A comparative analysis of the automatic modeling of Learning Styles through Machine Learning techniques

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***Abstract*—This Research Full Paper introduces a machine learning methodology to automatically identify the learning style of students interacting with a Learning Management System. Studies in Cognitive Psychology and Pedagogy have already reported that each individual has a specific Learning Style, which describes her/his best means of perceiving and acquiring knowledge. The detection of the personal Learning Style of each student has long been made by using questionnaires; an analysis that demands too much effort, mainly in courses with hundreds of students. Therefore, the automatic modeling of learning styles has gained attention in the computing and education areas. This study compares different Machine Learning algorithms for the detection of students' Learning Styles. As such, a dataset is extracted from a real course in the Moodle learning platform. This course had 105 students interacting with 252 learning objects during 12 months. The learning styles were described using the classic model of Felder- Silverman. According to the experimental results using these data, a single machine learning algorithm was not able to induce models with predictive accuracy comparable to those from existing alternatives. However, when models from different algorithms were combined, it was possible to obtain a predictive accuracy superior to those reported in the related literature.**

I. Introduction

The concept of Learning Styles (LS) has motivated a large number of research projects both in computing and education. It all started after student-profile models improved the processes of teaching-learning. This is the case, for instance, of content recommendation based on the students' preferences, which can make teaching more effective by improving the students' learning performance. LSs can be detected through questionnaires answered by the students. However, although accurate, these questionnaires have limitations. Several authors [1–3] reported them as imprecise, as they directly depend on current knowledge and motivation of the students to answer the questionnaire. This approach demands a laborious effort to create questionnaires and their resulting model is static. In fact, as LSs can vary over time [4], style model must also vary, otherwise, it will become outdated.

An alternative to overcome this problem is the use of automatic modeling. Since automatic modeling is independent of the forms and of the students' knowledge regarding their own preferences, they usually are more accurate than questionnaire-based detection. In automatic modeling, the student's model is built dynamically, adopting a learning model when the user interacts with a learning management system. As a result, it maintains a concise classification even if the student LS changes.

This paper investigates the use of machine learning algorithms in the classification of LSs using data from the Moodle learning platform. In particular, we propose and evaluate the use of a set of different algorithms, from distinct machine-learning paradigms to classify the students according to their interactions with a learning management system. As such, Moodle data from a Speech Therapy course, to which the Felder-Silverman model of LS was applied, is used [5]. This model was chosen because it synthesizes findings from several studies in four specific dimensions: **(i)** active/reflexive, **(ii)** visual/verbal, **(iii)** sequential/global, and **(iv)** sensorial/intuitive. According to the experiments performed in this study, the predictive performance obtained by combining predictive models induced by different machine learning algorithms was superior to those obtained in the related literature.

The remainder of this paper is structured as follows: Section II presents concepts required for the understanding of this research; Section III describes related works; Section IV outlines the proposed methodology; Section V gives details about the experiments and analyze the results obtained; final considerations, conclusions, and future directions are presented in Section VI.

II. Background

A. Learning Styles (LS)

According to Jonassen and Grabowski [6], each student has unique characteristics that define her/his profile, including, but not limited to, **(i)** previous knowledge in certain contexts, **(ii)** cognitive abilities, **(iii)** motivations, **(iv)** social references, and **(v)** LS. The term LS does not have a specific definition, but can be understood as a description of the actions and behaviors that determine the preferences of a given student during the learning process. Keefe [7] provides the most accepted definition, which considers LS as *"a composite of cognitive, affective, and physiological factors that serve as relatively stable indicators of how a student perceives, interacts and responds to the learning environment"*, whereas Felder [8] defines such term as *"characteristics and preferences in the way students collect and process information"*.

Many educational theorists and researchers regard LS as an important factor in the learning process and agree that

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incorporating them into classes has the potential to make the knowledge acquisition easier for students [9]. Felder [5], for instance, claim that students with a strong preference for a specific LS may have difficulty in studying if their Learning Style is not supported by the teaching-learning process. On the other hand, it can be assumed that incorporating the students' LS into the learning methods makes learning easier and effective.

