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Application of Data Mining to describe Multiple Intelligences in University Students

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Abstract. Nowadays, a great challenge for the teaching work consists in finding the right resources to achieve significant learning in students. However, the fact that every student learns differently from others, leads us to find most appropriate routes to facilitate the learning process, considering that the knowledge of the abilities or multiple intelligences along with being conscious of the inner cognitive processes of students, will help in developing the most suitable strategies for students to construct their own learning. All the time we need to consider the needs, specific qualities, understanding, the level of emotional development and especially the way they learn. This research focuses on the application of different algorithms of data mining, using the technique of Clustering on the Weka tool to bring together university students according to their multiple intelligences based on Gardner's model [1] which describes eight intelligences, as they are : linguistic, musical, logical mathematical, spatial, bodily kinesthetic, intrapersonal, interpersonal and naturalist. Thus, knowing the development of multiple intelligences in students, faculty will be able to contribute to the conditions in the learning environment, facilitating the achievement of the learning objectives of the students.
Keywords: Multiple Intelligences, Data Mining, Cluster, grouping.

1. Introduction

1.1 Multiple Intelligences

Along his career, Howard Gardner has developed a number of concepts related to cognitive abilities of people. More than twenty years ago, Gardner established the notion of multiple intelligences. This concept now comes to be ratified in education for the twenty-first century. These multiple intelligences include linguistic, logical, bodily kinesthetic, visual and spatial, musical, interpersonal (social) and intrapersonal intelligence.

The Information and Communications Technology (ICT) have come to greatly complement this concept, since according to Gardner [2] an important part of the construction of these intelligences is based on both the talent and effort. ICT have come to join what was known as "formal learning", supporting traditional classes with technology designed for a heterogeneous group of students.

From this diversity in the form of learning, it is that ICT have become important for teaching in the twenty-first century. Thus, the teaching process has to be adapted to the scenarios in which it takes place. These technologies allow students through various forms or methodologies to achieve a deeper learning of the subject.

1.2 Gardner’s Theory of Multiple Intelligences

Howard Gardner has maintained that the traditional notion of intelligence is too limited and that we have multiple intelligences, all of them important, which education should consider equally for all children to maximize their individual capacities. In practice, not all people learn the same way or have the same interests

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and in a changing world like today, where the diversity of information is a reality, choosing is unavoidable [3].

The educational implications of the theory of multiple intelligences are enormous [4]. Professor Howard Gardner is suggesting the need for teachers to implement pedagogical strategies beyond the linguistic and logical that predominate in classrooms and to adopt creative approaches that depart from traditional distributing seating in rows and columns with the teacher in front of the slates or excessive reliance on textbooks. New times require environments that foster creativity and collaboration.

So, this theory focuses on the following features for student assessment:

Learner Type	Likes To	Is Good At	Learns Best By
Verbal / Linguistic ***"The Word Player"***	➢ Read / Write ➢ Use Puns ➢ Tell Stories	➢ Memorizing names, places, dates, trivia	➢ Saying, hearing, and seeing words and stories
Logical / Mathematical ***"The Questioner"***	➢ Conduct experiments ➢ Figure things out ➢ Work with numbers ➢ Ask questions ➢ Explores patterns and relationships	➢ Math ➢ Reasoning ➢ Logic ➢ Problem solving ➢ Quantitative analysis	➢ Categorizing ➢ Classifying ➢ Working with abstract patterns and relationships ➢ Quantifying
Spatial ***"The Visualizer"***	➢ Draw, build, design, and create things ➢ Daydream ➢ Look at pictures / slides ➢ Watch movies ➢ Play with machines	➢ Imagining things ➢ Sensing changes ➢ Mazes / puzzles ➢ Reading maps / charts ➢ Diagramming ➢ Charting	➢ Visualizing ➢ Dreaming ➢ Using the mind's eye ➢ Working with colors / pictures ➢ Outlining
Musical ***"The Music Lover"***	➢ Sing, hum ➢ Listen to music ➢ Play an instrument ➢ Respond to music	➢ Picking up sounds ➢ Remembering melodies ➢ Noticing pitches and rhythms ➢ Keeping time	➢ Rhythm ➢ Melody ➢ Music ➢ Sound ➢ Drumming ➢ Listening
Bodily /Kinesthetic ***"The Mover"***	➢ Move around ➢ Touch and talk ➢ Use body language ➢ Engage in activity ➢ Interact physically ➢ Experiment	➢ Physical activities (sports/dancing/acting) ➢ Crafts ➢ Making things ➢ Mapping ➢ Body models of concepts	➢ Touching ➢ Moving ➢ Interacting with spaces ➢ Proceeding knowledge through bodily positions
Interpersonal ***"The Socializer"***	➢ Have lots of friends ➢ Talk to people ➢ Join groups ➢ Interest ➢ Network ➢ Personalize	➢ Understanding people ➢ Leading others ➢ Organizing ➢ Communicating ➢ Manipulating ➢ Mediating conflicts	➢ Sharing ➢ Comparing ➢ Relating ➢ Cooperating ➢ Interviewing ➢ Leading ➢ Interacting ➢ Listening
Intrapersonal ***"The Individual"***	➢ Work Alone ➢ Pursue own interest ➢ Reflect ➢ Observe	➢ Understanding self ➢ Focusing inward on feelings/ dreams ➢ Following instincts ➢ Pursuing interests ➢ Being intuitive	➢ Reflection ➢ Individualized projects ➢ Self-paced instruction ➢ Having own space ➢ Intuition
Naturalist ***"Nature Lover"***	➢ Observe/explore nature ➢ Read about nature ➢ Grow plants and garden	➢ Outdoor recreation activities ➢ Learning taxonomies for plants/animals ➢ Understanding how	➢ Collecting data through observation ➢ Drawing/photographing outdoor subjects ➢ Reading/writing ➢ Performing

