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Motivation and personalization of teaching with machine learning.

Motivación y personalización de la docencia con machine learning.

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ABSTRACT

The motivation of the student causes the teaching experience to be more enjoyable for the student and results in better utilization of the teaching activity. The key is to identify where that motivation lies in order to adapt the content to the student's expectations. The objective of this work is to establish a method to identify the student's motivation regarding the training they are going to receive and be able to personalize the learning experience according to this motivation. To achieve this, we describe an experience in which a machine learning model of decision trees was trained using a voluntary survey generated through LinkedIn. By consulting the LinkedIn profiles of the respondents, a training dataset was created, which resulted in a model that achieved a 72% accuracy rate in a 10-fold stratified cross-validation. During the presentation of the students who enrolled in the activity, the necessary information was captured to generate a test dataset, which was used to validate the trained model. The accuracy rate of this validation was 100%. Although the sample size and predictors used are limited, we believe that this experience sufficiently illustrates the potential of artificial intelligence to identify student motivations and thus personalize the teaching experience, with the aim of increasing motivation and improving student performance.

Keywords. Teaching Innovation, Motivation, Machine Learning, Artificial Intelligence, Decision Trees.

RESUMEN

La motivación del alumno provoca que la experiencia docente sea más grata para el alumno y se genera un mejor aprovechamiento de la actividad docente. La clave es identificar dónde está esa motivación para adaptar los contenidos a la expectativas del alumno. El objetivo de este trabajo consiste en establecer un método para identificar la motivación del alumno sobre la formación que va a recibir, y poder personalizar la experiencia de aprendizaje acorde a esta motivación. Para ello describimos una experiencia en la que se entrenó un modelo de inteligencia artificial de árboles de decisión, a partir de una encuesta voluntaria generada a través de LinkedIn. Consultando el perfil de LinkedIn de los encuestados se generó un dataset de entrenamiento con el que se generó un modelo que ofrecía un 72% de tasa de acierto en una validación cruzada de 10 particiones estratificadas. En la presentación de los alumnos que se inscribieron en la actividad se capturó la información necesaria para generar un dataset de test que se utilizó para validar el modelo entrenado. La tasa de acierto de esta validación fue del 100%. Aunque la muestra y los predictores empleados es escasa, creemos que es una experiencia suficientemente ilustrativa del potencial que tiene la inteligencia artificial para identificar las motivaciones del alumno, y así personalizar la experiencia docente, con el objetivo de aumentar la motivación y mejorar el rendimiento del alumno.

Palabras clave. *Innovación docente, motivación, machine learning, inteligencia artificial, árboles de decisión.*

INTRODUCTION

Santos-Rego (1990) defines motivation as "the degree to which students strive to achieve academic goals that they perceive as useful and meaningful." From the teacher's point of view, it means "motivating students to do something through promotion and awareness" (Campanario, 2002). "Motivating involves predisposing students to actively participate in classroom activities. The purpose of motivation is to arouse interest and direct efforts towards defined goals."

Tapia and García-Celay (1991) classify the goals pursued by students, in a non-exclusive manner, into goals related to the task, goals related to the "ego," goals related to social evaluation, and goals related to the achievement of external rewards. Focusing on the latter objective, we can consider a motivational aspect where the student believes that the training can provide access to social status, economic status, or other external rewards such as scholarships, awards, certificates, or professional promotion.

Motivation in university students is a complex issue influenced by emotional and motivational components and characteristics (Plaza Casado, et., 2020). These factors can enhance student motivation, such as linking new knowledge with previously acquired knowledge, offering meaningful material, organizing learning experiences based on students' needs rather than the teacher's, setting expectations in each class that generate interest for the next lesson, and structuring content in a way that stimulates students' interest (Hernández, 2005).

