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Research Paper

Academic performance problems: A predictive data mining-based model

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ABSTRACT

Often times, universities are not able to deal with the variety of factors that may affect the academic performance of students. This kind of situation generates the need for tools that establish academic performance patterns, setting profiles as a basis to detect potential cases of underachieving students who need support in their academic activities. This paper proposes the use of Data Warehousing and Data Mining techniques on performance, social, economic, demographic and cultural data from students who took "Algorithms and Data Structures", which is a subject in the Information Systems Engineering curricula at UTN-FRRe (Resistencia, Chaco, Argentina) in an attempt to establish generic academic performance profiles. From the descriptive analysis obtained during the 2013 to 2015 period from the subject aforementioned, a predictive model was used. It establishes the possibility of students´ academic failure, taking into account the factors earlier mentioned.

Key words: Academic performance, educational data mining, predictive data mining, higher education, course assessment, student assessment.

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INTRODUCTION

There is a positive correlation between the defection of students and their academic performance that is, the productivity of the student (Maletic et al., 2002). Academic performance is linked to the correct assimilation of contents, other related activities and personal characteristics (social and individual), being a critical element of analysis since it may reflect many features of educational institutions. During the first years of university, the performance impacts strongly on the decision to continue or abandon the studies and that is why universities should focus their efforts on motivating and retaining students who, from the beginning, show shortcomings in their academic performance (Oloriz et al., 2007).

Academic performance can be measured by observing the marks obtained by students when their knowledge, skills and abilities are tested. However, hardly does this evaluation provide any information that can be used to detect and correct cognitive problems and apprehension, etc. This is the reason why other factors which affect directly or indirectly, both social and financial situations should be considered, as well as, prior educational experiences that establish student performance profiles (Tinto, 1993).

Considering that the performance during the first year serves as a very good indicator of the student's future academic career (Oloriz et al., 2007), this paper examines academic performance in the core subject of the first level of the Information Systems Engineering (ISE) career in UTN-FRRe, Algorithms and Data Structures (ADS). This subject has a very high rate of students that either failed or quit it, that is, students who will take the subject again because they failed at the several instances of evaluation. For this reason, there is a need to analyze the existence of socio-economic and behavioral patterns that distinguish different profiles of academic performance.

There are several ways to evaluate academic performance using indicators such as graduation rates differentiated by types of centers and analyzing performance from individual data (Vivo Molina et al., 2004) through the grades obtained in seminars of admission to the University, performing data analysis using statistical technique of "ROC" curve (Receiver Operating Characteristic) (García-Jiménez et al., 2000) or by applying the production function approach to estimate the factors that determine academic performance (Di Gresia, 2007). There are also several studies using mathematical techniques for performance evaluation. In this sense, the capacity of the linear regression and logistic regression in predicting the performance and academic success / failure was studied based on variables such as attendance and class participation (García and San Segundo, 2001).

One way to achieve this is to develop evaluation methods that take advantage of the capabilities of the information technologies available. In this way, Data Warehouse techniques (DW) and Data Mining techniques (DM) are extremely useful tools for obtaining knowledge in large volumes of data. A DW is a collection of data-oriented topics, integrated, non-volatile and variable in time used to support the process of management level decision making (Inmon, 1992). A DM is the knowledge discovery stage in databases which consist of the use of specific algorithms that generate a list of patterns from pre-processed data (Fayyad et al., 2001).

This paper proposes the use of Data Warehousing and Data Mining techniques on the performance, social, economic, demographic and cultural data obtained from students of Algorithms and Data Structure from Information Systems Engineering career in the Facultad Regional Resistencia, branch of the Universidad Tecnológica Nacional (Resistencia, Chaco, Argentina), in order to establish profiles of academic performance characteristics. From the descriptive analysis obtained during the 2013 to 2015 school years in the class aforementioned, a predictive model was used and this established the possibility of students´ academic failure taking into account the factors earlier mentioned.

DATA MINING

Data mining is a process whose purpose is to discover, extract and store relevant information from large databases through search programs as well as, to identify patterns and global relationships, trends, deviations and other indicators.

Its main objective is to exploit the value of localized information by using pre-established patterns to better understand the data and optimize decision making (Larrieta and Santillán, 2004).

Several authors consider data mining an essential step in the process of knowledge discovery in database. It consists of an iterative sequence of steps (Han et al., 2011):

- Data cleansing, to remove noise or irrelevant data;
- Data integration, where multiple data sources can be combined;
- Selecting data, where data relevant to the analysis task are retrieved from the database;
-Transforming data, when the data are transformed or consolidated into appropriated forms for mining operations by, for example, performing summary or aggregation;
- Data mining, an essential process in which intelligent methods are applied in order to extract data patterns;
- Evaluation of patterns, to identify patterns of interest that represent knowledge based on some interesting measures;
- Presentation of knowledge, where visualization techniques and knowledge representation are used to present the user´s knowledge extracted.

Data mining includes the basic algorithms that make it possible to obtain fundamental information and knowledge from massive data. It is an interdisciplinary field of concepts of related areas, such as database systems, statistics, machine learning and pattern recognition. In fact, data mining is part of a process of discovering greater knowledge.

The discovered knowledge can be applied to decision making, process control, information management and query processing among others (Zaki and Meira, 2014).

Data mining algorithms

Data mining algorithm is a set of calculations and heuristic rules that enables the creation of a data mining model from the data. To create a model, the algorithm first analyzes the data provided, looking for specific types of patterns or trends. The algorithm uses the results of this analysis to define the optimal parameters for creating data mining model. Then, these parameters are applied over the data set to extract processable patterns and detailed statistics (Microsoft, 2017). While there are several data analysis algorithms used in data mining solutions, choosing the right algorithm is a challenge because there are different ways to accomplish the same task. Each of them can generate a different result and some can generate more than one type of result. For example, you can use the decision tree algorithm not only for prediction, but also as a way to reduce the number of columns of a data set, as the decision tree can identify columns that do not affect the final data mining model. For these reasons and because it is possible to create groups of people with specific profiles in terms of attributes defined as demographics and behavior the following data mining algorithms are used for this work (Baker and Yaceff, 2009).

Decision trees

This algorithm is most one of the supervised of the

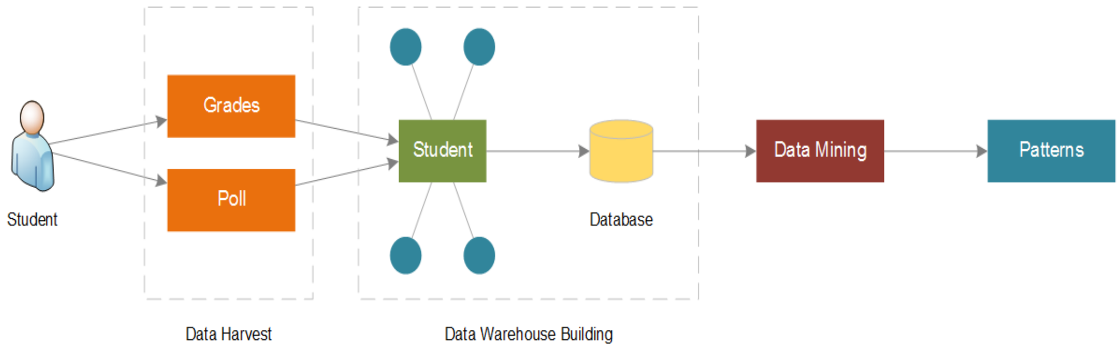

Figure 1: Profile obtaining process.

learning methods used. One of its main virtues is the simplicity of the models obtained (Roche, 2009). The algorithm generates the model by creating a series of divisions in the tree. These divisions are represented as nodes. The algorithm adds a node to model every time an input column has a significant correlation with the predictable column (Microsoft, 2017). A critical step in building a decision tree is to define how to structure these nodes in the tree. A good guide for this is the entropy, which measures the uncertainty associated with a data set and is used to help decide which attribute should be the next to be selected. Basically, an attribute is chosen as the next level of the tree if it can help discriminate more objects and it tends, in fact, to reduce entropy (Theophano, 2010).

