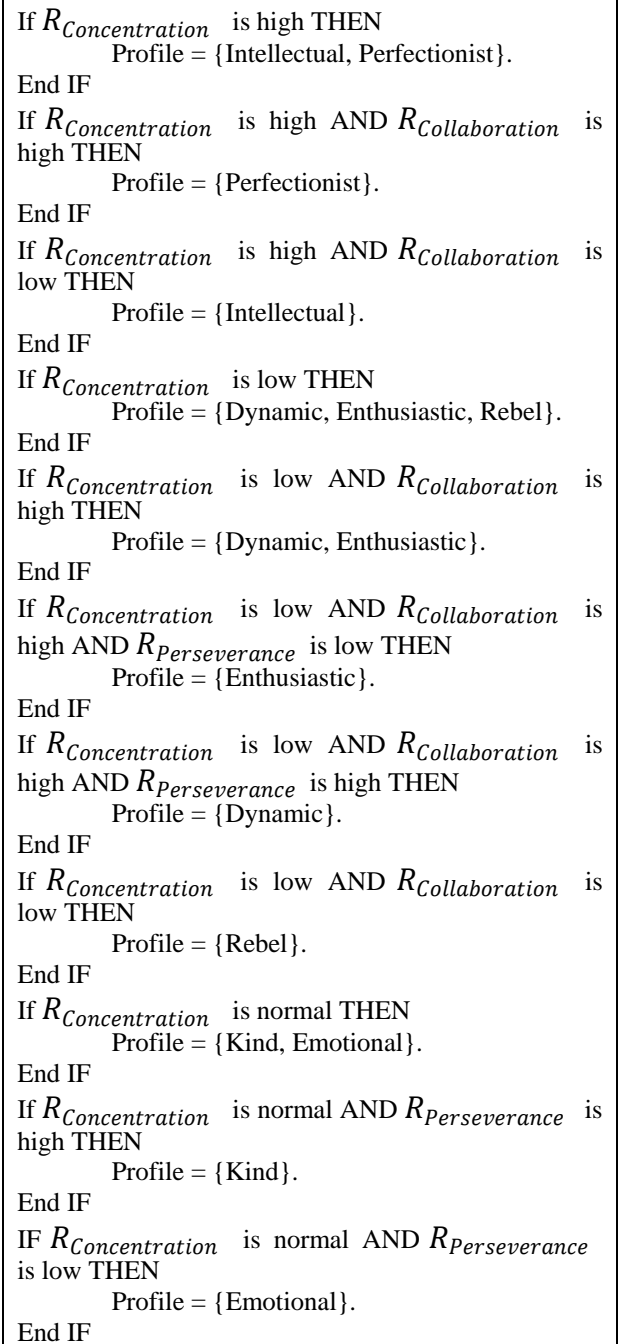


Fig. 2. Profiling rules established through the study of the seven learning profiles.

B. Rules Designer

Rules designer applies clustering method to create rules equivalent to the rules defined in the knowledge base, and then use these rules to infer learning profiles. This module allows to create seven rules based on numeric values representing the seven learning profiles, and this is thanks to the ANTClust algorithm of classification (Fig. 3). Indeed, it allows classifying learners into groups according to their similarities and then associating each created group with the profile it represents the better [22]-[24]. Classification algorithms have been widely used in order to deduce learners' learning profiles [25]-[27].

The choice of algorithm ANTClust [28], [29] was random when it responds to two major problems:

- 1) The algorithm used allows to classify a large number of learners

2) ANTClust is a non supervised clustering algorithm, it is not necessary to specify the group number. In fact, we used a clustering algorithm in order to ensure the appropriateness of selected indicators.

Each ant has:
 Label = a nest
 genetic genome = ant's genetic odor, unalterable
 A template = vision in relation to the nest, constantly updated,
 Estimator M = the ant's estimation about its nest's size.
 Estimator M + = the ant's estimation about its level of integration in the nest.
 The ANTClust algorithm
 1) Simulation of meetings between ants randomly drawn
 Behavioral rules:
 a. Two ants with label = 0 meet and agree ⇔ creating a new label
 b. Ant without label meets another belonging to a nest and accept each other ⇔ ant's label without label = ant's nest label encountered
 c. Two ants meet with the same label and accept each other ⇔ they increment the value of M and M +
 d. Two ants meet with the same label but do not accept each other ⇔ the less integrated ant is ejected from its nest.
 e. Two ants meet with different labels and accept each other ⇔ the ant nest with the smallest nest integrate the largest nest.
 This rule was inspired by the behavior of certain species where it is possible to deceive the chemical recognition system by accepting a worker ant in another nest.
 2) Destroy uninteresting nests
 3) Reassign the 'orphan' ants into the most appropriate nest

Fig. 3. The ANTClust algorithm of classification.

C. Learning Profiles Inductor

The inductor profiles can exploit profiling rules explicitly presented by experts and rules implicitly defined by the classification algorithm to decide on student learning profiles. Thus, the two groups created with the highest values of $R_{Concentration}$ represent the perfectionist's learners and the intellectual's learners, and the intellectual's learners are one of two groups with low $R_{Collaboration}$. And with the same logic the other profiles are derived ... etc.