B. Felder-Silverman Learning Styles model (FSLSM)

The dimensions proposed by Felder and Silverman [5] relate to the strategies of capturing, perceiving, organizing and processing information during the learning process. The authors synthesized findings from several studies resulting in a model of Learning Styles composed of four dimensions: **(i)** processing, **(ii)** input, **(iii)** perception, and **(iv)** organization. This approach was developed and validated by a group of engineering students and became one of the main models of Learning Styles adopted in studies about adaptive learning. The four dimensions of the FSLSM are defined as follows:

- **Processing (active vs. reflexive).** Active students need to experiment to understand, they can start the assignments prematurely and they enjoy working in groups. Reflective students need to understand to experiment, they take time to start activities and prefer individual assignments.
- **Input (visual vs. verbal).** Visual individuals have a better comprehension of the information presented through visual approaches. Verbal individuals prefer learning by reading and hearing.
- **Organization (sequential vs. global).** Sequential students organize the information in details to derive understanding about generalized information. Contrarily, global students organize the information in general rules so to achieve further, more detailed, information.
- **Perception (sensory vs. intuitive).** Sensory individuals make decisions and perceive information heavily based on their four senses. Intuitive individuals have higher ability to distinguish and interpret symbols and texts.

Felder-Silverman's model was chosen due to several reasons. As previously mentioned, it combines important discoveries from other authors, including Kolb [10], Pask [11] and the Myers-Briggs Types Indicator [12]. Another important feature is its ability to identify the students' Learning Styles; the authors developed a questionnaire containing 44 questions (11 questions for each dimension), called Index of Learning Styles, (ILS) [13] that points out the preferences of each individual according to their model. Finally, the FSLSM is the most employed model for automatic modeling of students [14, 15], it is widely used in adaptive systems, showing good results in the classification of profiles and in content recommendation tasks.

III. Related Work

Several approaches have been proposed for the automatic identification of Learning Styles in virtual learning environments. Next, those more related to this study are briefly described.

García [1] used Bayesian networks to observe 11 patterns of behavior in 10 students enrolled in an online Artificial Intelligence course. They validated their proposal through a systematic comparison between the results obtained by the algorithm and the results indicated by the ILS questionnaire, which was answered by the students at the beginning of the course. Additionally, they proposed the Virtual Assistance Software for Remote Education (SAVER), which calculates the students' preference in the dimensions of the FSLSM.

Graf, Kinshuk, and Liu [2] proposed an automatic identification of LS in learning management systems based on students' interaction. The authors explored rule-based techniques to assess the correlation between patterns of behavior and the Felder-Silverman model. The authors validated their proposal over 75 students, comparing the results of the automatic approach with those obtained through the ILS questionnaire. The experimental results presented accuracies of 79.33%, 76.67%, 73.33%, and 77.33% in processing, input, organization, and perception dimensions, respectively. They also proposed a tool to identify LS in web courses, named Detecting Learning Styles (DeLes).

Another approach for the automatic modeling of students using the FSLSM was proposed by Dung and Florea [3]. They evaluated their approach over a nine-month course on Artificial Intelligence with 44 undergraduate students, all of which also answered the ILS questionnaire. Their approach was based on rule mapping, considering the number of visits and the time spent by the students in each one of the 204 learning objects of the learning management system analyzed. Their methods achieved accuracies of 72.73%, 79.54%, 65.91%, and 70.15% in the dimensions of processing, input, organization, and perception of the FSLSM, respectively. Additionally, the authors generalized their findings and the proposed method on an adaptive system named POLCA.

Liyanage *et al.* [16] proposed a framework for adaptive systems divided into three phases. In the first, they applied the ILS questionnaire to assess the students' LS according to the FSLSM. In the second phase, they recommended learning objects based on each student's LS. In the third phase, they provided the teachers with tools to calibrate the engines of the adaptive system. Experiments were conducted over 80 students enrolled in a Moodle system and reached accuracies 65.00%, 76.25%, 77.50%, and 75.00% for the dimensions of processing, input, organization, and perception, respectively.

As pointed out by Truong [15], despite the variety of works performed in the area, there are still open questions and gaps to be investigated. One of them is that, although many classification algorithms have been explored, among which Bayesian Networks and Rules-based are the most widely used, only a small proportion of papers experimentally compares classification algorithms Another open issue pointed out by Feldman *et al.* [14], is that the automatic modeling of Learning Styles, in general, is characterized by sets of students with low cardinality. In fact, small populations of students are used:

10 [1], 44 [3], 75 [2], 80 [16].