A decision tree is a set of conditions or rules organized in a hierarchical structure such that the final decision can be determined following conditions that are met from root to some of its leaves. A decision tree has entries which can be an object or a situation described by a set of attributes and from this returns a response which ultimately is a decision that is taken from the entries. The values that can take the inputs and outputs can be discrete or continuous.

A decision tree performs a test while it is traversed to the leaves in order to reach a decision. The decision tree usually contains internal nodes, chance nodes, leaf nodes and arcs. An internal node contains a test on a value of a property. A node indicates probability that a random event should occur according to the nature of the problem. This type of node is round whereas others are square. A leaf node represents the value returned by the decision tree. The branches provide the possible paths which are in agreement with the decision (Vizcaino Garzon, 2008).

Demographic clustering

This provides a quick and natural grouping of large databases. The number of clusters to be created is automatically determined and these distributions are characterized by the value of its members (IBM Knowledge Center, 2017; Xu et al., 1998). The demographic clustering algorithm builds sets by comparing each record with all groups created previously by assigning the registration of grouping that maximizes a similarity score (Brause and Hanisch, 2000). This is an iterative process that makes multiple passes over the record set before converging to a level of optimum grouping. The quality of a partition is evaluated by a global measure, which favors groups with high similarity. In each step, the algorithm uses this criterion to decide whether to assign a record in an existing cluster or to create a new one. This process ends when the results of the iteration are unchanged in the group (Manganaris et al., 1999).

PROPOSED MODEL

The performance profiles obtaining process consists of different phases namely: data collection, data warehouse assembling and data mining (Figure 1).

Data collection

The first phase involves the collection of the needed information that feeds the subsequent phases for determining the academic performance profiles. These profiles allow relating students who have certain socio-economic characteristics with a certain academic performance (success or failure).

First, to establish the profiles some information about previous academic and socio-economic factors that may affect the student academic performance is required. These aspects were defined by the study group based on previous research. Some of the covered aspects are high school, current residence, time spent studying, employment status of both parents and student, parent's studies and considerations about the use of ITC.

Information regarding the student's academic performance during the school year is also required, including the grades obtained in the different examination instances and practical exercises. Here, the performance over the course was only considered and not the grades of final examinations, since both instances are independent of each other and exceeds the scope of this work. As a result, the participation of both students and professor is required in the obtaining phase. In order to obtain personal aspects, initially the students participated actively giving direct answers. To do so they completed an online quiz on their academic and socio-economic status. The aspects covered were the factors earlier mentioned which have, over the years proven to influence academic development. The students' grades at the different instances of term examinations and their final condition (promoted, regular or free) are provided at the end of the course by the algorithms and data structures class.

DW assembling

There might be incompleteness, inconsistencies and incoherencies throughout the data, because some values of many features do not have certain restrictions. Therefore, the data obtained in the previous step must be subjected to a process of purification: null fields removing or filling, typographical errors correcting and integration with examination results. This process ensures consistency and coherence of the data loaded into the DW.

The structure of the DW model used is very simple; it consists only of a student fact table and several tables for associated dimensions. The fact table includes student's specific information, academic performance and final situation, promoted, regular, or free in the course of analysis. The dimensions are the characteristics over study; they contain descriptive information obtained in the quiz about the student´s socio-economic background.

Data mining

The phase of data mining comes after the DW assembling and loading. For this, some techniques were selected, creating related mining flows, which parameterize the respective algorithms.

The selection of the different algorithms was based on the advantages each one provided. Hence, the clustering technique (Demographic cluster) was chosen. It allows finding useful characterizations for the building of classifiers and also enables the discovery of groups and sub-groups to reveal the nature of the problem structure. The object of this technique is to obtain groups or sets from similar elements. The Decision trees classification technique was used in a greater extent.

Decision trees are easy to use, they provide discrete and continuous attributes support and process properly non-significant attributes and missing values. Their main advantage is the ease of interpretation and useful for high-dimensional problems; the problem is presented for analyzing all options. Their aim is to make classifications on known data and create models with them that can be used to predict or classify new or unknown values.

The previously described techniques were used to determine the performance profiles; they allowed a dimensional analysis of data considering the variable related to the final status of the student as mining parameter determined by their status on the subject at the end of the school year (promoted, regular or free). The results obtained were patterns that determined the data descriptive model from which the performance profiles were estimated.

RESULTS AND DISCUSSION

Dimensional analysis of students

In order to determine academic performance patterns, tests were made to the data of students over the 2013 to 2015 school years, with a total of 615 students. The main parameter taken for the analysis was their final condition at the end of the school year, that is, if the student was "regular", "free" or "promoted", it was considered "free" status of those students who did not pass the term examination or no longer attended the class. Students who "have regularized" the class are those who passed the three term examinations with a score greater than or equal to 60% but did not reach 75%. Finally, students who "have promoted the class" are those who have passed the three instances of examinations with a score of over 75%. According to the data collected, from the 615 students analyzed, 60% were free, 28% regular and 12% promoted.

Besides the final condition, the factors earlier mentioned- high school education, current residence, time spent studying, employment status of parents and student, parents' education and consideration regarding the use of TIC were also taken into consideration to define the profiles.

Analyzing each of the socio-economic and cultural factors and comparing them with the final condition of the student, the decision tree and demographic clustering algorithms were applied and the results obtained. The images represent the number of students for each dimension and inside each one the corresponding percentages is according to their final condition.

Figure 2 shows the results considering the type of high school the student attended, while in Figure 3 we can visualize the percentages of students accounting for their final condition. The greatest academic performance was reached by students from private religious high schools with 14% promoted and 28% regular. This shows that students who come from private religious high schools have better academic performance compared to those coming from other educational institutions which have the highest percentage of free students: 60% for public high schools, 61% for private entities and 72% for others.

Considering the criteria displayed in Figure 4, weekly hours of study and the percentages observed in Figure 5,

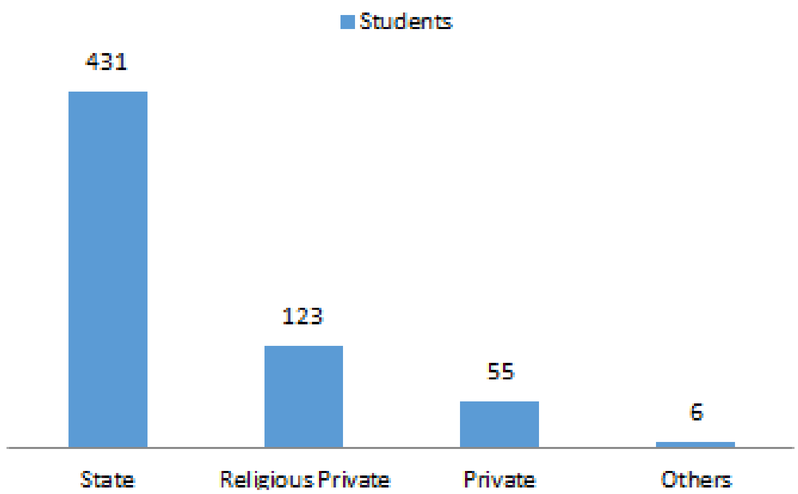

Figure 2: Number of students per high school type.

