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A Rule-Based Expert System for Teachers' Certification in the Use of Learning Management Systems

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Abstract

In recent years and accelerated by the arrival of the COVID-19 pandemic, Learning Management Systems (LMS) are increasingly used as a complement to university teaching. LMS provide an important number of resources and activities that teachers can freely select to complement their teaching, which means courses with different usage patterns difficult to characterize. This study proposes an expert system to automatically classify courses and certify teachers' LMS competence from LMS logs. The proposed system uses clustering to stablish the classification scheme. From the output of this algorithm, it defines the rules used to classify courses. Data registered from a university virtual campus with 3,303 courses and two million interactive events have been used to obtain the classification scheme and rules. The system has been validated against a group of experts. Results show that it performs successfully. Therefore, it can be concluded that the system can automatically and satisfactorily evaluate and certify the teachers' LMS competence evidenced in their courses.

Keywords

Academic Analytics, Automatic Course Classification, Learning Management System (LMS), Rule-Based Expert System.

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I. Introduction

Learning Management Systems (LMS) are widely used across universities to support teaching and learning. LMS are a driving force in online courses; however, they are increasingly used as complement to face-to-face classes [1], [2], and much more with the advent of the COVID-19 pandemic and the new educational needs.

LMS provide a wide variety of tools (communication, skills, and productivity) as well as reports of learning progress [3]. Teachers choose the resources and activities that best suit their needs and the way they teach. Thus, in an institutional LMS, there are courses with different usage patterns difficult to characterize [4], [5].

In this context, many universities want to know the usage given by teachers to certificate and evaluate their competence in technology-based learning. This task is done manually and subjectively by experts based on the presence/absence of LMS activities and resources. This is a hard and difficult task; therefore, it would be interesting to automatize this certification process and define an expert system that was able to certificate courses based on the use of LMS by teachers and students.

Moreover, supporting teachers with feedback about their LMS usage could be a motivating factor to make the most of LMS as well as improve their learning designs [6]. This could be also an interesting point, since the lack of motivation to integrate technology is one of the biggest challenges to the implementation of blended teaching [7]. Some studies indicate that the most common use of LMS is as a repository [8]. However, it should be desirable to further utilize LMS capabilities, especially those tools that improve student interaction and increase engagement [9].

This paper presents and validates an expert system that automatically classifies courses and certifies the teachers' competence in the use of LMS from scarce and partial data. For that end, it is previously necessary to stablish the different classes of courses according to the LMS usage [10]. The definition of course types could be done manually by some agent (educational authorities, for example) or automatically by means of some type of clustering analysis. We propose a whole automatic system that firstly applies clustering to categorize courses, like described in our previous work [10], and then estimates the courses typology based on the use of LMS.

In section II, a review of the related work is presented. Section III describes the expert system, along with the used methods and tools. In section IV, the results of this study and the accuracy of the estimations are presented and discussed. Finally, section V contains outcomes and insights about future work.

II. State of Art

Expert systems improve decision-making processes by reasoning through accumulated experience together with an inference or rules engine. Most expert systems are rule-based reasoning, where the knowledge base is represented using rules in the form of IF-THEN. For example, some studies use a forward chaining method to support learning assessment and to assist new-comer students [11], [12]; whereas Hossain et al. [13] develop a belief rule base, an extended form of traditional IF-THEN rules, to predict the student performance under uncertainty. Other authors incorporate fuzzy logic in the expert system to improve students' learning performance [14].

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In the last years, expert systems for educational purposes are increasingly demanded [15]. Applied on LMS, most expert systems are Intelligent Tutoring Systems [16]. They are recommenders or feedback systems that deal with learning adaptation or personalization [17]–[22]. There are also systems based on students' drops or outcomes prediction and learning problem solving [23], [24].

On the other hand, very few systems are addressed to the teachers' view or improvement [25]–[27]. For example, Hossain et al. [28] describe a data mining tool that supports teachers in making decisions about how to improve their e-learning courses. Villagrá-Arnedo et al. [29] propose a system that provides time-dependent predictions of students' performance so that teachers can select the best moment for intervention. Moreover, expert systems for higher level functions, such as outcomes-based teaching planning [30] or assessment of academic credentials and competencies [31] are also few.