Despite the concern of most teachers for their students' learning (Alghamdi, 2023; Aragonés-Jericó & Canales-Ronda, 2022), there is a widespread lack of motivation among students to develop a genuine interest in their educational process, often focusing only on passing their courses and completing their degree with minimal obstacles (Anaya-Durand and Anaya-Huertas, 2010). There is a lack of success story (Gómez-Martínez, et al. 2022). Referring to Maslow's hierarchy of needs, it is observed that stress's effect on learning (within certain positive limits) allows for optimal student performance. Therefore, teaching strategies should promote self-motivation in students, particularly in terms of learning to learn and excelling in their educational process (Anaya-Durand and Anaya-Huertas, 2010). Undoubtedly, one strategy that can influence motivation is identifying what the student will use the training for and personalizing the teaching experience accordingly.

Low motivation among university students is a common factor in various fields of study across many countries. This element is recognized as a cause of students' poor learning outcomes and as a generator of attitudes that hinder success. The type and intensity of motivation that students develop are conditioned, among other factors, by the social environment they live in and can lead them to adopt behavior patterns that either foster learning per se or tend towards seeking rewards (Ardisana and Fidel, 2012).

Given these theoretical positions and research, it is clear that both cognitive and motivational components involved in learning need attention (Rianudo, Chiecher, and Donolo, 2003). One method of fostering motivation is the use of questionnaires that identify the aspects that most attract the student's attention. The Motivated Strategies for Learning Questionnaire (Pintrich, Smith, García, and McKeachie, 1991) is a questionnaire that evaluates motivational and cognitive aspects. Using these questionnaires for the personalization of teaching activities (Pintrich and García, 1993) confirms the existence of significant relationships between motivation, activity evaluation, and self-efficacy beliefs with the use of learning strategies.

In this article, we will link this theoretical framework with the identification of student motivation using machine learning techniques. The objective is to establish a method to identify the student's motivation regarding the training they are going to receive and to personalize the learning experience according to this motivation.

HYPOTHESIS AND METHODOLOGY

The objective of this article is to describe an educational experience in which machine learning was used to identify the main motivation of students when seeking this training. The created model was used to a priori identify the student's profile and thus personalize the teaching activity according to their interests.

The research hypothesis is:

H0: Machine learning is a useful tool for identifying a student's motivation to enroll in a training activity.

We will validate this hypothesis if, using machine learning models, we achieve an accuracy rate higher than 70% in predicting the student's motivations in the next experience.

Description of the Experience

As part of the activities of the Camilo Prado Foundation, its main objective is to contribute to teaching and research in Business Economics through training and research programs aimed at both teachers, researchers, professionals, and university students. The Foundation organizes conferences and meetings with experts, research programs in university teaching, training programs for teachers and university students, and awards to promote the teaching and research quality of teachers and researchers, as well as to foster the research excellence of university students.

Within the scope of its activities, a training titled "Machine Learning in Business Economics" was planned for February 15 and 16, 2023:

https://fundacioncamiloprado.org/machine-learning/

The description of the activity was as follows:

"The maturity of machine learning and artificial intelligence (AI) is reflected in its increased adoption across various sectors and poses a real risk of exclusion for entities that do not adopt it. However, this maturity does not mean that the use of this technology is limited to programmers and data scientists. With the right training, any user or researcher, using tools that do not require programming, can undertake a complete machine learning project that can be implemented to optimize business decisions.

The training will primarily use free Machine Learning tools (Gretl, Weka, Knime) with datasets specific to each method, in a participative context, working with data and exchanging ideas about the models obtained, among others."

The topics to be covered were:

• "Introduction to Machine Learning
• Understanding the main types of machine learning.
• Supervised Learning.
- Linear Regression
- Panel Data Models
- Logistic Regression
- Decision Trees
- Random Forest
- Bayesian Networks
- Support Vector Machine (SVM)
• Unsupervised Learning.
- K-means Clustering
- Hierarchical Clustering."

