Multivariate Analysis for Students' Evaluation of Teaching Effectiveness in Teleinformatics Engineering

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***Abstract*—In this work, we propose the use a multivariate analysis tool, called principal components analysis (PCA), to address the problem of Students' Evaluation of Teaching Effectiveness (SETE). We conducted a research with Engineering Students in an undergraduate course. The values obtained after collecting research data were transformed from a 3D array to a 2D array performing an average of students' responses. The PCA was applied in order to take same intrinsic information of the dataset collected. The Cronbach's α validates the PCA application in the dataset. The results show that our study allows an analysis of how students perceive different disciplines about different criteria, which may serve as an indicator for an educational assessment area.**

***Index Terms*—principal components analysis; engineering education; evaluation; university teaching**

I. Introduction

The constant evolution of resources and computer technology in contemporary society is a reflection of several research studies in engineering and technological innovation that emerged in recent years in the areas of computing, telecommunications and information technology (IT). In this scenario, increasingly industry, research centers and several companies all over the world demand for professionals and researchers in IT engineering and this has led to a growing number of people to choose this career [1], [2].

However, what we see is that a lot of engineering courses in the world suffer high withdrawal and failure rates of students in their early years, especially in fundamental discipline areas like mathematics and science [1], [2]. Moreover, during the formation of a basic engineering course, it's necessary that the student in the first year obtains knowledge and skills in core content basic areas of Physics, Calculus, Algebra, Chemistry and technological area. Moreover, the number of engineering graduates is increasing as a problem, since high school enrollments in mathematics and physics are currently significantly higher [1].

In particular, the Federal University of Ceará (UFC) by the Department of Teleinformatics Engineering of Technology Center, located in northeastern Brazil, offers the Teleinformatics Engineering (TIE) undergraduate course. This course was created in 2003 under the direct responsibility of Department of Teleinformatics Engineering and put together two important research areas with a great impact to the actual society, these are: Informatics and Telecommunications. The information related to telecommunications is largely responsible for the agility and integrability of the flow of information, constituting therefore a key element in ensuring reliable and affordable communication among people, leading them to the widespread development [3]. The telecommunications and computing technological development as well as the industry that integrates teleinformatics, in the last decade has reached an extremely high level of complexity, pointing to new forms of relationships that strongly indicate a better quality of life for people in general. Worldwide, the effects of this new era are felt in different ways, both in social and professional experience. Job opportunities in these sectors are increasing, giving rise even repressed demands, where the labor market is eager for a highly qualified workforce, reflecting the global reality.

In order to detect possible indicators in the quality of education as well as explaining the factors such as evasion, failure rates and to promote possible suggestions for restructuring the TIE courses curriculum, a study was conducted to assess the effectiveness of teaching students (Student Evaluation of Teaching Effectiveness – SETE) [4]–[7] in the basic disciplines of the TIE first-year course.

Research indicates that the student can provide valid information and opinions about many aspects of teaching and this assessment can often be taken into account for the success in the process to level up teaching staff, that can be to approved or even promote the reformulations in a course curricular structure [3].

Universities and education programs around the world regularly use the student by means of evaluation of teaching effectiveness to determine the quality of their courses (SETE), although some faculty members question the usefulness and validity of student ratings [4]–[7]. Although some disagreements have occurred, the SETE is an important tool

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applied for measuring the quality of education courses, especially in the context of higher education [8].

The dimension of learning fundamental concepts to the professional context in an engineering course in the technology area focuses on students' perceptions of the importance and quality of learning contents in the basic sciences such as Mathematics, Physics, Chemistry and Computer Programming belonging to the basic curriculum of the first year. In general, learning refers to student perceptions of personal growth and progression and development in different areas of development of professional knowledge [9].

The SETE was applied to TIE students who had attended all the basics disciplines of the first-year engineering course in which students are interviewed to assess the performance of their teachers and the quality of education taking into consideration various aspects of the disciplines and students themselves in terms of quality through a survey that used the Likert scale.