Finally, there are several studies on the characterization of courses according to the level of LMS usage, as we detailed in our earlier work [10]. Previous studies [32]–[34] classified courses from LMS interactions with the aim of supporting instructors in the development of course plans, improving designs or increasing the impact of LMS use. To our knowledge, only the results of Whitmer et al. [34] have been used for actual support systems. Their "course archetypes" have been incorporated into the learning analytics product of Blackboard LMS [35], a proprietary software. However, the implementation and design of that classification system is not provided and presented in the literature. Moreover, their archetypes are defined from courses previously selected, and not from all courses offered. Only courses incorporating the gradebook have been used in the analysis [34], which, as it has been verified in our previous study [10], is quite limited in blended learning environments. Other issue is the great variability of contexts: they work with courses from 60 minutes long (a short workshop) to a whole semester or year. In fact, they use later their course archetypes for a correlation analysis of students' grades and course patterns at a single university and they find unexpected results [36]. Caglayan et al. [6] use also the archetypes provided by Blackboard Analytics to investigate the degree of agreement between instructors' opinion on their course type and the classification done by Blackboard Analytics. The experiment is also at university level and face-to-face classrooms. Their results show a low level of consistency between instructors' view and the analytics findings. However, they conclude that knowing the automatically labelled archetype helps instructors to think about and redesign their courses [6]. In any case, it is another proof of the need of more customized classifications that consider the instructional and cultural context as well as some type of validation.

Other recent studies about characterization of LMS courses can be found in the literature. Machajewski et al. [4] use latent class analysis to characterize courses at a university; whereas Su et al. [27] analyse the behavioural patterns of university teachers while using an LMS. Both find three distinct patterns or clusters but any of them use their findings to give feedback or feed an expert system. Finally, Bennacer et al. [37] are developing a self-assessment tool based on a teacher behavioural model, but this model is not automatically obtained. Instead, they do a mixed analysis that includes a quantitative LMS analysis as well as a qualitative one with some interviews to pedagogical experts. Besides, it is at a very early state.

III. The Expert System

We have designed a rule-based expert system that qualifies the teacher's competence in Moodle and establishes how the teacher makes use of the Learning Management System. To that end, it is necessary to first establish the different types of LMS uses. Subsequently the rules that define the expert system can be designed from expert knowledge or by learning from real data. A data-driven design has the advantages of working automatically and objectively while avoiding experts doing a hard manual work [10].

The process takes place in two phases (see Fig. 1). During the first phase, the clustering system learns from students' and teachers' activity logs and the classification rules and facts base are defined. In the second phase, the expert system infers the certification of teachers' Moodle competence for each course from the obtained rules and facts base.

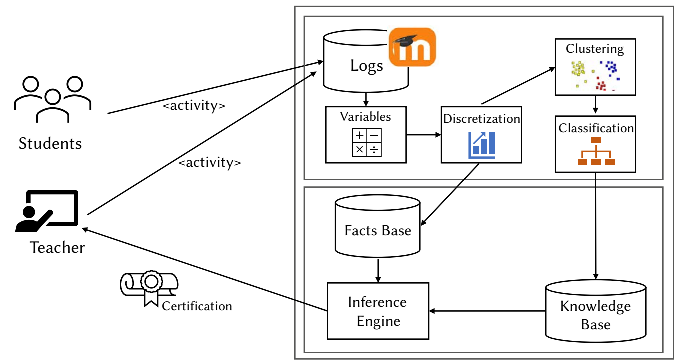

Fig. 1. Architecture of the Expert System.

A. Methods for Clustering Analysis

We used clustering analysis to automatically identify different types of courses in accordance with the LMS usage patterns [10].

From the Moodle logs for all courses given at the University, a process of transformation and selection of variables was conducted to stablish the input variables to the clustering algorithm.