The training was conducted online, and students were required to have access to a set of datasets provided to them. They were also required to install the following software beforehand:

GRETL: https://gretl.sourceforge.net/es.html
WEKA: https://waikato.github.io/weka-wiki/downloading_weka/
KNIME: https://www.knime.com

The objective of the training was to provide students with the skills to use free Machine Learning tools (Gretl, Weka, Knime) with datasets specific to each method in a participative context, all within the span of two days of class.

Data Collection for Training the Model

Three weeks before the seminar, a post was published on LinkedIn to promote the seminar and propose a survey asking the following question:

"What is your motivation for learning #AI and #machinelearning?"

Four possible responses were provided:

- For my Bachelor's/Master's thesis or dissertation
- For my research articles

- For my business decisions
- I prefer intuition over data

The post can be viewed through this link:

https://www.linkedin.com/posts/raul-gomez-martinez-3b2a6927_ia-machinelearning-activity-7023582032614023168-ElIO?utm_source=share&utm_medium=member_desktop

Over the course of one week, the survey received 39 voluntary responses, with the following results:

For my Bachelor's/Master's thesis or dissertation:	26%
For my research articles:	13%
For my business decisions:	54%
I prefer intuition over data:	8%

By accessing the LinkedIn profiles of the respondents and examining the basic information available at first glance, the following training dataset was completed, as shown in Table 1.

Table 1. Training dataset

Gender	Work	Sector	Experience	Formation	Demand_For
H	Si	Consulting	2	Master	TFG
H	Si	Consulting	8	Master	TFG
H	Si	Consulting	5	Grado	TFG
M	Si	Finanzas	5	Master	TFG
H	Si	Educación	17	Grado	TFG
H	Si	Consulting	3	Grado	TFG
H	Si	Finanzas	3	Master	TFG
H	Si	Finanzas	6	Master	TFG
H	Si	Finanzas	3	Master	TFG
H	Si	Finanzas	6	Master	TFG
H	Si	Others	32	Master	Papers
H	Si	Educación	8	Doctor	Papers
M	Si	Educación	22	Doctor	Papers
M	Si	Educación	11	Doctor	Papers
H	Si	Finanzas	10	Master	Papers
H	Si	Finanzas	4	Master	Business
H	Si	Finanzas	6	Master	Business
H	Si	Consulting	19	Master	Business
H	Si	Finanzas	11	Master	Business
H	Si	Finanzas	15	Master	Business
H	Si	Consulting	15	Grado	Business
H	Si	Finanzas	5	Master	Business
H	Si	Finanzas	1	Grado	Business
H	Si	Finanzas	1	Grado	Business
H	Si	Finanzas	3	Master	Business
M	Si	Finanzas	20	Master	Business

H	Si	Finanzas	1	Master	Business
M	Si	Finanzas	19	Master	Business
H	Si	Finanzas	4	Master	Business
H	Si	Finanzas	4	Grado	Business
H	Si	Finanzas	4	Grado	Business
H	Si	Finanzas	24	Grado	Business
H	Si	Finanzas	5	Master	Business
M	Si	Consulting	7	Master	Business
H	Si	Finanzas	5	Master	Business
H	Si	Finanzas	8	Master	Business
H	Si	Others	15	Master	No-Demand
H	No	Others	0	Grado	No-Demand
H	Si	Others	17	Secundaria	No-Demand

RESULTS

Using Weka, a decision tree was trained, which achieved an accuracy of 72% with a 10-fold cross-validation system. Table 2 displays the most relevant information generated during the model training, while the complete output is documented in the Appendix.