Although SETE is used as an important tool for evaluating teaching effectiveness, it is noticed in several studies [2], [4], [9] that the data analysis often limits the use of basic descriptive statistical analysis using means or factor analysis in order to validate the instrument for data collection and to form a cluster on scales of issues present in the form applied to students. However, descriptive statistics does not reveal the correlation between the factors analyzed. In this research, which was implemented in the TIE course in Brazil, in addition to the classic statistical techniques traditionally used in previous studies [10], [11], multivariate analysis is proposed to analyze the SETE dataset, called Principal Component Analysis (PCA) [17]–[21].

PCA is a bilinear method that allows the dataset decomposition into scores and loadings data array that describes the dataset in a more condensed form than the original data matrix [12], [13]. This assumes that there is a latent structure of the dataset, allowing a compact description by a reduced number of factors, which facilitate the interpretation of a relevant information or integrative.

In this context the PCA analysis seems promising as well as innovative since results may be relevantly obtained through this analysis regarding the effectiveness of the teaching process promoted by the disciplines and in relation to quality of teacher's performance in each of them belonging to the same category. In other words, they are basic disciplines of the course's first year but are sometimes noticeably different for the students' point of view.

This paper is structured as follows. Section II presents a review of the relevant SETE literature. Section III describes the mathematical tool used in this research. Section IV shows the course context and the methodological approach of the proposal. The main findings of the paper are presented in Section V. Finally, Section VI discusses some concluding remarks.

II. Students' Evaluation of Teaching Effectiveness

The Students' Evaluation of Teaching Effectiveness (SETE) methodology was created by Herbert M. Marsh [14]. The main purposes of SETE are [15]: 1) diagnostic feedback to teachers about the effectiveness of their teaching that will be useful for the improvement of teaching; 2) measuring of teaching effectiveness to be used in personal decisions; 3) information for students to use in the selection of courses and teachers; and 4) an outcome or a process description for research on teaching. Certain student rating forms provide important feedback that can be used to improve teaching performance [14]–[16].

Researchers [4]–[7] agree that teaching is a complex activity consisting of multiple dimensions and that formative diagnostic evaluation of teachers should reflect this multidimensionality. This contention is supported by common sense and a considerable amount of empirical research [15].

Marsh [4], [14] concluded that SETE is: 1) multidimensional; 2) reliable and stable; 3) primarily a function of the instructor who teaches a course rather than the course that is taught; 4) valid in relation to a variety of indicators of effective teaching; 5) relatively unaffected by a variety of variables hypothesized as potential biases; and 6) considered to be useful by students to use in course selection, by administrators to use in decisions about staff and by teachers as feedback on teaching.

An instrument was created in order to obtain the students feedback. This instrument is called Students' Evaluation of Educational Quality (SEEQ) that appears to measure the most broadly representative set of scales and has the strongest factor of analytic support of these instruments [15].

The strongest support for the multidimensionality of SETE is based on the nine-factor (Learning/Value, Instructor Enthusiasm, Organization/Clarity, Group Interaction, Individual Rapport, Breadth of Coverage, Examinations/Grading, Assignments/ Readings, and Workload/Difficulty) SEEQ instrument [14]–[16]. These factors are based on various sources (e.g., reviews of current instruments, interviews with students and teachers) and psychometric analysis and have been supported by Marsh and Dunkin's evaluation in relation to theories of teaching and learning.

III. Principal Components Analysis

Principal Component Analysis (PCA) is a multivariate statistical method, which aims to identify the relationship between features extracted from the data regarding its reduction, elimination of overlap and the choice of the most relevant linear data combinations from the original variables [17], [19], [21]. Known as Hotelling Transform, the PCA transforms discrete uncorrelated variables in coefficients through a linear transformation applied in data, so that the resulting data has its most significant component in the first dimension, referred to as principal component.