TABLE I. Description of Initial Variables [10]

Variable	Description	Role
Resources	Number of resources	Teacher
ResourceViews	Number of resource views or downloads	Student
Forums	Number of discussion forums	Teacher
ForumNews	Number of teachers' forum posts	Teacher
ForumInteractions	Number of students' forum views and posts	Student
Assigns	Number of assignments	Teacher
AssignSubmissions	Number of assignment submissions	Student
Quizzes	Number of quizzes	Teacher
QuizSubmissions	Number of quiz submissions	Student
OtherActivities	Number of other activities	Teacher
OtherActivitySubmissions	Number of other activity submissions	Student
GradeItems	Number of gradebook items	Teacher
GradeFeedbacks	Number of feedbacks	Teacher
CalendarEvents	Number of manual calendar events	Teacher

A Moodle course can integrate both resources (such as files, links, pages...) and activities (for example, forums, assignments, quizzes, glossaries...). It is also possible to configure tools such as the events calendar and the gradebook for management purposes. According to the possible interactions, 14 variables were selected. Instead of considering items separately, we grouped some of them, especially those with limited use. We only selected the three activities with a more extensive use, and we grouped the rest in another variable as well as all types of resources, as it is detailed in our previous work [10]. Table I shows the description of variables as well as who carries out the corresponding action (teacher or student), where all activity-related variables are normalized to the number of students enrolled on the course. From these 14 variables, a process of preselection was carried out, by removing the redundant features and the zero and near-zero variance predictors and, therefore, keeping the features of interest.

Once the attributes were selected, the data were discretized to significantly reduce the number of possible values of the variables. We used an unsupervised method (k-means clustering) with three intervals and labels (low, medium, and high) for all variables. From transformed data, we compared different methods of clustering. Finally, we chose LCA (Latent Class Analysis) as clustering method and BIC (Bayesian Information Criterion) as a good indicator of the number of latent classes.

More details about data collection and selection, data pre-processing and transformation and clustering methods are available in our previous work [10].

B. Generation of Rules

Once stablished the different types of courses, we employed decision tree learning to extract information of the courses. This technique visually and explicitly provides a decision representation by deploying a recursive partitioning.

In the field of machine learning, there are different ways to obtain decision trees. We used CART (Classification And Regression Trees), which is a supervised learning technique to obtain classification as well as regression trees. Therefore, we have a target or dependent variable (the course type) and our goal is to obtain a function that allows us to predict, from independent variables, the value of the course type variable. As long as our target variable was discrete, we used the classification variant of CART. We employed the R implementation of CART that is known as Recursive Partitioning and Regression Trees or RPART (the R package 'rpart'). This algorithm finds the independent variable that best separates our data into groups, which correspond to the categories of the target variable. This best separation is expressed with a rule, where each rule corresponds to a node. The main advantage of this method is its interpretability, since it provides a set of rules from which decisions can be made.

We randomly partitioned the data into a training dataset (70%), used to prepare the model, and a test dataset (30%), used to evaluate the model performance, by using data splitting. We measured the goodness of fit of the proposed model by generating a confusion matrix or contingency table, through the 'confusionMatrix' function of caret R package. We repeated the process by changing the training and test dataset to compare the results. Then, we could select the best model depending on our objectives and what accuracy and specificity we wanted to obtain in our predictions.

Finally, once the classification model was chosen, we could use these results to obtain the rules through 'rpart.rules' function and validate their accuracy.

C. Definition of the Expert System

We used CLIPS (C Language Integrated Production System) to define the expert system, since it provides a complete environment for the construction of rule-based expert systems and it is widely used in the definition of expert systems [12], [38]. CLIPS is a forward-chaining rule-based language based on the Rete algorithm for pattern-matching to determine which rule should be fired by the inference engine.

In CLIPS, we defined the template associated to the courses with their features (input to the expert system) and type (output from the expert system). We also implemented the rules that define the system and that had been obtained from the decision tree. From the selected features of each course, the expert system defined in CLIPS obtained the type of course. Next step was to validate the obtained output with the experts' opinion.

IV. Results and Discussion

The hypothesis to be tested in this paper is that the designed expert system performs as a human expert in the task of certificating the teachers' technology competence about the use of LMS.

To analyse and validate the performance of the expert system, it was implemented in CLIPS and tested with real data.