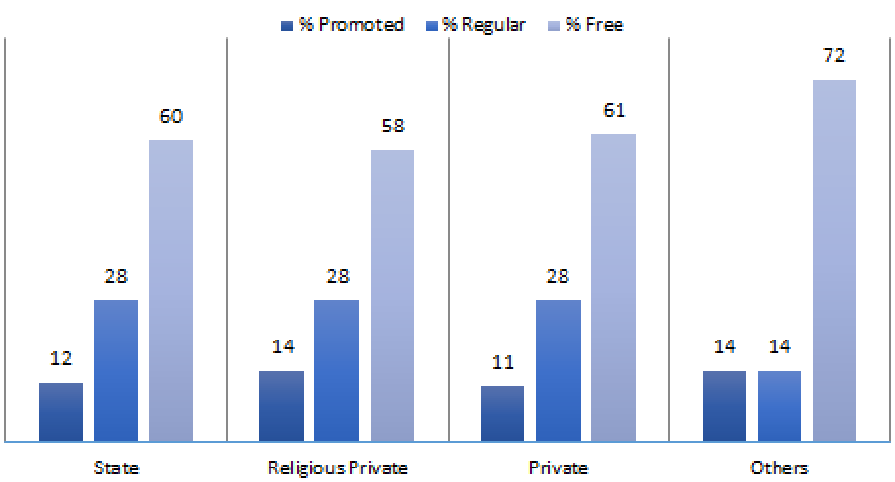

Figure 3: Percentage of students considering their final condition and type of high school.

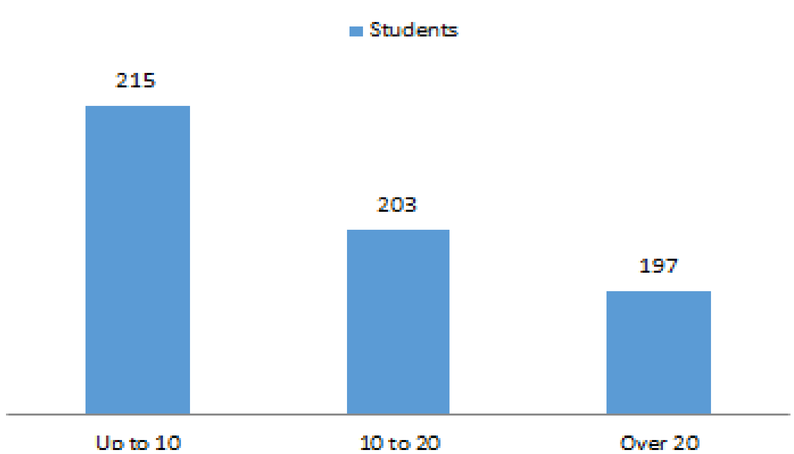

Figure 4: Number of students considering weekly hours of study.

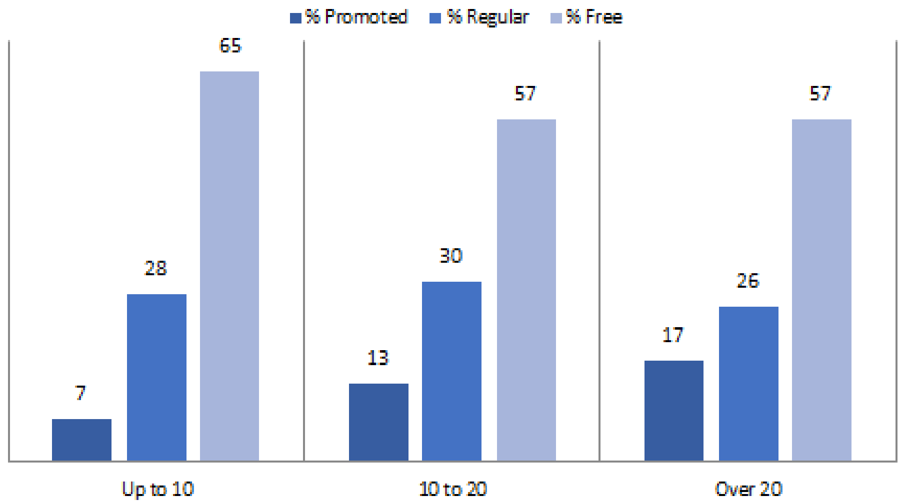

Figure 5: Percentage of students considering their final condition and weekly hours of study.

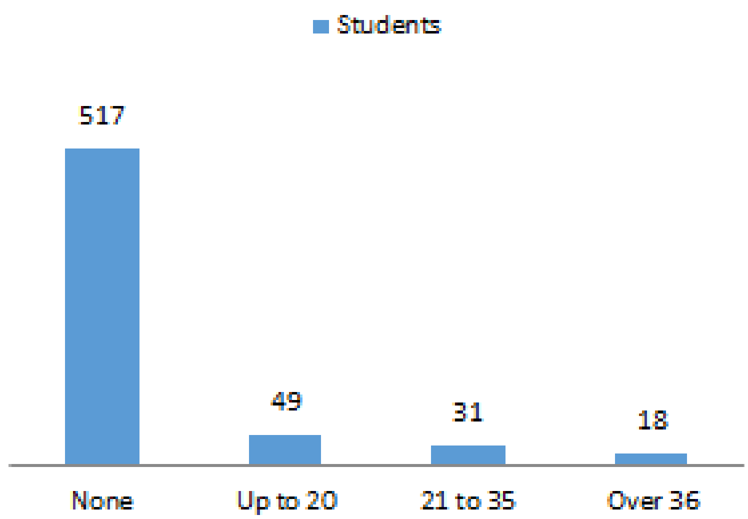

Figure 6: Number of students considering weekly study hours.

the highest percentage of promoted and regular students is seen in groups who study over 10 h per week reaching a total of 43% in each.

On the other hand, the highest percentage of students free appears in the group that study up to 10 hours per week, say 65%.

Considering the employment status of the students and the number of weekly hours devoted to studying, it can be observed that the greatest academic success is among those who work up to 20 h, (53%) and from 21 to 35 h, (52%), while the largest percentage of free students is among those who are not working (62%) and those working more than 36 h, (64%) (Figures 6 and 7).

In the criteria weekly working hours of the mother (Figures 8 and 9) shows that the highest percentage of academic success (promoted and regular) corresponds to the group whose mothers work more than 36 h per week, in total 48% (15 and 33% respectively). The highest rates of free students correspond to those whose mothers do not work or work from 21 to 35 h per week, reaching 64%.

In Figures 10 and 11, weekly working hours of the father shows that the highest percentage of academic success (promoted and regular) is the group whose fathers work more than 36 h per week reaching a total of 44%. The highest percentage of free students obtained corresponds to those student's whose fathers do not work (64%), or work up to 20 h, (68%).