Table 1 Multiple Intelligences development adapted by Nuña del Salvador [5]

It was based on identifying the multiple intelligences of students to verify the development of a profile. Identification of multiple intelligences of students is no easy task [6]. This assessment requires a continuous process of observation collecting useful information, gathering reports, talking with parents or other teachers, asking the students themselves and also organizing special activities.

He wanted to test with students conducting questionnaires with 48 questions in a group of 21 high school students of science, which was adapted from a list proposed by one of the leading experts in the theory of multiple intelligences, Thomas Armstrong (Armstrong, 2006) [7]. Although there are no evidence to directly identify the different abilities of students, we wanted to analyze the information provided by the questionnaire with the known information.

There were six issues relating to each of the eight initial intelligences proposed by Gardner. The students were asked to rate each issue with a score from 1-10 in increasing order of identification, i.e. 1 corresponding to the minimum identification with the assumption raised to 10 for the maximum. Once the questionnaire was completed and after an explanation of its function and relationship to the theory of multiple intelligences, students were asked to choose the two intelligences that they believed were more developed by them. Subsequently, using the graphics, we came to the conclusion on which intelligences were dominating in that group in particular.

The best way to approach the curriculum development assuming the theory of multiple intelligences will be planning the teaching units taking into account the different intelligences, although it is not necessary to design classes considering the eight areas. The units must have an interdisciplinary approach, promote collaborative work and relate purely academic knowledge with extracurricular interests.

1.3 Application of Multiple Intelligences

Luca, S.L. explains that in advance to the application of any learning model based multiple intelligences, we must at first instance apply it to ourselves as educators and adult students, because if we do not have an understanding of the theory intimately linked to the experience and we have made this knowledge our own, being in condition of applying it, not as copy, but as an own model, we cannot transmit it successfully [8].

So the first step is to determine the nature and quality of our own multiple intelligences and seek ways to develop them in our own lives. This theory is particularly useful for observing our strengths and weaknesses in areas that we use as teachers because it allows us to see all our activities to achieve our goals, and also what actions we ignore because we do not feel comfortable with them.

The development of each intelligence to an acceptable degree of competition, depends on three main factors, according to Armstrong:

- Endowment biological, including genetic or hereditary factors, and damage or injury that the brain may have received before, during or after birth.
- History of personal life, including experiences with parents, teachers, peers, friends and others who help grow the intelligences or stay at a low level of development.
- Background cultural or historical, including the time and place where one was born and raised, and the nature and status of cultural or historical developments in different domains.

Luca, S.L. states that making an assessment of the potential of children and considering this grid, you can select the activities to be performed depending on the type of intelligence.

Moreover, Armstrong, in his book *The multiple intelligences in the classroom*, shows how to plan and conduct classes based on IM. He proposes various exercises, class models and excellent information to help teachers.

1.4 Data Mining Techniques

Data mining is a field of computer science which refers to the process that attempts to discover patterns in large volumes of data sets. It uses the methods of artificial intelligence, machine learning, statistics and databases systems. The overall objective of the process of data mining is to extract information from a data set into an understandable structure for later use.