A. Experiment

The study was carried at the Virtual Campus of the University of Valladolid, a Spanish public university, which offers more than 3,000 face-to-face courses. It has more than 2,000 teachers and around 32,000 students enrolled each academic year. This institution has its own virtual campus, based on Moodle LMS, which is being used as a support to face-to-face classes since 2009. All courses have a corresponding course in Moodle, on which both teachers and students are automatically enrolled. However, how to use the platform is decided by each teacher, resulting in different manners and intensities. In this context, the university could be interested in classifying the courses according to LMS usage by using an expert system that would replace manual certification of teachers' on-line competence.

From the anonymized logs, after applying the methods for data pre-processing described in Section III.A, nine variables were selected: 'Resources', 'ResourceViews', 'Forums', 'ForumNews', 'ForumInteractions', 'Assigns', 'AssignSubmissions', 'GradeItems' and 'GradeFeedbacks'. Then, we discretized them using k-means cut-off thresholds. After applying LCA for these variables, six classes were found (see Table II). See our previous work [10] for more details.

TABLE II. Description of Course TYPES [10]

Type of Course	Description
Type I or Inactive	Low use of Moodle
Type S or Submission	Some content and considerable use of assignments
Type R or Repository	A lot of content and low student interaction
Type C or Communicative	High interaction teacher-students
Type E or Evaluative	Some content and considerable use of evaluative elements
Type B or Balanced	Considerable and balanced use of Moodle tools

Then, decision tree learning was employed to extract information of the courses, as shown in Fig. 2. In this figure, each of the rectangles represents a node of the tree, with its classification rule, the proportion of cases belonging to each category (B C E I R S), and the proportion of the total data that have been grouped there. Each node is coloured according to the category predicted by the model for that group, following the greatest proportion within each region. These proportions give us an idea of the accuracy of the model in making predictions.

We repeated the process by changing the training and test dataset to compare the results and to obtain the best model in accordance with the accuracy, sensitivity (true positive rate) and specificity (true negative rate) shown in the confusion matrix. A confusion matrix is a very useful tool for calibrating the performance of a model and evaluating all possible outcomes of the predictions. Results of Fig. 3 show that the model has a high accuracy (95.8%), and high sensitivity and specificity for the six classes. The worst results were obtained for class B sensitivity, which indicates that the type B is the most difficult to identify correctly by the model.