Figures 12 and 13 shows important criteria indicating that the highest percentage of academic success is the group that claim to give greater importance to study than

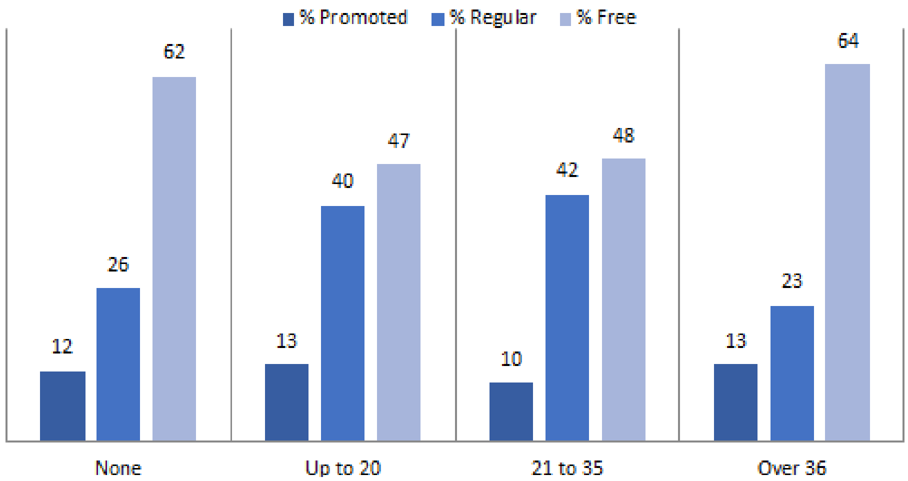

Figure 7: Percentage of students considering their final condition and weekly study hours.

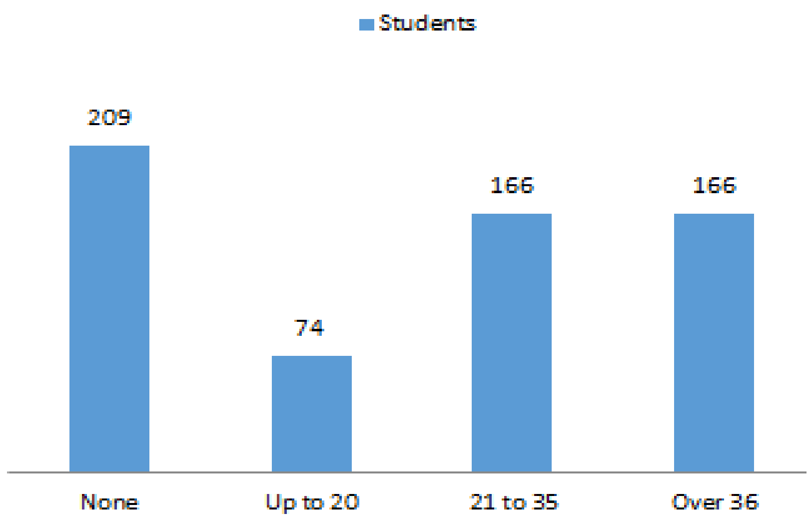

Figure 8: Number of students considering weekly working hours of the mother.

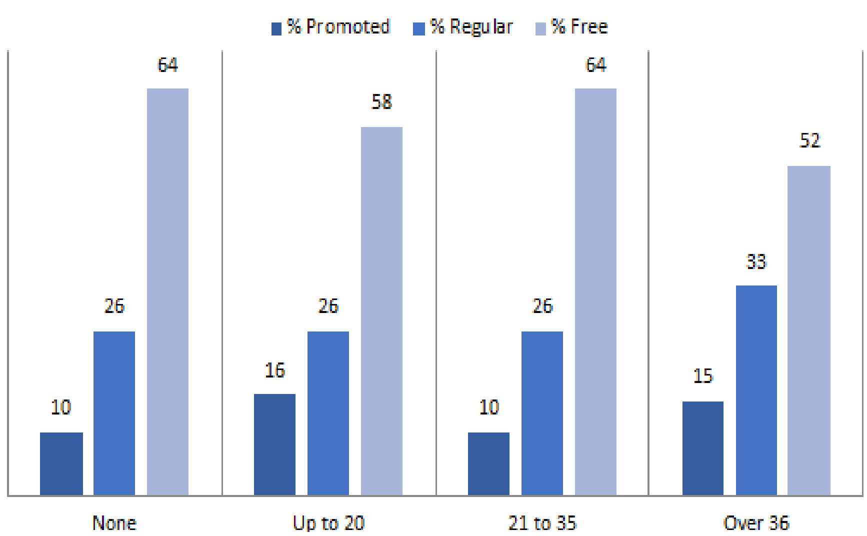

Figure 9: Percentage of students considering their final condition and weekly working hours of the mother.

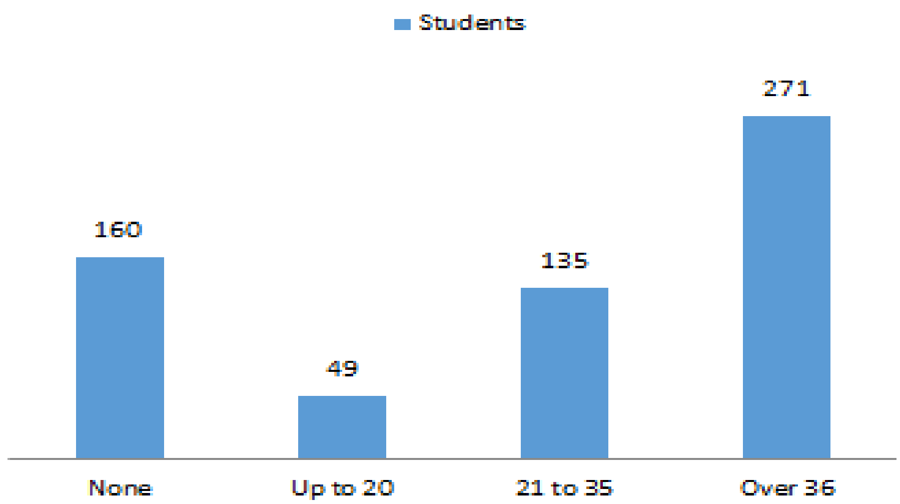

Figure 10: Number of students considering weekly working hours of the father.

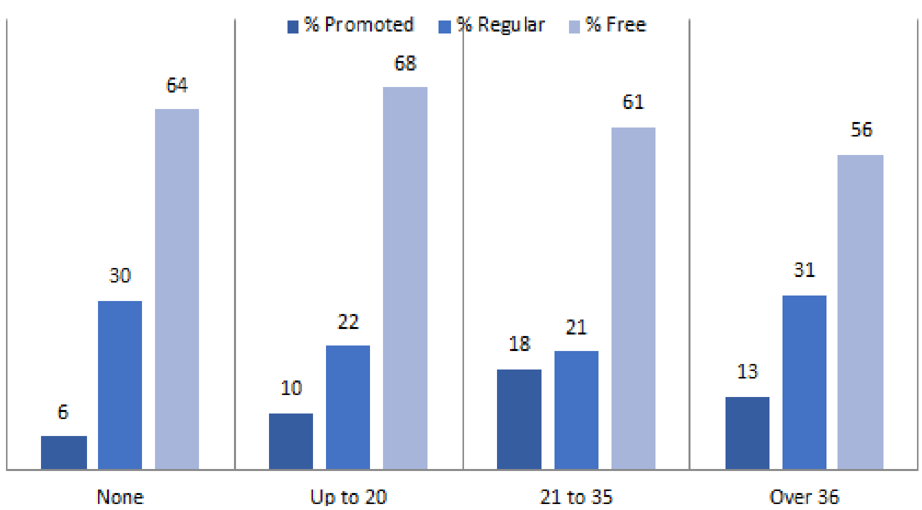

Figure 11: Percentage of students considering their final condition and weekly working hours of the father.