Table 2. Weka training information

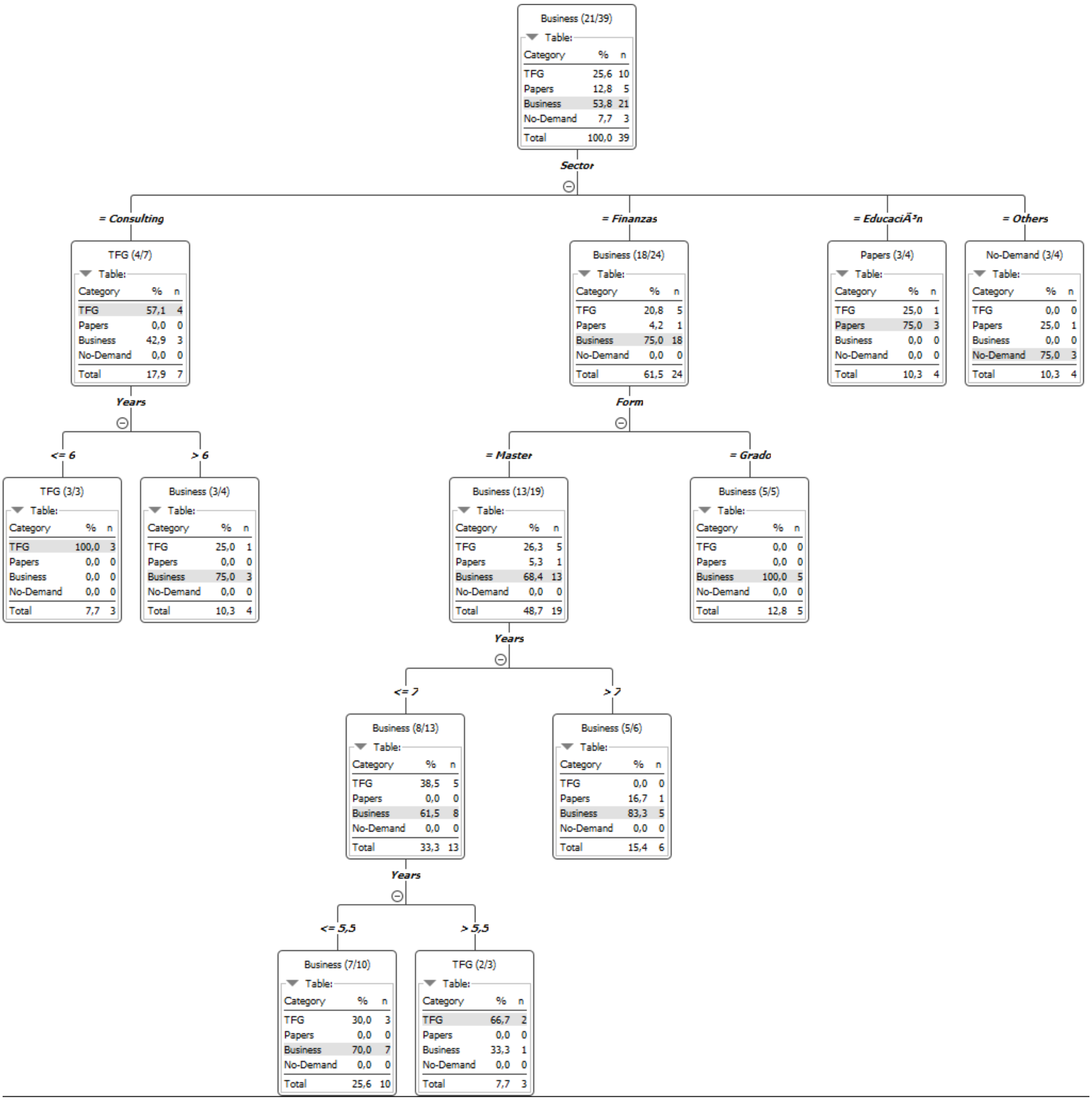
```
=== Run information ===

Scheme:       weka.classifiers.trees.J48 -C 0.25 -M 2
Relation:     Encuesta_Demanda_ML
Instances:    39
Attributes:   6
              ï»¿Gender
              Work
              Sector
              Experience
              Formation
              Demand_For
Test mode:    10-fold cross-validation

=== Summary ===

Correctly Classified Instances          28               71.7949 %
Incorrectly Classified Instances        11               28.2051 %
Kappa statistic                          0.5196
Mean absolute error                      0.2113
Root mean squared error                  0.358
Relative absolute error                 66.1827 %
```