Regarding the previous works, we define and experimentally investigate a method based on multiple techniques. According to the experimental results, each LS dimension is better modeled by a particular machine learning algorithm. By using the most suitable algorithm for each dimension, we improved the predictive accuracy obtained by the previous works. Furthermore, we use preprocessing techniques for class unbalancing, attribute selection, and instance filtering; in every case, we were able to improve the predictive performance. Finally, we used a dataset and a period of time significantly larger than those used in previous works.

IV. Materials and Methods

A. Context, participants and course characteristics

The data used comes from a postgraduate course in Speech Therapy that was fully taught with the support of the Moodle learning platform. This course, which usually lasts 18 months, had 105 students enrolled from all over Brazil. These students interacted with each other through discussion forums and communication-tools available in the learning platform. At the beginning of the course, the students answered the ILS questionnaire to record their preferences according to the FSLSM dimensions. Statistics from the filled questionnaires are presented in Table I, which indicates the percentage of preference in all four dimensions.

Table I: ILS questionnaire statics.

Processing	
Active	Reflective
79,38%	20,62%

Input	
Visual	Verbal
53,61%	46,39%

Organization	
Sequential	Global
69,07%	30,93%

Perception	
Sensing	Intuitive
87,63%	12,37%

From the Moodle platform, we collected usage logs in the interval of September 2015 and August 2016. During this period, students interacted with 252 educational resources.

B. Learning objects

The course we analyzed offers a high diversity of educational resources to the students. In Figure 1, it is possible to observe the distribution of educational resources available in the course. Textual materials and video lessons are predominant (70 and 54 objects respectively); this agrees with what is seen in most courses offered through learning management systems. Video files of teacher explanations and text materials are fundamental because they bring together the online learning experience and the traditional learning. The distinction of materials (video or text) is relevant for the Learning Style classification according to the FSLSM; this is due to the input dimension of the model, which differentiates individuals between visual and verbal.

The high number of discussion forums available in the course (total of 44 threads) stands out. This is mainly due to the geographical separation of the students, who used this tool as the main course-communication mechanism. A high amount of data was generated as a result of interactions in discussion forums, such as topic creation, views, responses, and posts. These interactions were recorded daily, which characterizes a high communication among all participants, who were strongly encouraged to use the system. This type of resource is often adopted in learning management systems because it supports collaborative learning among students.

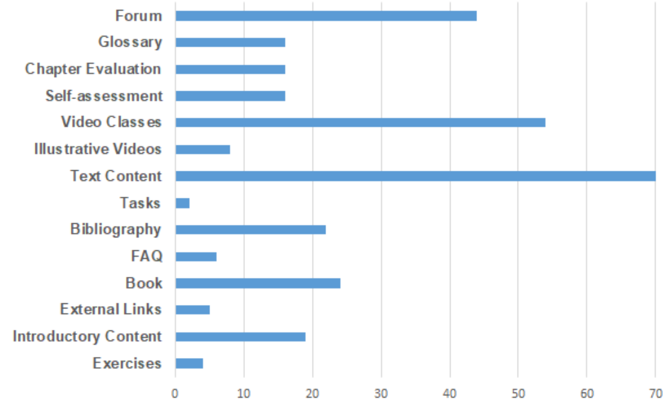

Figure 1: Learning resources available in the course.

Additionally, books, introductory materials, and references were also commonly used during the course. The books have an objective similar to the textual material previously mentioned, but they differ in how they are presented. In this case, the student can navigate the content in an orderly and sequential way. Students with a predilection for this type of resource may be more inclined to the sequential LS of the FSLSM, whereas those with a preference for conventional texts may be identified as global.

Besides, self-assessment forms, chapters review, and glossaries provide important information to the understanding of the students' behavior. For instance, glossaries require users to interact with each other and self-assessment forms assess the student's performance and satisfaction. Thus, it is clear that this information provides relevant characteristics about the students.