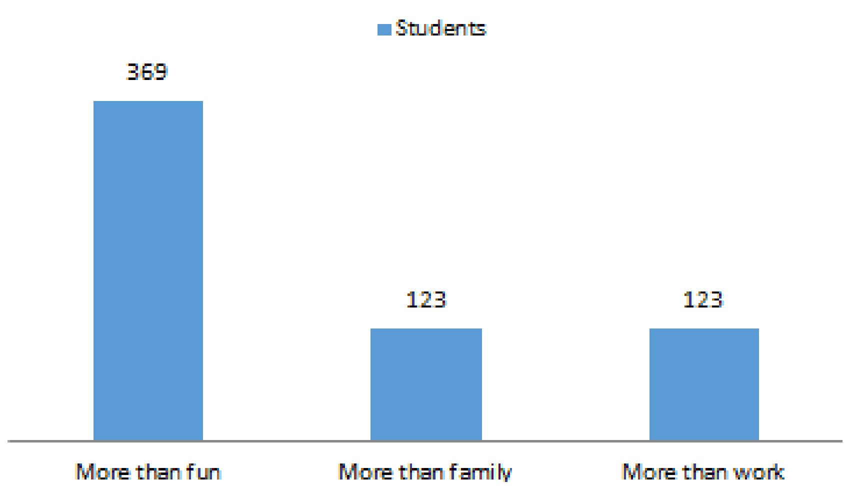

Figure 12: Number of students considering the importance given to study.

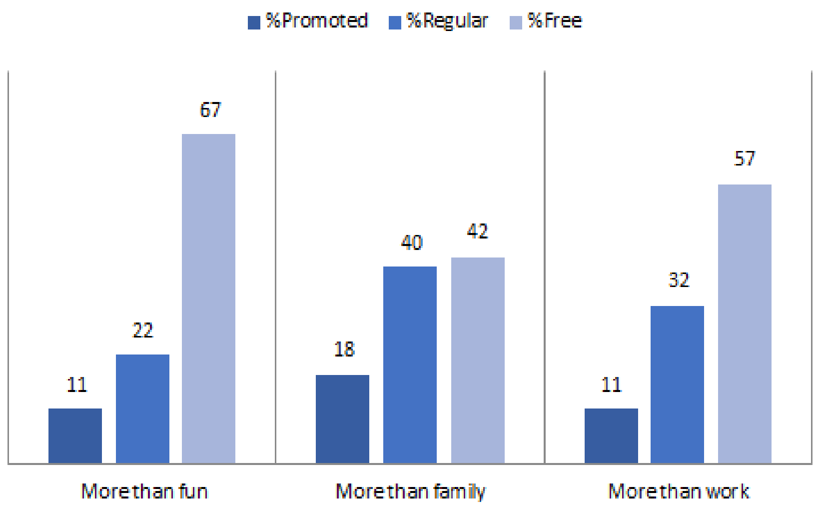

Figure 13: Percentage of students considering their final condition and importance given to study.

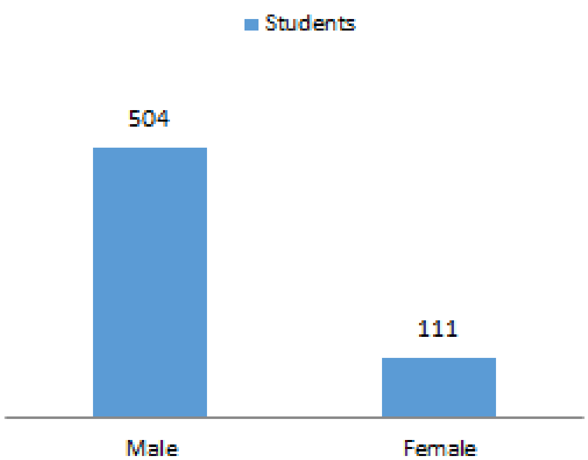

Figure 14: Number of students considering gender.

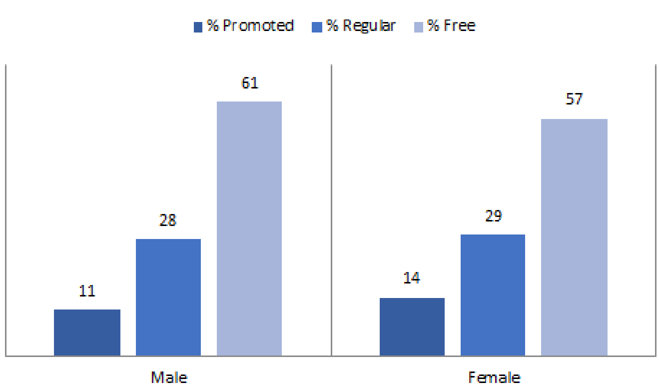

Figure 15: Percentage of students considering their final condition and gender.

to spending time with their families, which ascends to 58% compared with the highest percentages obtained from free students who stated that they give more importance to study than to having fun (67%).

Considering the gender criteria (Figures 14 and 15), the highest percentage of academic success (promoted and regular students) corresponds to the female group having 43% in total. The highest percentages of free students correspond to the male group, reaching 61%.

Concerning the residence of the student (Figures 16 and 17), the highest percentage of academic success (promoted or regular students) corresponds to those living independently (47%). Conversely, the highest percentages of free students correspond to those living with their families, reaching 63%.

Regarding the mother´s studies criteria shown in Figures 18 and 19, considering only those categories that include at least 40 students for a more representative analysis, the highest percentage of academic success (promoted and regular students) corresponds to the group whose mothers have completed higher studies, accounting for 50%. The highest percentages of free students correspond to the group whose mothers did not complete high school, 66%, or university (65%).

Concerning the father´s studies criteria (Figures 20 and 21), the highest percentage of academic success (promoted and regular students) corresponds to the group whose fathers completed their higher education - 46% - and university, corresponding to 43%. The highest percentages of free students correspond to the group whose fathers did not finish college (67%).

Taking into account the consideration of the TICs (Figures 22 and 23), the highest percentage of academic success is the group that considers that the TICs skills will be essential for professional practice (44%). The highest percentage of free students with a representative sample of students belongs to the group that believes that TICs are a present reality (66%).

Analyzing student's motivation to study, it can be

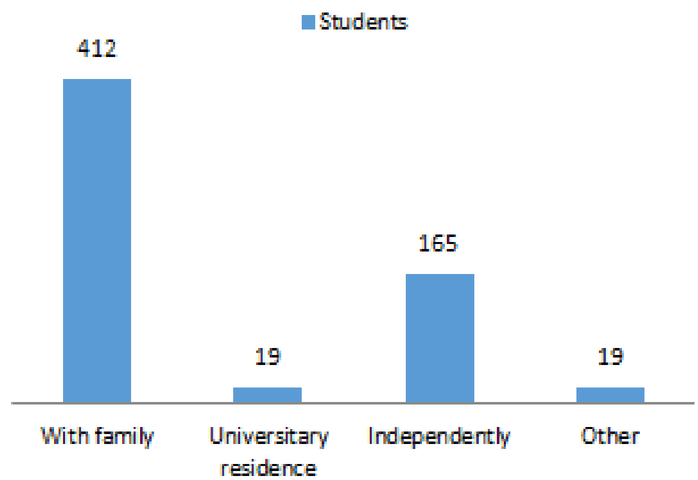

Figure 16: Number of students considering residency.