Figure 1. Trained decision tree



The tree from which the rule engine represented in Table 3 can be deduced:

Table 3. Rule engine

```
$Years$ <= 6.0 AND $Sector$ = "Consulting" => "TFG"
$Years$ > 6.0 AND $Sector$ = "Consulting" => "Business"
$Years$ <= 5.5 AND $Years$ <= 7.0 AND $Form$ = "Master" AND $Sector$ =
"Finanzas" => "Business"
$Years$ > 5.5 AND $Years$ <= 7.0 AND $Form$ = "Master" AND $Sector$ =
"Finanzas" => "TFG"
$Years$ > 7.0 AND $Form$ = "Master" AND $Sector$ = "Finanzas" =>
"Business"
```

```
$Form$ = "Grado" AND $Sector$ = "Finanzas" => "Business"
$Sector$ = "EducaciÃ³n" AND TRUE => "Papers"
$Sector$ = "Others" AND TRUE => "No-Demand"
```

During the activity presentation, the students were introduced, and they were told that a "crystal ball" would reveal why they were there. The test dataset for the model, which could be generated from the students' presentations, is summarized in Table 4.

Table 4. Test dataset

Gender	Work	Sector	Experience	Formation	Demand_For
H	Si	Educación	32	Doctor	?
H	Si	Educación	5	Master	?
M	Si	Educación	21	Doctor	?
M	Si	Educación	22	Doctor	?
H	Si	Educación	2	Master	?
M	Si	Consulting	6	Master	?
H	Si	Educación	5	Master	?
H	No	Educación	0	Grado	?
H	Si	Finanzas	2	Grado	?
M	Si	Educación	8	Doctor	?
H	No	Educación	0	Master	?
M	Si	Educación	23	Doctor	?
M	No	Educación	0	Grado	?
M	No	Educación	0	Grado	?
M	Si	Educación	19	Doctor	?

The "crystal ball" was the trained decision tree. Through a Knime workflow, this decision tree was used to predict the students' motivation for attending this seminar. The result of the prediction was that all participants had enrolled in the seminar to improve their scientific output, either for their Bachelor's or Master's thesis or research articles, except for one student whose motivation was to incorporate machine learning into their professional activity. The accuracy rate was 100%.

Given that the students had a predominantly academic profile, as expected due to their association with the Camilo Prado Foundation (which was confirmed by the artificial intelligence model), the seminar cases were personalized to make them more understandable and motivating for the students.

CONCLUSIONS, DISCUSSION, LIMITATIONS

In this article, we have described an experience aimed at using machine learning techniques to identify student motivation. In a public LinkedIn survey conducted prior to the seminar, 39 responses were obtained, which, together with the respondents' profiles, were used to create a training dataset. With this dataset, a supervised machine learning model based on decision trees was trained, achieving an accuracy rate of 72%. This model was then used to predict the objectives of the seminar attendees, resulting in a 100% accuracy rate and contributing to the personalization of the seminar's teaching experience.

Moreover, although the sample size is very small, the predictors are limited, and the test dataset is highly concentrated (almost all participants come from the academic environment), this experience illustrates how easy it is to use machine learning to personalize training proposals and course delivery based on students' interests. In analyzing motivation, future research may take into account the gender issue, contrasting differences between business students (Díez-Martín, et al. 2023).

This article has described an experience with few observations and resources but has had a successful outcome. The challenge will be to apply this methodology, based on artificial intelligence and machine learning, to identify student motivation, which should lead to a personalized teaching experience and ultimately better academic results. In doing it, academics may research about the legitimacy of learning methodologies and students' motivations (Díez-Martín, et al. 2021). Our results may complement previous research worried about how to reduce dropout intention (Olmedo-Cifuentes & Martínez-León, 2022).