Grouping technique (cluster): it groups data within a predetermined number of classes, pre-arranged or not, based on distance or similarity criteria, so that the classes are similar among themselves and different to the other classes. Their use has provided significant results regarding the classifiers or pattern recognizers, and modeling systems. Due to its flexible nature, this method can be easily combined with other data mining techniques, resulting in a hybrid system [9].

A problem related to cluster analysis is the selection of factors in classification tasks, because not all variables are equally important when grouping objects. Another major problem and now arouses great interest is the fusion of knowledge, since there are multiple sources of information on a theme, which do not use a uniform categorization of objects. To solve these problems it is necessary to merge the information when collecting, comparing and summarizing data [10].

SimpleKmeans algorithm is a Cluster technique which gathers on a chart various attributes with similarities, dividing them in a certain amount of Clusters (grouping) and obtains the percentage for each of them.

2. Development

2.1 Methodology

For the realization of this research, CRISP-DM (Cross Industry Standard Process for Data Mining) [11] methodology has been chosen. This is a methodology of free distribution that can work with any tool to develop any project that focuses on the implementation of data Mining as shown in figure 2. The standard includes a model and a guide, structured in six phases. Some of these phases are bidirectional, meaning that some phases allow partially or complete revision of the previous phases.

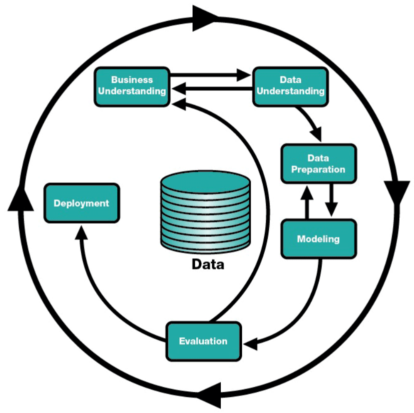

Figure 1. CRISP DM Methodology

These phases are:

a) Understanding the business or case study,
b) Understanding data,
c) Preparation of data,
d) Modeling,
e) Evaluation,
f) Deployment.

2.2 Case Study

Based on Howard Gardner's model of the multiple intelligences theory to identify the types of intelligence, such as logical and mathematical, physical and kinesthetic, interpersonal, musical, spatial, linguistic, interpersonal and naturalist, in different kinds of people who possess the eight intelligences mentioned above, but, due to their natural capacities, have specifically developed some of them more than others, emerges the need to know which of those multiple intelligences dominates amid the students of the Bachelor of Computer Systems at Escuela Superior de Huejutla, of the Universidad Autónoma del Estado de Hidalgo. To this purpose it was considered a sample of 50 students, corresponding to the 48% of the enrollment of this specific program. Once the results were obtained, they were processed using Weka tool [12] to create a model reflecting these intelligences from our students.

2.3 Understanding data

The instrument used to perform our study is the Test of Multiple Intelligences: Evaluation of the 8 intelligences. This test evaluates each of the intelligences, using a scale of 1-5, where 1 indicates absence and 5 notable presence of what is said.

LOGICAL MATHEMATIC INTELLIGENCE

	1	2	3	4	5
likes to classify and prioritize things					
has a good sense of cause and effect					
enjoy math classes					

Figure 2 Sample questions of the test

The Test of Multiple Intelligences evaluates the 8 intelligences, containing a total of 75 items, divided into eight sections, alluding to the eight intelligences with statements related to each of them [13].

logical mathematical					
	1	2	3	4	5
asks many questions about how things work					
makes arithmetic operations mentally rapidly					
enjoy math classes					
likes math computer games					
likes games and puzzles that require logic					
likes to classify and prioritize things					
think of a more abstract and conceptual level than their peers					
has a good sense of cause and effect					

Figure 3 Test used for logical mathematical intelligence

2.4 Preparation of data

In this section, we proceeded to the discretization, cleaning and preparation of the results obtained from the tests [14].

The discretization of data corresponds to the range of values that must be established for each of the vectors analyzed. The same procedure was applied to each section of the test, considering the eight intelligences shown in them [15].

Each vector will be represented by each respondent student, that is, we will have 50 vectors. Discretization is the range of results for each intelligence, thus avoiding outliers, i.e. data impossible or simply useless.

The discretization is defined as follows for each of the intelligences:

Number of questions x 1 – Number of questions x 5

Once we had the formula we proceeded to determine the range of values for each of the intelligences. For example, if the musical intelligence has 8 statements, then the minimum value that can be obtained in this test are 8 points, and the maximum value is 40 points. This value is found by multiplying the number of questions (8), for the maximum weighing (5), resulting in the maximum value (40), and this gives us a range of 8-40 points. Moreover, if we obtain a value outside this range (e.g. 7, 0, -1, 45 ...), the vector is obsolete.