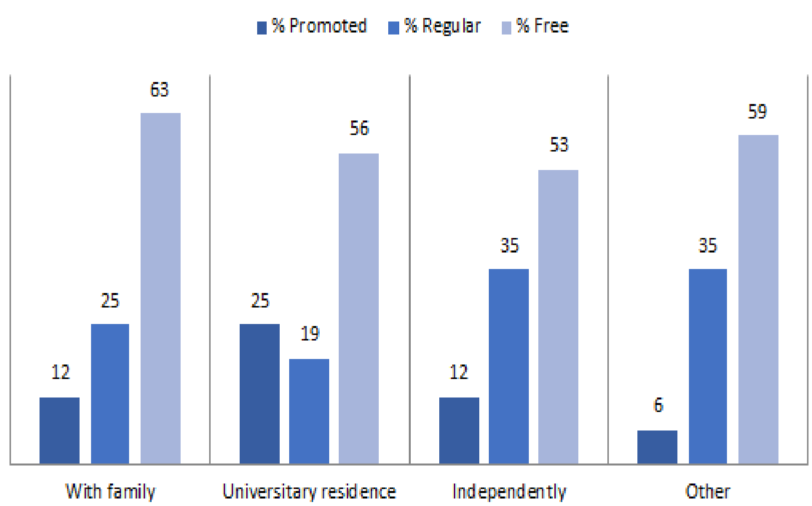

Figure 17: Percentage of students considering their final condition and residency.

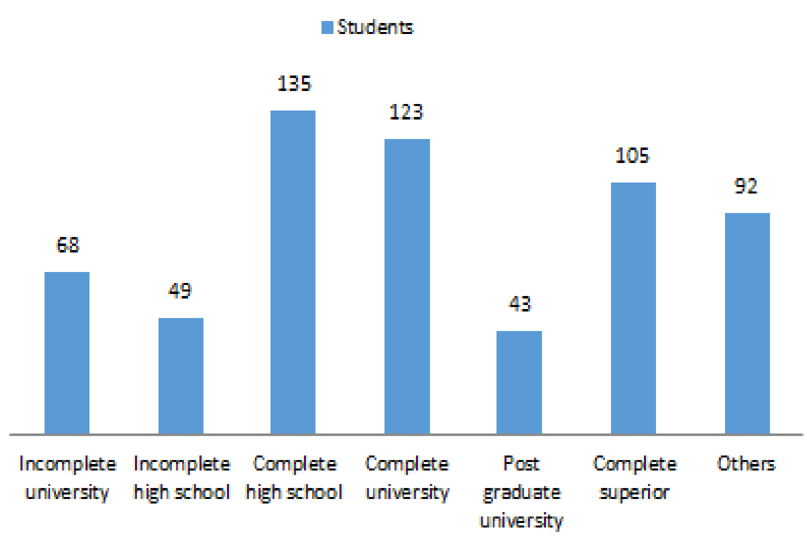

Figure 18: Number of students considering their mother´s studies.

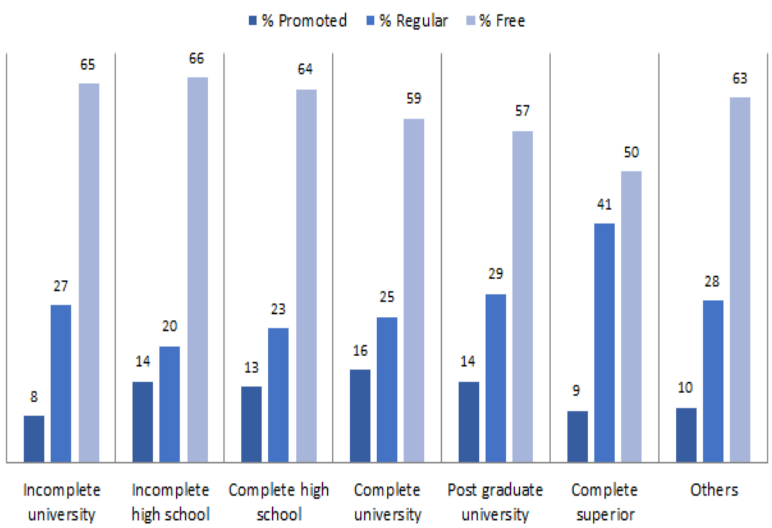

Figure 19: Percentage of students considering their final condition and mother´s studies.

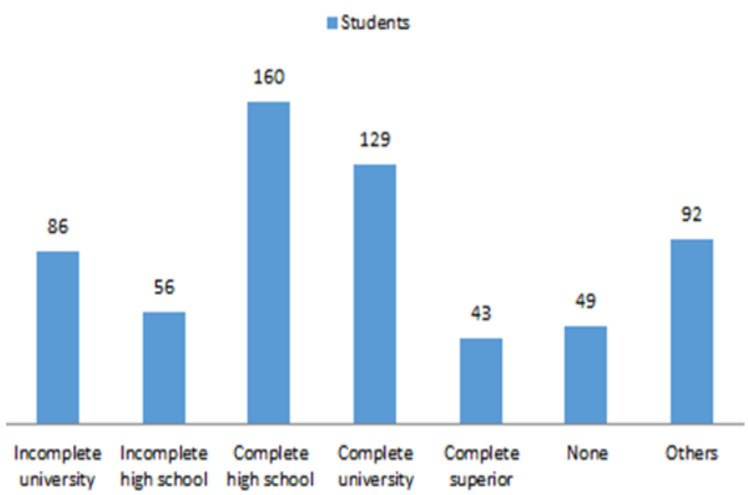

Figure 20: Number of students considering their father´s studies.

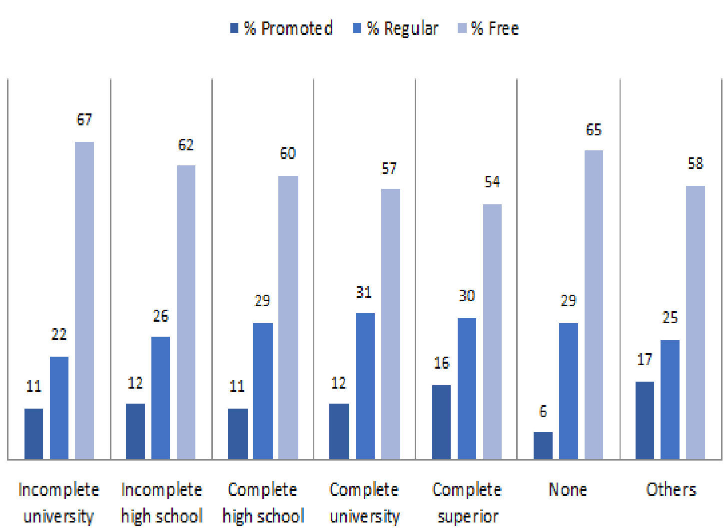

Figure 21: Percentage of students considering their final condition and father´s studies.