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ANEXO

```
=== Run information ===

Scheme:       weka.classifiers.trees.J48 -C 0.25 -M 2
Relation:     Encuesta_Demanda_ML
Instances:    39
Attributes:   6
              ï»¿Gender
              Work
              Sector
              Experience
              Formation
              Demand_For
Test mode:    10-fold cross-validation

=== Classifier model (full training set) ===

J48 pruned tree
------------------

Sector = Consulting
|   Experience <= 6: TFG (3.0)
|   Experience > 6: Business (4.0/1.0)
Sector = Finanzas: Business (24.0/6.0)
Sector = EducaciÃ³n: Papers (4.0/1.0)
```

```
Sector = Others: No-Demand (4.0/1.0)

"Number of Leaves  :    5"
"Size of the tree :     7"

Time taken to build model: 0.01 seconds

=== Predictions on test data ===

inst#,actual,predicted,error,prediction
1,1:TFG,3:Business,+,0.75
2,3:Business,3:Business,,0.75
3,3:Business,3:Business,,0.75
4,3:Business,3:Business,,0.75
1,1:TFG,3:Business,+,1
2,3:Business,3:Business,,0.727
3,3:Business,3:Business,,0.727
4,2:Papers,2:Papers,,0.667
1,1:TFG,3:Business,+,0.762
2,3:Business,3:Business,,0.762
3,3:Business,3:Business,,0.762
4,2:Papers,2:Papers,,0.667
1,1:TFG,1:TFG,,1
2,3:Business,3:Business,,0.727
3,3:Business,3:Business,,0.727
4,2:Papers,4:No-Demand,+,1
1,1:TFG,3:Business,+,0.773
2,3:Business,3:Business,,0.773
3,3:Business,3:Business,,0.667
4,2:Papers,2:Papers,,0.667
1,1:TFG,3:Business,+,0.8
2,3:Business,3:Business,,0.8
3,3:Business,3:Business,,0.8
4,2:Papers,3:Business,+,0.8
1,1:TFG,1:TFG,,1
2,3:Business,3:Business,,0.727
3,3:Business,3:Business,,0.727
```

```
4,4:No-Demand,4:No-Demand,,0.667
1,1:TFG,2:Papers,+,1
2,3:Business,1:TFG,+,0.8
3,3:Business,1:TFG,+,0.8
4,4:No-Demand,4:No-Demand,,0.667
1,1:TFG,3:Business,+,0.762
2,3:Business,3:Business,,0.762
3,3:Business,3:Business,,0.762
4,4:No-Demand,4:No-Demand,,0.667
1,1:TFG,1:TFG,,1
2,3:Business,3:Business,,0.727
3,3:Business,3:Business,,0.727

=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances          28               71.7949 %
Incorrectly Classified Instances        11               28.2051 %
Kappa statistic                          0.5196
Mean absolute error                      0.2113
Root mean squared error                  0.358
Relative absolute error                 66.1827 %
Root relative squared error             90.1411 %
Total Number of Instances               39

=== Detailed Accuracy By Class ===

TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
0,300    0,069    0,600      0,300    0,400      0,302    0,460     0,461     TFG
0,600    0,029    0,750      0,600    0,667      0,629    0,641     0,501     Papers
0,905    0,389    0,731      0,905    0,809      0,546    0,672     0,626     Business
1,000    0,028    0,750      1,000    0,857      0,854    0,972     0,750     No-Demand
Weighted Avg.    0,718    0,233    0,701     0,718    0,689     0,517    0,637    0,577

=== Confusion Matrix ===

  a  b  c  d   <-- classified as
  3  1  6  0 |  a = TFG
```

```
 0  3  1  1 |  b = Papers
 2  0 19  0 |  c = Business
 0  0  0  3 |  d = No-Demand
```

DECLARATION OF CONFLICTING INTERESTS

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

CRediT AUTHOR STATEMENT

All authors have contributed equally to all parts of the work.