C. Behavior patterns

FSLSM, like other models proposed in the literature, is based on the concepts from traditional learning. For this reason, to be able to detect Learning Styles automatically, it is necessary to map the behavior of the students from traditional learning environments to the actions they perform in a learning management system. To this end, we explored a set of interactions and behaviors capable of describing the preferences of each student during the learning process in a learning system. These patterns of behavior were strongly influenced by the studies of Garcia *et al.* [1], Graf [2], and Dung and Florea [3], which mapped user usage-patterns in Moodle systems regarding the FSLSM.

The major requirement of this task is that the behavioral patterns must be relevant enough to support the automatic prediction of LS. Thus, the observed data must be representative enough to the machine-learning algorithms to infer efficient and accurate models. Although the experiments conducted in this research were carried out with data extracted from the Moodle system, the methods proposed through the experiments can be generalized and replicated to different learning systems.

Based on the previous discussions, we selected a subset of data to be incorporated into this experiment. This subset includes learning objects from the didactic material: basic readings within each discipline, sample materials, videos, self-assessment forms, chapter reviews, exercises, FAQ pages, bibliographic references, and communication resources (forum and glossary). The interaction of users and data was taken into account by considering the number of visits that each object received and the average time spent during the accesses.

In the case of the books, we counted the number of page changes. The same information was collected regarding access to basic readings, examples, videos, FAQ pages, bibliographical references, and training exercises. For the self-assessment forms, we considered more detailed information, the number of answered questions and the time spent during the test. For the glossary-activities, we used information about the number of visits to the glossary pages, the time spent and the number of publications of each student. Finally, to the communication resources, we included the number of visits to the forum topics, the number of topics created by each user, the number of posts, the average time spent in the forum, the number of searches, and the average number of words per publication. Table II summarizes all the patterns of behavior that are investigated in this proposal.

D. Automatic modeling of Learning Styles

Machine learning allows the extraction of new and useful knowledge from previous experiences. One of the main machine learning approaches, use labeled objects to induce predictive models. In classification tasks, each label corresponds to a class, *i.e.*, the classification answer that the learning algorithm must take into account to learn a classification model able to accurately predict the class label of new, unlabeled, objects. The first step in the application of a supervised learning algorithm to a classification task is to collect and label a set of objects, named dataset. Part of this dataset will be used as training set. Next, in a training phase, the supervised learning algorithm will be applied to the training set to induce the classification model.

The training set is composed of a collection of objects, each described by a set of independent predictive attributes, able to the main characteristics of the object. Notice that the predictive attributes must represent meaningful and relevant information about the real-world object (students in our case). Additionally, it is necessary to inform the class of each object, target attribute, so the learning algorithm can associate predictive attribute values to the correct class.

Several supervised learning algorithms have been proposed in the literature for classification tasks. They use concepts of statistics, linear algebra and logic to induce a predictive model able to map predictive attribute values to the correct class label. The induced models must have a high generalization ability, being able to, given the predictive values of a new, previously unseen, object, predict its class label with high accuracy.

In a test phase, the predicted performance of the induced model is assessed using an independent, test set. In this phase, the class predicted the model for several unlabeled objects are compared with the true class of the objects. The number of misclassifications is used to compute a predictive performance evaluation metrics.

E. Experimental protocol

We started our experiments by building the dataset to be used. For such, we considered each student as an observed object of the training set. For each student, a set of attributes describing their characteristics and preferences was collected from the Moodle system and were associated with the user. Those attributes correspond to the patterns of behavior described in Table II. All information extracted from Moodle was obtained through SQL queries in the course database. Once we

Table II: Observed patterns of behavior.

Group	Resources	Extracted data
Learning materials	Basic readings	Views; Time spent.
	Book	Views; Time spent; Navigation.
	Text content	Views; Time spent.
	Video content	Views; Time spent.
Activities	Tasks	Views; Time spent.
	Exercises	Views; Time spent.
Support materials	FAQ	Views; Time spent.
	Bibliography	Views; Time spent.
	External links	Views; Time spent.
Interaction	Discussion Forums	Posts; Searches; Time spent; Topic visits; Forum visits; Word average; Topic creation.
	Glossary	Posts; Views; Time spent.
Evaluation	Self-assessment	Views; Time spent; Answered questions.
	Chapter review	Views; Time spent; Answered questions.