According to the above criteria our discretization would be as follows:

Intelligences	Discretization
Linguistic	10-50
Musical	8-40
Logical Mathematical	8-40
Spatial	9-45
Bodily Kinesthetic	10-50
Intrapersonal	10-50
Interpersonal	10-50
Naturalist	10-50

Table 2. Discretization of multiple intelligences

Thus, each vector consists of 8 data concerning the 8 multiple intelligences and these data will be sorted and separated by commas respectively. For example:

23, 15, 24, 40, 23, 32, 23, 21

Each value corresponds to the score obtained in each intelligence referring the surveys.

Once obtained the results of this instrument, they were gathered in a text document for group analysis. Later, we used a note block application to format the file .arff as follows.

```
@RELATION inteligencia
@ATTRIBUTE logica_matematica INTEGER
@ATTRIBUTE fisica_cinestetica INTEGER
@ATTRIBUTE interpersonal INTEGER
@ATTRIBUTE musical INTEGER
@ATTRIBUTE espacial INTEGER
@ATTRIBUTE linguistica INTEGER
@ATTRIBUTE intrapersonal INTEGER
@ATTRIBUTE naturalista INTEGER
@DATA
28,37,37,20,21,37,33,33
n…
```

This way, the .arff file is ready to be used at Weka [16].

2.5 Modeling

For this research it was decided the use of data mining tasks of the descriptive type. In particular, clustering was applied [12] to identify homogeneous subgroups within the sample of surveyed students. To do this we used the WEKA software [17].

In particular, for implementing the Cluster option is selected. In addition, it was decided the use of the kmeans algorithm because it is a problem of k centers. To detect the dominant multiple intelligences we decided to keep in two the number of clusters.

Once the different clusters were calculated, and in the post-processing phase, we proceeded to replace each of the elements included in the centroids by the code of multiple intelligences related. Then we proceeded to count the number of occurrences of each style to determine the present combination thereof. The result of running the model used is shown on Figure 6.

```
Clusterer output
=== Run information ===

Scheme:       weka.clusterers.SimpleKMeans -N 2 -A "weka.core.EuclideanDistance -R first-last" -I 500 -S 10
Relation:     inteligencia
Instances:    50
Attributes:   8
              logica_matematica
              fisica_cinestetica
              interpersonal
              musical
              espacial
              linguistica
              intrapersonal
              naturalista
Test mode:    evaluate on training data

=== Model and evaluation on training set ===


kMeans
======

Number of iterations: 6
Within cluster sum of squared errors: 14.397803521038046
Missing values globally replaced with mean/mode

Cluster centroids:
                              Cluster#
Attribute            Full Data          0          1
                          (50)       (20)       (30)
=====================================================
logica_matematica        29.82       25.6    32.6333
```

Figure 4. Results of the model in Weka.

2.6 Evaluation

In the construction of the model Kmeans, Weka took the 100% out of the 50 records that formed our minable view to build the model and 39 instances (78%) to test it, with an accuracy of 80%. The algorithm was run with 2 clusters and 8 seeds, using the Euclidean distance with 500 iterations. Likewise, eight attributes corresponding to multiple intelligences analyzed were used. The evaluation was conducted on training data represented in the following table:

```
Cluster centroids:
                              Cluster#
Attribute            Full Data          0          1
                          (50)       (20)       (30)
=====================================================
logica_matematica        29.82       25.6    32.6333
fisica_cinestetica       35.54      31.25       38.4
interpersonal            36.86      31.45    40.4667
musical                  26.94      22.95       29.6
espacial                 31.72       26.6    35.1333
linguistica              37.22      30.45    41.7333
intrapersonal            38.52      32.45    42.5667
naturalista              37.76       30.3    42.7333


Clustered Instances

0       20 ( 40%)
1       30 ( 60%)
```

Figure 5. Outcome Evaluation of Clusters in Weka

2.7 Deployment

We can analyze any of the 64 different graphics, given that each of them reflects one intelligence with respect to another. In this case, interpersonal intelligence is shown with respect to the intrapersonal intelligence:

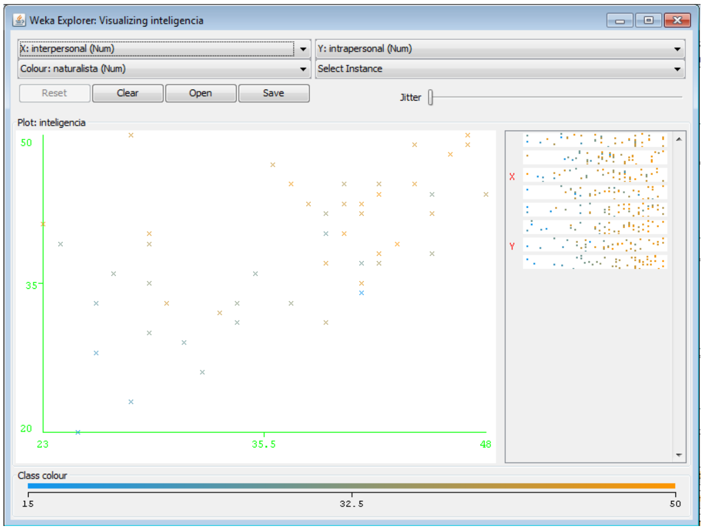

Figure 6. Scatter graph interpersonal vs. intrapersonal intelligences

Tabulating our information according to output results in Weka, the following percentages were generated and grouped into two clusters, which correspond to the 8 types of multiple intelligences:

Attribute	% Cluster 0	% Cluster 1
Logical mathematical	11.07%	10.7%
Bodily kinesthetic	13.52%	12.66%
Interpersonal	13.61%	13.34%
Musical	9.93%	9.76%
Spatial	11.51%	11.58%
Linguistic	13.17%	13.76%
Intrapersonal	14.04%	14.03%
Naturalist	13.11%	14.09%
TOTAL	100%	100%

Figure 7. Table of results of Cluster Conformation

Finally, in the following graphic it is shown the integration of the different groups and their composition of different multiple intelligences identified during the exploitation of the results of questionnaires administered to students.

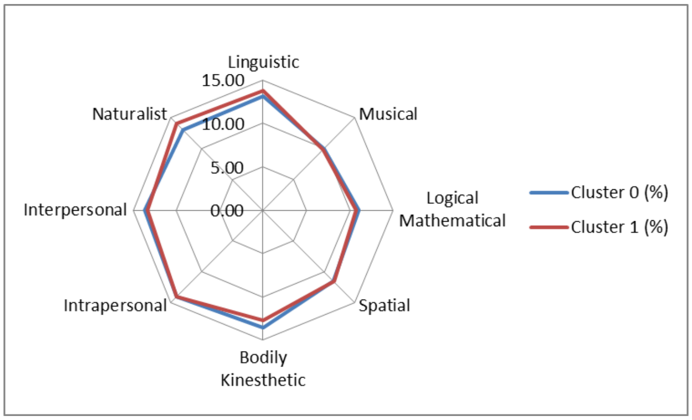

Figure 8. Graphs obtained from the cluster model applied.

It can be noticed that the predominant intelligences in the students are intrapersonal and the naturalist. However, there are some students that handle a multimodal style. In the first graph it can be observed that intrapersonal intelligence predominates with a value of 14.07%, followed by interpersonal intelligence equivalent to 13.61% and in the third place comes the physical kinesthetic equals to 13.52%.

Later, in the second cluster, the naturalist intelligence is the largest presence with a value of 14.09%, then intrapersonal intelligence follows with the equivalent of 14.03% and linguistic equals to 13.76%.

In both clusters we obtain ultimately the musical intelligence with a value of 9.93% in the first cluster and 9.76% in the second cluster.

3. Conclusions and Future Work

The study data mining shows that in the sample taken from the students of the Bachelor of Computer Systems at the Escuela Superior de Huejutla, from the Universidad Autonoma del Estado de Hidalgo, the intrapersonal intelligence really prevails. This means that students develop within their own thinking, understanding their inner life, they think to meet their needs and thoughts and their preferences are reflecting and/or planning. In the second place we found the naturalist intelligence.

According to the results obtained in the case study, for the Educational Program of Computing Science they will open projects focused on the development of teaching materials to meet the needs of development of these two intelligences as a determinant factor in the achievement of academic goals sought for the students. Therefore, we suggest the development of the Integral Didactic Folders to cover such objectives within the Escuela Superior de Huejutla.

An opportunity area in the use of Mining Data it is that of describing the behavior of the students in a virtual environment so we are able to adapt the virtual platforms to our students' behavior. So, our next work will be to describe the students' behavior in virtual environments.

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