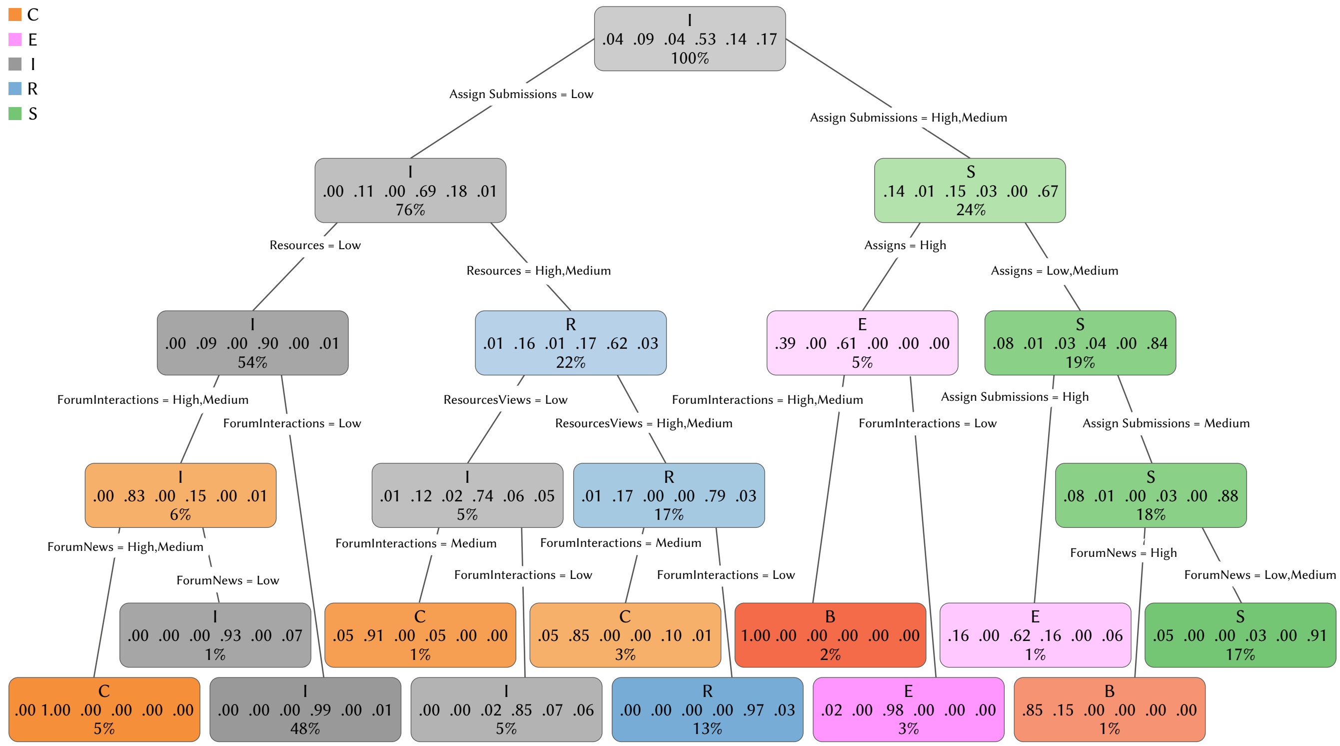

Fig. 2. Decision tree.

```
>>Contusion Matrix and Statistics
               Reference
Prediction     B     C     E     I     R     S
         B    71     3     0     0     0     0
         C     6   260     0     1    10     1
         E     7     0   107     5     0     2
         I     0     0     4  1600    10    21
         R     0     0     1     0   398    12
         S    25     2     0    18     0   482
Overall Statistics
                Accuracy : 0.958
                  95% CI : (0.9502 , 0. 9648)
     No Information Rate : 0.5332
     P-Value [Acc > NIR] : < 2.2e-16
                   Kappa : 0.9359
  Mcnemar's Test P-Value : NA

Statistics by class:
                  Class:B  Class:C  Class:E  Class:I  Class:R  Class:S
Sensitivity       0.65138  0.98113  0.95536  0.9852   0.9522   0.9305
Specificity       0.99898  0.99353  0.99523  0.9754   0.9951   0.9822
Pos Pred Value    0.95946  0.93525  0.88430  0.9786   0.9684   0.9146
Neg Pred Value    0.98721  0.99819  0.99829  0.9830   0.9924   0.9857
Prevalence        0.03578  0.08700  0.03677  0.5332   0.1372   0.1701
Detection Rate    0.02331  0.08536  0.03513  0.5253   0.1307   0.1582
Detection Prevalence 0.02429  0.09127  0.03972  0.5368   0.1349   0.1730
Balance Accuracy  0.82518  0.98733  0.97529  0.9803   0.9736   0.9564
```

Fig. 3. Confusion Matrix.

We obtained the rules associated to each model to compare them. We could verify that, while the obtained accuracy and statistics were somewhat different in each repetition, the rules obtained were the same ones, which shows the stability of the rules. From these rules, the expert system was defined: first, the facts template with course features and later, the associated set of rules.

The facts template includes the formal definition of the data. It provides the structure with the names and type associated to all data fields or slots. The course template contains, besides the course identifier, nine slots with the features used to obtain the class and another slot for storing the resultant type (see Fig. 4).

The inference engine of the expert system consists of a set of IF-THEN rules, such as the one shown in the example of Fig. 5. The set of rules is a direct mapping of the decision tree obtained in R (see Fig. 2).

Therefore, a total of 12 rules were defined; since, there were types of courses defined with only one rule (types R and S) and other ones with two or three rules (types I, C, E and B).

```
;;*****************
;;* INITIAL STATE *
;;*****************

> (deftemplate course
           "Template far the description of the course"
           (slot IdCourse (type INTEGER))
           (slot Resources (type SYMBOL))
           (slot ResourceViews (type SYMBOL))
           (slot Forums (t ype SYMBOL))
           (slot ForumNews (type SYMBOL))
           (slot Foruminteractions (type SYMBOL))
           (slot Assigns ( t ype SYMBOLJJ
           (slot Assignsubmissions (type SYMBOL))
           (slot Gradeitems (type SYMBOL))
           (slot GradeFeedbacks (type SYMBOL))
           (slot Type (type SYMBOL))
)
```

Fig. 4. Facts template for the expert system.

```
(detrule course_repository
           "Type Repository
           ?f <- (course (IdCourse ?id)
                 (Resources ~Low) (ResourceViews ~Low)
                 (AssignSubmissions Low) (ForumInteractions Low))
           =>
           (modity ?t (Type R))
           (printout t ?id "is Type R" crlf)
)
```

Fig. 5. Example of rule for the expert system.