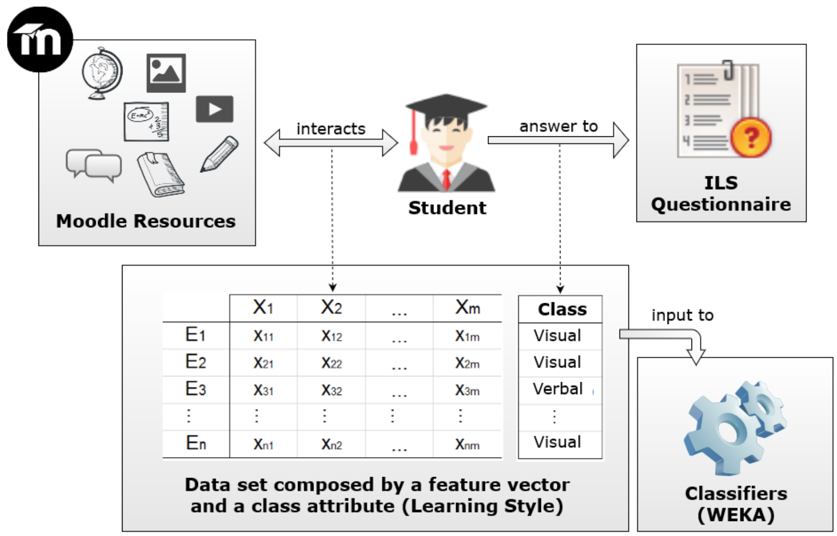

Figure 2: Learning Styles automatic modeling methodology.

labeled the educational resources, the queries in the user logs served to sum the total visits (and other information) of the students in each learning object.

In addition to this information, each object received a label corresponding to the student Learning Style — identified through the ILS questionnaire; all the steps are shown in Figure 2. At the end, the dataset consisted of 105 examples, where each example corresponds to a student. In addition, 35 attributes were considered to describe the each student behavior. Such numbers are not high when compared to complex problems involving machine learning, but have shown to be able to produce an accurate classification model.

Before the classification, the data were preprocessed to avoid class unbalancing and redundant attributes. In summary, the experiments occurred according to the following set of steps: **(1)** data acquiring from the Moodle system; **(2)** labeling the Moodle data with respect to the ILS questionnaire; **(3)** instance-filtering through class balancing; **(4)** attribute selection; **(5)** classifier training and test using 10-fold cross-validation; and, **(6)** model evaluation through Precision-Recall and F-measure.

Regarding the scope, four classification processes were performed during the experiments, one for each dimension of the Felder-Silverman model. The same dataset was evaluated in four binary perspectives as follows: **(i)** processing dimension (active or reflective); **(ii)** input dimension (visual or verbal); **(iii)** organization dimension (sequential or global); and, **(iv)** perception dimension (sensitive or intuitive). Finally, the resulting classification models were tested in a 10-fold cross-validation, and further assessed through the metrics of Precision-Recall, and F-measure. All the experiments were carried out using Weka[1], an open-source platform that implements a variety of machine-learning techniques. This platform was chosen because it provides several functionalities for the extraction of measures, attributes selection, and analysis of the results.

[1] Available at https://www.cs.waikato.ac.nz/ml/weka/

V. Experiments and Results

The experiments centered on evaluating four paradigms of classification, that are: **(i)** statistical classification, **(ii)** neural networks, **(iii)** instance-based learning, and **(iv)** symbolic classification. In the first category, we used Bayesian networks, Naive Bayes and Support Vector Machine. In the second category, we used Multilayer Perceptron and Weka's DL4J, a deep neural network. The third category focused on the kNN classifier, referred to as IBk, and the K-Star classifier. Finally, in the fourth category, we used the Hoeffding decision tree (J48), Random Forest, and Random Tree. In our experiments, some algorithms did not achieve good classification performance. Thus, in the next sections, we will discuss only the algorithms that achieved the best performance in each of the four paradigms: **(i)** Naive Bayes, **(ii)** Multilayer Perceptron, **(iii)** IBk, and **(iv)** J48.