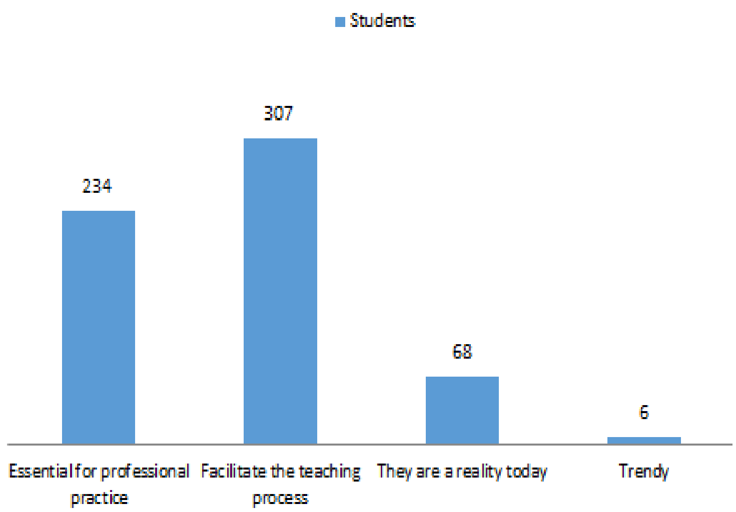

Figure 22: Number of students on account of their consideration of the TICs.

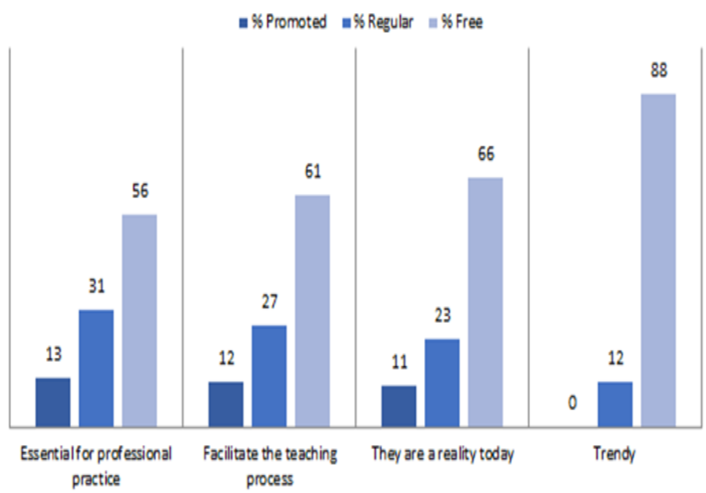

Figure 23: Percentage of students on account of their final condition and consideration of the TICs.

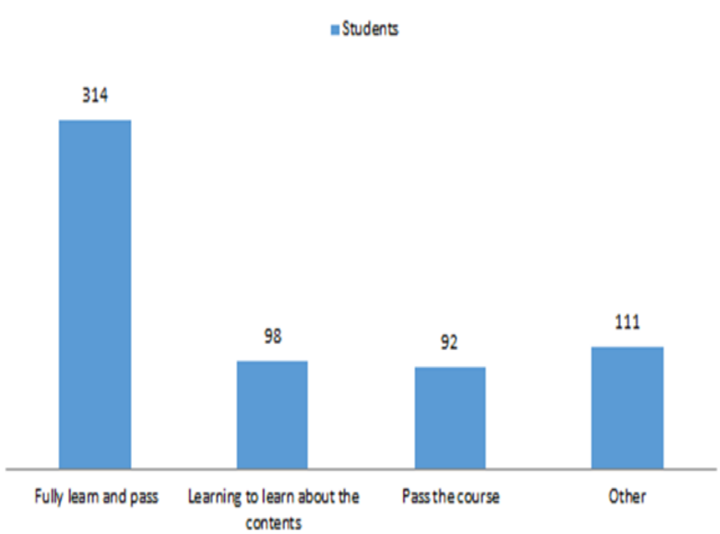

Figure 24: Number of students considering their motivation to study.

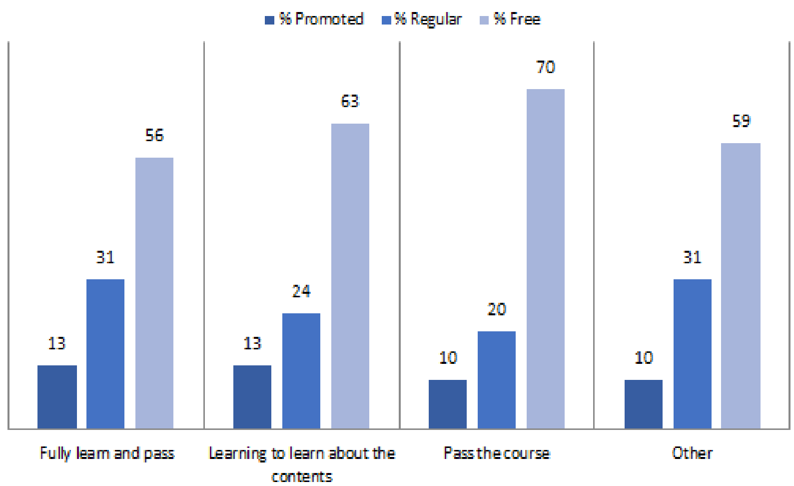

Figure 25: Percentage of students considering their final condition and motivation to study.

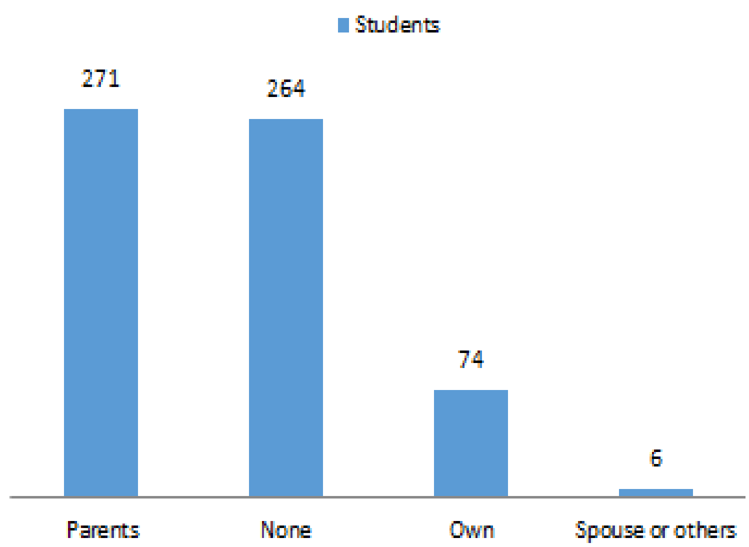

Figure 26: Number of students considering their medical insurance.

observed in Figures 24 and 25 that the highest percentage of promoted and regular students belongs to those seeking to thoroughly learn and succeed with 13 and 31% respectively. The highest percentage of free students (70%) is seen in those who only seek to pass the course.

Finally, considering the medical insurance of the student (Figures 26 and 27), we can see that the best academic performance with 49% of promoted and regular students is situated among those who have their own medical insurance, while the highest percentage of free students, 62%, lies on those without a medical insurance.

Performance profiles obtained

The previous dimensional analysis provides the main features that mainly determine the profiles of academic performance, either success or failure. Table 1 summarizes those patterns having been mostly observed according to the analysis dimensions.