B. Validation

The chosen method for validation was “validation against a group of experts” based on the one of Mosqueira-Rey et al. [39], which we had used before successfully [40]. This method provides a measure of agreement between the human experts and verifies if the expert system performs as one of them. In that case, it can be incorporated into the group of experts keeping the agreement level.

TABLE III. Expert System Vs. Human Experts

	Human Expert 1	Human Expert 2	Human Expert 3	Human Expert 4	Human Expert 5
Expert System	I S R C E B	I S R C E B	I S R C E B	I S R C E B	I S R C E B
Inactive – I	20 0 0 0 0 0	20 0 0 0 0 0	20 0 0 0 0 0	9 0 11 0 0 0	20 0 0 0 0 0
Submission – S	0 16 0 0 0 4	0 11 0 0 3 6	0 13 0 0 3 4	0 9 0 0 4 7	0 13 0 0 3 4
Repository – R	0 0 20 0 0 0	0 0 20 0 0 0	0 0 20 0 0 0	0 0 20 0 0 0	0 0 20 0 0 0
Communicative – C	0 0 0 19 0 1	0 0 0 16 0 4	0 0 0 16 0 4	0 0 0 19 0 1	0 0 0 15 0 5
Evaluative – E	0 0 0 0 18 2	0 0 0 0 18 2	0 0 0 0 18 2	0 0 0 0 18 2	0 0 0 0 18 2
Balanced – B	0 0 0 0 0 20	0 1 0 0 0 19	0 1 0 0 0 19	0 4 0 0 0 16	0 0 0 0 0 20

TABLE IV. Values of Weighted Kappa

	Human Expert 1	Human Expert 2	Human Expert 3	Human Expert 4	Human Expert 5	Expert System
Human Expert 1	–	0.89	0.87	0.78	0.93	0.93
Human Expert 2	0.89	–	0.98	0.79	0.94	0.84
Human Expert 3	0.87	0.98	–	0.77	0.92	0.86
Human Expert 4	0.78	0.79	0.77	-	0.77	0.71
Human Expert 5	0.93	0.94	0.92	0.77	-	0.86
Expert System	0.93	0.84	0.86	0.71	0.86	-

In this experiment, the group of experts consisted of five experts on LMS usage, that is, they were at the same time both teachers with a high level of experience using LMS and researchers in LMS. Since it involved a large workload for one person to evaluate all the courses used to establish the expert system, 20 courses of each typology (120 courses in total) were randomly selected. To classify courses, the experts analysed both the course structure in Moodle and the teachers and students' activity recorded in logs by considering the description of the types of courses obtained above (see Table II). The experts were also asked to talk about the difficulty when classifying the courses and to give their opinion on the quality of the classification scheme.

Table III shows the agreement among the human experts and the expert system for the 120 courses. First column indicates the class obtained by the expert system, 20 courses of each typology, and the other five columns incorporate the classification given by each of the five experts.

Firstly, we can observe that, in general, the human experts agreed with the expert system, especially in the types of courses classified by the expert system as I, R, B and E, and somewhat less in types S and C. Moreover, in most cases, when the human experts differed from the expert system, they classified the course as B type. Therefore, results show also that the type B is the most difficult to identify correctly by the expert system, which is coherent with the sensitivity for B class, as observed in Fig. 3.

The level of agreement between each pair of experts (humans and system) was measured through the weighted kappa [39], which most often deals with data resulting from a judgement. Values of kappa higher than 0.80 indicate an almost perfect agreement whereas values in the range 0.61–0.80 indicate a significant agreement [41]. The results of the measure of kappa (see Table IV) show a good agreement between the expert system and the group of experts. The level of agreement between the expert system and each human expert varies from a significant agreement (kappa = 0.71, with Expert 4) to an almost perfect agreement (kappa = 0.93, with Expert 1), similar to the level of agreement obtained between the human experts.