A. Data preparation

Unbalanced datasets usually harm the predictive of learning algorithms. To reduce this problem, we used the Weka's "Class Balancer" algorithm for data preparation and preprocessing. The Class Balancer assigns weights to the data, assuring that, despite the number of objects per class, the total weight is even to all of them. By doing so, we ensure that no class has preference when compared to the other classes.

Another source of problems that can harm predictive performance is the presence of redundant and irrelevant predictive attributes. Therefore, we applied an attribute selection technique to the balanced datasets. By selecting the most relevant attributes, we also decrease data complexity and training time. We tested the following attribute selection techniques: "CFS Subset Eval", "Correlation Attribute Eval", "Info Gain Attribute Eval", "Principal Components", and "Wrapper Subset Eval". Among them, we selected "Wrapper Subset Eval", due to its superior ability in increasing the accuracy of the classifiers.

We observed that the "Wrapper Subset Eval" focused on removing from the target data, information about the forum discussions, which corresponds to the number of topics, visits, searches, and publications that were made/created by each student. This may be due to the high degree of interaction between students in the forum threads, which reduce the importance of the other learning objects.

B. First experiment

Figure 3 presents the predictive performance of the classifying algorithms for the post-processed data considering each dimension of the Felder-Silverman model. These approaches reached a maximum accuracy of 79.4% (Naive Bayes), 76.2% (IBk), 76.3% (Naive Bayes), and 85.9% (IBk) while classifying students in the dimensions of processing, input, organization, and perception, respectively. Clearly, not a single technique was able to provide the best classification in all the dimensions. This is not surprising since each algorithm has a bias that makes it more suitable for particular data conformations.

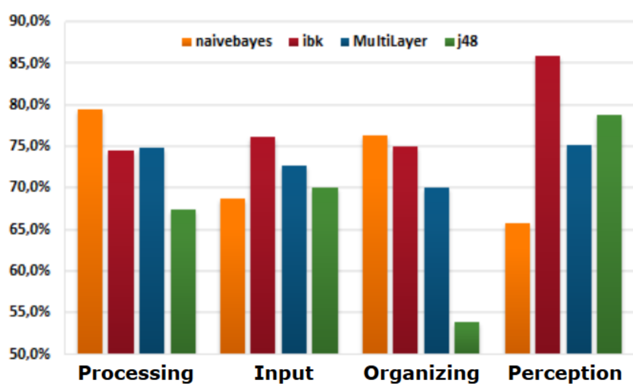

Figure 3: Comparative analysis of classifiers accuracy.

The Bayesian learning paradigm (Naive Bayes) obtained the best performance in the processing and organization dimensions, whereas the instance-based learning paradigm (IBk) had the best performance in the input and perception dimensions. Considering the average accuracy over all the dimensions, the IBk achieved the highest performance, with an average of 77.9%, whereas the J48 algorithm obtained the worst, nearly 67.6%. According to the experimental results, the best classifier to infer Learning Styles, through this set of methods, is the IBk from the instance-based learning paradigm. However, we already assumed that the use of a single classifier is not suitable enough for all the dimensions. For this reason, the best approach is to combine the classifiers from the Bayesian (Naive Bayes) and instance-based learning (IBk) paradigms to provide a more accurate classification.

Regarding the dimensions of the Felder-Silverman model, the results showed that the perception dimension was the most suitable for the classifying techniques, reaching more than 85% of accuracy, followed by the dimensions of processing, input, and organization. These results allow investigating the identification of which characteristics led to the success (or failure) of the classification. Such meta investigation can provide clues about how to improve the online content of a given course, improving the learning process and fine-tuning the content recommendation.

C. Refining results with instance filters

There are some advantages in using the Felder-Silverman model; one of them is the possibility of applying the ILS questionnaire, which defines a straight manner to identify the Learning Styles in a discrete scale of $[-11, 11]$. The quantitative analysis of these values reveals how much an individual is inclined to a certain style. In this way, an adaptive learning system can differentiate the student behavior, according to how much the student is aligned with some style. We are assuming that this differentiation can bring more precise results to tasks of learning personalization.