Conclusions

This paper proposes a model which allows the definition of academic performance profiles using DW and DM techniques; these are based on "Algorithms and Data Structures" students' summary data during 2013, 2014 and 2015. The paper includes the students' final academic status and the socio-economic, cultural and attitudinal influence of the environment to their studies, establishing possible profiles of academic success or failure.

The obtained profiles determine generally, that those female students who study more than 20 h per week, work

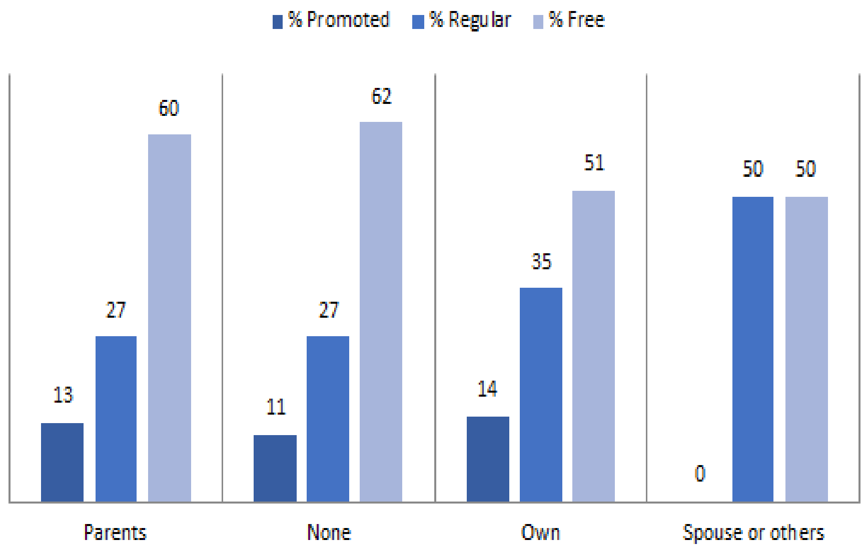

Figure 27: Percentage of students considering their final condition and medical insurance.

Table 1: Patterns of features for each performance profile.

Academic success	Academic Failure
Study more than 10 hours per week.	Study up to 10 hours per week.
Work up to 35 hours per week.	Do not work or work 36 or more hours per week.
Their mothers work 36 or more hours per week.	Their mothers do not work.
Their fathers work 36 or more hours per week.	Their fathers do not work or work up to 20 hours per week.
Give more importance to study than spending time with their family.	Give more importance to study than having fun.
They have medical insurance.	They have no medical insurance.
The highest percentage of academic success is for the female group.	The highest percentages of academic failure is for the male group.
Live independently.	Live with their families or in any unforeseen situation of residence.
Their mothers are college postgraduates or have higher non-university studies completed.	Their mothers are high school graduates or did not finish their college studies.
Their fathers are college graduates or have a higher non-university education.	Their fathers are high school graduates, did not graduate from university, or have no studies.
They consider the dominance of TICs is essential for professional practice.	They considered that TICs are a trending reality.
Their motivation to study is to learn and pass the course.	Their motivation is to study and pass the course.

up to 20 h per week, whose parents work more than 36 h per week and have complete superior studies give more importance to study than spending time with family, reside independently, consider the TICs as an essential tool for professional practice, seeking to fully learn and pass and have Medical Insurance have a tendency to succeed.

On the other hand, those male students who study up to 10 h per week, do not work or work more than 36 h per week, whose parents do not work or work up to 20 h per week and did not finish high school or college and give more importance to study than to having fun, still live with their families, consider TICs only as a reality, seek only to pass the subject and have no Medical insurance have a tendency to fail.

The determination of these profiles provides the ability to predict the students´ future academic performance from the knowledge of the factors that affect them, verifying the correspondence that each of these have with the previously determined profiles. These predictions are a powerful tool for the professorship to tell apart those students with high probability of academic failure at the beginning of the school year, which allows to prepare and define different pedagogical strategies for those students identified and to help them overcome a possible academic failure. As a consequence, it also aims to contribute to reducing the high drop-out rate existing in the early years of the career.

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REFERENCES

Baker R, Yaceff K (2009). The State of Educational Data Mining in 2009: A Review and Future Visions. J. Edu. Data Mining. 1-1.
Brause R, Hanisch E (2000). Medical Data Analysis. *First International Symposium. ISMDA*. Frankfurt, Germany.
Di Gresia L (2007). RendimientoAcadémicoUniversitario. Tesis Doctoral. Universidad Nacional de La Plata, Argentina.
Fayyad UM, Grinstein G, Wierse A (2001). Information Visualization in Data Mining and Knowledge Discovery. Morgan Kaufmann. Harcourt Int.
García MM, San Segundo MJ (2001). El Rendimiento Académico en el Primer Curso Universitario. *X Jornadas de la Asociación de Economía de la Educación*. Libro de Actas. España.
García-Jiménez MV, Alvarado Izquierdo JM, Jiménez Blanco A (2000). La predicción del rendimiento académico: regresión lineal versus regresión logística. Psicothema. 12-2.
Han J, Kamber M, Pei J (2011). Data Mining: Concepts and Techniques. 3rd edition. Morgan Kaufmann.
IBM Knowledge Center (2017). Distribution-based Clustering.
Inmon WH (1992). Data Warehouse Performance. John Wiley & Sons. USA.
Larrieta MIA, Santillán Gómez AM (2004). Minería de datos: Concepto, características, estructura y aplicaciones.
Maletic JI, Collard L, Marcus A (2002). Source Code Files as Structured Documents. *10th IEEE International Workshop on Program Comprehension*. Paris, France. 27-29.
Manganaris SCM, Zerkle D, Hermiz K (1999). A Data Mining Analysis of RTID Alarms. IBM.
Microsoft (2017). Algoritmo de árboles de decisión de Microsoft.
Microsoft TechNet (2017). Algoritmos de minería de datos (AnalysisServices: Minería de datos).
Oloriz M, Lucchini ML, Ferrero E (2007). Relación entre el Rendimiento Académico de Ingresantes en Carreras de Ingeniería y el Abandono de los Estudios Universitarios". Mar del Plata, Argentina. 29.
Roche A (2009). Árboles de decisión y Series de tiempo. Tesis de Maestría en Ingeniería Matemática. Facultad de Ingeniería, UDELAR. Montevideo, Uruguay. 21.
Theophano M (2010). Temporal Data Mining. 1st Ed. Chapman & Hall/CRC.
Tinto V (1993). LeavingCollege. Rethinking the Causes and Cures of Student Attrition. Chicago: The University of Chicago Press.
Vivo Molina JM, Franco NMY, Sánchez de la Vega M, del M (2004). Estudiov del rendimiento académico universitario basado en curvas ROC. *Revista de Investigación Educativa, RIE*. 22-2.
Vizcaino Garzon PA (2008). Aplicación de técnicas de inducción de árboles de decisión a problemas de clasificación mediante el uso de WEKA (WaikatoEnvironmentfor Knowledge Analysis). Fundación Universitaria Konrad Lorenz. Facultad de Ingeniería de Sistemas. Bogotá, Colombia.
Xu X, Ester M, Kriegel HP, Sander J (1998). A Distribution-Based Clustering Algorithm for Mining in Large Spatial Databases. *Proceedings of 14th International Conference on Data Engineering (ICDE'98)*. Orlando, Florida, USA.
Zaki JR, Meira W, Jr (2014). Data mining and analysis: fundamental concepts and algorithms. Cambridge University Press.

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