Fig. 6 shows a heatmap with the level of agreement between the experts and the expert system to analyse visually the results of Table IV. Here, we can see a high degree of agreement provided by the expert system, although it is not perfect. We can also check how there is no total agreement even among the human experts themselves, with expert 4 being the one with the lowest level of agreement with the rest of the experts. This shows how complicated it is to classify courses and how the existence of a system that automates the process is an important advance. Moreover, this is connected to the difficulty and the time spent by experts to classify the courses, since they related that it is not a trivial task.

Finally, it is important to comment the opinion of the experts on the quality of the classification scheme defined by the expert system. They thought that it was very useful and in tune with a subjective analysis of the courses. In addition, they valued positively that it was not a gradual classification but different types of use.

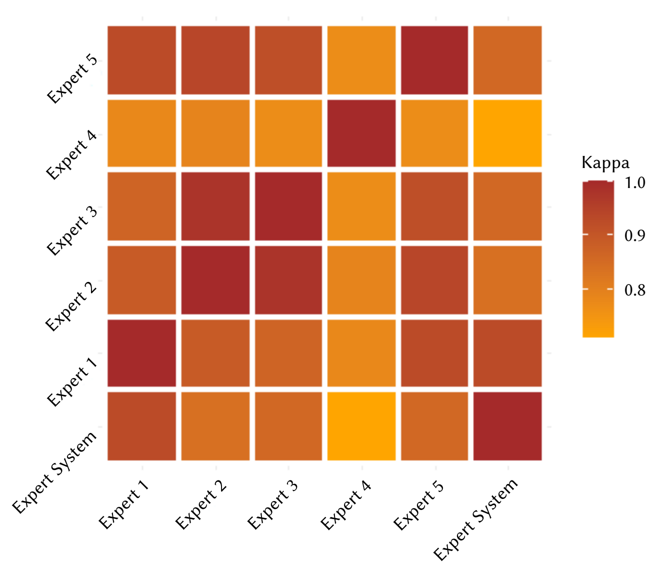

Fig. 6. Heatmap of agreement between experts and the expert system.

V. Conclusions

We propose an expert system that satisfactorily classifies the courses according to their usage, by both teachers and students. The expert system estimates the typology of the courses according to the real LMS use of students and teachers. The system has been tested with real data and the results have been successfully validated against human experts.

The information provided by the expert system can also be used for reinforcing teachers' continuance commitment to e-learning, when the perceived self-efficacy is not enough [7], [26]. Besides, it could be adapted to be used by academic administrators in some type of professional career development program, what, in fact, could contribute to Academic Analytics adoption for improving the learning environments, as suggested by some researchers [42], [43].

A generalized comment from the experts was how difficult it was for them to manually classify many of the courses, so they valued very positively that there was a tool capable of automating this process.

This clustering based expert system could support human experts for quick identification of different course types, providing an understanding of how they differ, just like it occurs in other fields [44]. Atypical usages could be also identified for further study.

The experiment may have some limitations that would need to be addressed in further research. For example, many universities offer mainly face-to-face courses and the LMS is only a complement to the face-to-face methodologies. This is an important source of data noise and bias when trying to qualify the online usage of the LMS. Another limitation is the hidden relationship between course categories and time-dependent patterns of events. This experiment only addresses aggregated features over one semester, while it would be valuable to measure the temporal distribution of some features. Some researchers suggest that exploiting time-dependent nature of learning data is both viable and desirable [29]. Moreover, some important subjective aspects such as students' motivation and satisfaction have shown to be sensitive to temporal patterns [2]. These could be used to obtain a better characterization of courses by finding correlations between the structural organization and the emotional effect caused on students.

Future expert system should also incorporate teachers' opinion about the typology of their courses, since they have the best understanding of their learning goals and contexts [6]. Teachers' input could be used to adjust the model.

Finally, a complete intelligent system could incorporate a module to recommend teachers best practices according to the way in which they would like to teach. Teachers would select a course typology. Then, the system would make a proposal about which tools they should use, and some best practices observed in courses of that type with good students' performance and satisfaction.

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