According to Felder and Silverman [5], a student who answers the ILS questionnaire, and scores between -3 and 3 for a certain FSLSM dimension, can be considered neutral in relation to that style. The authors explain that there are cases in which the student is not necessarily adherent to a dimension, and therefore, presents a balanced classification with respect to the two possible behaviors. Some studies in the related literature explore the student modeling considering only individuals strongly inclined to a Learning Style. Thus, all the individuals scoring above -3 and bellow 3 are removed from the classification training set of the assessed dimension. In another approach, other studies created a third label — the "neutral" one — to the automatic classification of Learning Styles, with the aim of considering all observed students as part of the training set.

Along these lines, we proposed a refinement on our own approach, considering that the more strongly inclined a student is to a particular style of learning the more accurate should be the classification. This refinement includes the information about the ILS score in the task of data preparation, providing more resources and information about the student and further enhancing the classifier decision-making accuracy.

This data preparation can be understood as a filtering step, in which only individuals strongly aligned to the Learning Style will be considered during the training phase. This approach seeks evidence that stronger patterns of behavior in learning systems can more effectively model the machine learning algorithms.

D. Second experiments

Figure 4 illustrates the predictive accuracy of the algorithms over the specialized data that just contains individuals well-aligned to a specific learning style. The results point to maximum accuracies of 82.2% (IBk), 84.6% (J48), 83.7% (Multilayer Perceptron), and 89.8% (IBk) for the dimensions of processing, input, organization, and perception, respectively. The new strategy resulted in a significant progress in the accuracy when compared to the first experiment, which reached 79.4%, 76.2%, 76.3%, and 85.9% of accuracy in the same dimensions. It is possible to conclude that the automatic modeling of students' Learning Styles based on patterns of behavior tends to produce better results for students who are strongly inclined to a specific LS.

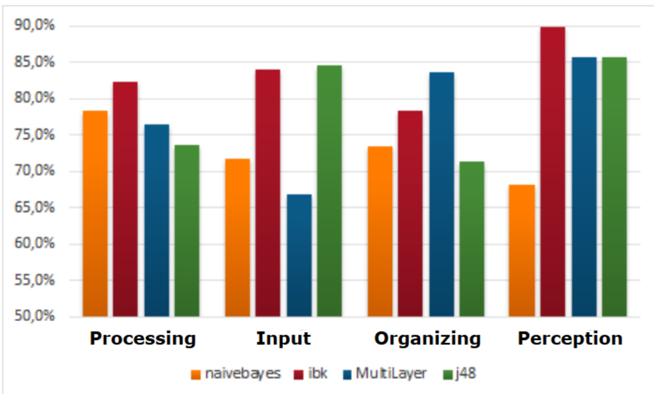

Figure 4: Analysis of classifiers with refined objects.

Regarding the performance of each technique, the experiments demonstrated that the instance-based learning (IBk) paradigm reached the best accuracy in the dimensions of processing, input, and perception, whereas the neural network (Multilayer Perceptron) paradigm reached the best precision for the dimension of organization. The Decision Tree Induction Algorithm J48, in turn, presented the most significant improvement when compared to the first experiment, being as accurate as the IBk for the input dimension. Again, the IBk classifier obtained the best average of precision in all the four dimensions now with an accuracy of 83.6%. Consequently, this experiment validated the findings from the previous experiment, showing that the best classifier to infer Learning Styles in all the dimensions of the FSLSM is the IBk from the instance-based learning paradigm.

Regarding the dimensions of the Felder-Silverman model, the results showed that the perception dimension is the most suitable for the classification techniques, reaching more than 89% of accuracy using the IBk classifier and more than 85% through the Multilayer Perceptron and the Decision Tree J48.

E. Discussion

This section aims to demonstrate how different machine-learning algorithms perform while classifying Learning Styles. In short, we performed a comparative analysis of several algorithms with different configurations, in addition to a variety of preprocessing techniques, so to establish an adequate experimental protocol. The experiments allowed the validation of the proposed methodology, as well as the validation of the case study. Also, we have reported that our approach achieved a feasible performance when applying machine learning for the automatic modeling of the students' Learning Styles.