V. EXPERIMENTATION

To ensure the relevance of the classification algorithm ANTClust and indicators chosen for classification, we have tested the algorithm in a database containing 1000 learners. The following Table shows the obtained results using behavioral indicators chosen:

TABLE II: THE RESULTS OF CLASSIFICATION

	Created groups						
	G_1	G_2	G_3	G_4	G_5	G_6	G_7
ANTClust	273	209	166	107	87	68	48

The clustering algorithm creates 20 different groups, 958 of them are grouped into the busiest seven groups, others are scattered in 13 other groups. Thus, the algorithm classifies ANTClust learners through behavioral indicators with a rate of misclassification equal to 4.2%.

In the classification, we note that much of students gathered in the seven main groups, others contain less than 10 learners. This confirms the validity of our choice of three behavioral indicators. To better understand the steps of deduction system of learning profiles (DSLPL), we present an illustrative example.

After each learner is connected to the e-learning platform and to make his first learning stage. Our system DSLP

calculates behavior indicators of each learner and constructs the behavioral vector. The following Table shows the initial information of DSLP:

TABLE III: INITIAL INFORMATION OF DSLP

Learner	R_{Con_j}	R_{Collab_j}	R_{Pers_j}	Profile
L_1	0.443	0.395	0.690	Nul
L_2	0.873	0.427	0.351	Nul
...				
L_{500}	0.323	0.087	0.561	Nul
...				
L_{1000}	0.613	0.348	0.343	Nul

These data are then presented to the rules designer to classify learners according to their similarities and create seven groups representing the seven learning profiles (Table III):

TABLE IV: RULES DESIGNER RESULTS

Group	R_{Con_j}	R_{Collab_j}	R_{Pers_j}	Number of learners
G_1	0.079	0.149	0.152	273
G_2	0.186	0.155	0.052	209
G_3	0.089	0.049	0.219	166
G_4	0.181	0.042	0.127	107
G_5	0.136	0.187	0.078	87
G_6	0.112	0.121	0.136	68
G_7	0.103	0.265	0.078	48

Not to be output without learners profile, we combined the 13 other groups of learners in a $G_i / i = \{1 .. 7\}$ the most suitable.

After each learner is associated with one of seven groups established, the learning profiles inductor retrieves profiling rules defined in the knowledge base (Fig. 2) and the results of the rules designer to associate each group to profile that represents it the best (Table V, Table VI, Table VII).

TABLE V: ASSOCIATING GROUPS TO THE BEST LEARNING PROFILE ACCORDING TO THE VALUE OF $R_{Concentration}$

Group	R_{Con_i}	Profile
G_1	0.079	Dynamic, Enthusiastic, Rebel
G_2	0.186	Intellectual, Perfectionist
G_3	0.089	Dynamic, Enthusiastic, Rebel
G_4	0.181	Intellectual, Perfectionist
G_5	0.136	Kind, Emotional
G_6	0.112	Kind, Emotional
G_7	0.103	Dynamic, Enthusiastic, Rebel

TABLE VI: ASSOCIATING GROUPS TO THE BEST LEARNING PROFILE ACCORDING TO THE VALUE OF $R_{Concentration}$ AND $R_{Collaboration}$

Group	R_{Con_i}	R_{Collab_i}	Profile
G_1	0.079	0.149	Dynamic, Enthusiastic
G_2	0.186	0.155	Perfectionist
G_3	0.089	0.049	Rebel
G_4	0.181	0.042	Intellectual
G_5	0.136	0.187	Kind, Emotional
G_6	0.112	0.121	Kind, Emotional
G_7	0.103	0.265	Dynamic, Enthusiastic

TABLE VII: ASSOCIATING GROUPS TO THE BEST LEARNING PROFILE ACCORDING TO THE VALUE OF

$R_{Concentration}$ AND $R_{collaboration}$ AND $R_{Perseverance}$

Group	R_{Con_j}	R_{Collab_j}	R_{Pers_j}	Profile
G_1	0.079	0.149	0.152	Dynamic
G_2	0.186	0.155	0.052	Perfectionist
G_3	0.089	0.049	0.219	Rebel
G_4	0.181	0.042	0.127	Intellectual
G_5	0.136	0.187	0.078	Emotional
G_6	0.112	0.121	0.136	Kind
G_7	0.103	0.265	0.078	Enthusiastic

Consequently, DSLP system presents as output the learning profile of each learner (Table V):

TABLE VIII: NUMBER OF LEARNERS IN EACH LEARNING PROFILE

Group	Profile	Number of learners/group
G_1	Dynamic	278
G_2	Perfectionist	209
G_3	Rebel	166
G_4	Intellectual	119
G_5	Emotional	89
G_6	Kind	88
G_7	Enthusiastic	51

VI. CONCLUSION AND PERSPECTIVES

The e-learning systems increasingly interests researchers saw their ambitions to best support face-to-face learning. Unfortunately, this has not been realized and e-Learning systems are still experiencing significant dropout rate. In our paper, we propose a deduction system of learning profiles (DSLSP) to analyze the behavior of learners facing training in order to infer their learning profiles. However, this deduction is not easy to achieve because the rules defining the different profiles cannot be modeled with numerical values and thus difficult to handle by the machine. We propose, to solve this problem, to create behavioral indicators representing the criteria for the different profiles and to use them to classify the learners according to their similarities and associate each group created with profile that represents it the best using a knowledge filled by experts. The classification is achieved through the classification algorithm ANTClust that helped us to validate our choice of behavioral indicators and to deduce learners' learning profiles. We see as next work to improve the classification algorithm used to reduce the rate of misclassification found.

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