When comparing our results to those from related work, our experiments demonstrated similar results regarding the predictive accuracy in all of the cases. In the dimension of perception, our method presented the best result; in the dimension of input, our accuracy was similar to the best observed in the literature, 84.6% against 85.7%. Comparatively, our worst performance was in the dimension of processing, in which the work of Abdullah [17] achieved 90.0% of accuracy against 82.2% of our method. However, the work of Abdullah considered only 35 students, while we considered 105 students. Regarding the dimension of organization, Sena et al. [18] had the best performance, however, it is noteworthy that the authors of this work did not experiment with real data, but only on simulated data.

As pointed out in Table III, the results presented in this proposal outperform the literature that explores the automatic modeling of Learning Styles, such as Garciá et al. [1], Graf et al. [2], Dung and Florea [3], and Cha et al. [19]. Additionally, the accuracy obtained by the second experiment is similar to the ones from recent studies [16–18], supporting the effectiveness of the proposal. A comparative analysis of the precision achieved by other studies does not necessarily reflect an advantage of our approach. This is because each study was performed using different datasets and experimental protocols, considering different students, resources, and course characteristics. Nevertheless, we emphasize the importance of data preprocessing techniques, because our results were significantly impacted by approaches of class balancing, attribute selection, and the filtering of well-aligned students with the analyzed Learning Style dimension.

Table III: Comparing precision with related work.

Authors	Act/Ref	Vis/Ver	Seq/Glo	Sen/Int
García *et al.* [1]	58.0%	—	63.0%	77.0%
Graf *et al.* [2]	79.3%	76.7%	73.3%	77.3%
Dung and Florea [3]	72.7%	79.5%	65.9%	70.1%
Liyanage *et al.* [16]	65.0%	76.2%	77.5%	75.0%
Sena *et al.* [18]	86.4%	85.3%	86.8%	84.1%
Cha *et al.* [19]	66.7%	85.7%	71.4%	77.8%
Abdullah *et al.* [17]	90.0%	76.0%	70.0%	85.0%
$1th$ Experiment	79.4%	76.2%	76.3%	85.9%
$2nd$ Experiment	82.2%	84.6%	83.7%	89.8%

The behavioral patterns evaluated demonstrated to be adequate for the LS prediction. For the case study, we conclude that, in general, the IBk classifier achieved the best classification results. Such technique presented efficacy for modeling students in all the investigated scenarios and, accordingly, is able to provide a viable accuracy if applied individually to the prediction of the students' LS. Nonetheless, the combination of two algorithms proves to be more effective in some scenarios rather than using a single one. Finally, the FSLSM perception dimension proved to be the most predictable in both experiments, which allows for a detailed investigation of which are the factors that influenced the results obtained in this dimension.

VI. Conclusion

This paper investigates the use of machine-learning algorithms to characterize learning profiles according to the Felder-Silverman Learning Styles model. To this end, we used data from the Moodle learning platform for 105 students of a Speech Therapy course. Our results are based on the use of preprocessing and machine-learning technique, proposing ways to improve the automatic modeling of Learning Styles. We reviewed the performance of four classification techniques: **(i)** Naive Bayes, **(ii)** Multilayer Perceptron, **(iii)** Instance-based Learning, and **(iv)** Decision Tree J48.

The results demonstrated that the Bayesian learning paradigm has the best performance in the dimensions of processing and organization, whereas the instance-based learning paradigm had the best performance in dimensions of input and perception. We showed that these two paradigms can be improved with preprocessing techniques of class balancing, attribute selection, and instance filtering, overcoming some of the more recent works in the literature. We observed that, through our methodology, the perception dimension was the one with the highest potential of prediction when compared to the three other dimensions. The attribute selection and the class balancing had a significant impact on the prediction; besides, the use of a single classifier is not sufficient for all dimensions because the combined use of Bayesian together with instance-based learning provides more accurate results.

Further studies following this work include using more data collected from Moodle, adding new characteristics capable of describe students behavior (such as speech analysis in forums and data collected from social media), and/or using other learning models rather than the Felder-Silverman model. There is also room for investigating the patterns of behavior that render the best predictions and their relationship with Learning Styles. Finally, an evaluation of classification models regarding content recommendation is necessary. This could be an experimental analysis of how much the automatic modeling of Learning Styles influences the students' performance during the process in a learning management system.

Acknowledgment

The authors thank Brazilian agencies CNPq, FAPESP, and CAPES for the financial support.

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