As a principle for the PCA calculation considering a random vector $\mathbf{x} = (x_1, x_2, \dots, x_p)^t$ containing p components a vector of mean: $\mu = E(\mathbf{x}) = (\mu_1, \mu_2, \dots, \mu_p)^t$, where t means the transpose of the vector. The covariance matrix of the random vector $\mathbf{x}$ with square dimensionality of size p is denoted by $Cov(\mathbf{x}) = \mathbf{U}_{pxp}$. The covariance matrix is a symmetric nonnegative matrix $\mathbf{a}^t\mathbf{U}\mathbf{a} > 0$ for every constant vector $\mathbf{a} \in \mathbb{R}^p$. This condition implies that the matrix eigenvalues are denoted by $\lambda_1, \lambda_2, \ldots, \lambda_p$ are nonnegative ($\lambda_i > 0$ for any i = 1, 2,…, p). By the Spectral Decomposition Theorem [17] $\mathbf{U}_{pxp}$ is a covariance matrix, there exist an orthogonal matrix $\mathbf{O}_{pxp}$ where $\mathbf{O}^t\mathbf{O} = \mathbf{O}\mathbf{O}^t = \mathbf{I}$ as:

$$\mathbf{O}^t\mathbf{U}\mathbf{O} = \boldsymbol{\Theta} \qquad (1)$$

where $\boldsymbol{\Theta}$ is a diagonal matrix with entries $\lambda_1, \lambda_2, \ldots, \lambda_p$ that are the eigenvalues of the matrix $\mathbf{U}_{pxp}$, that are ordered in descending order. We say that the matrix $\mathbf{U}$ is similar to the matrix $\boldsymbol{\Theta}$.

The i^{th} column of the matrix $\mathbf{O}$ is the normalized eigenvector $\mathbf{e}_i$ corresponding to the eigenvector of λ_i with i = 1, 2,…, p which is denoted by $\mathbf{e}_i = (e_1, e_2, \ldots, e_p)^t$. Then the matrix $\mathbf{O}$ is given by $\mathbf{O} = [\mathbf{e}_1\mathbf{e}_2 \ldots \mathbf{e}_p]$ and the spectral decomposition theorem has the following identity:

$$\mathbf{U}_{pxp} = \mathbf{O}\boldsymbol{\Theta}\mathbf{O}^t = \sum_{i=1}^{p} \lambda_i \mathbf{e}_i \mathbf{e}_i^t \quad (2)$$

which $\mathbf{O} = \mathbf{e}_i\mathbf{e}_i^t$ form a basis of the decomposition of $\mathbf{U}$, that the projects components values are the eigenvalues.

For the application of PCA in a matrix $\mathbf{X}$, we can obtain a new coordinate system which axes are now in the direction of the eigenvectors related to $\mathbf{U}$. So we can rewrite PCA as a rank reduction problem that can be viewed in Equation 3:

$$\mathbf{U}_{pxp} \approx \sum_{i=1}^{p-n} \lambda_i \mathbf{e}_i \mathbf{e}_i^t \qquad (3)$$

where n indicates how much we will reduce the rank matrix to the new uncorrelated variables.

Among the main applications of PCA we have [18], [20]: 1. Information Compression (voice and image) and 2. Rank Reduction (attributes and model selection).

In the application of rank reduction, PCA has the property to minimize the mean square error between the reconstructed data and original data [21]. It is assumed, for example, which has input data $\mathbf{X}$ with rank m and output data Y with rank m_1 where $m_1 < m$.

The rank reduction, through the PCA method, in this study will allow the extraction and selection of the most significant features into the context of evaluating the teaching effectiveness related to the disciplines in focus.

IV. Methodology

A. Subjects and Course

1) TIE Course: The world is experiencing a transformation at a pace never before experienced. The world population is growing increasingly demanding for goods and services in an ascending scale, set in a finite ecosystem, society is demanding a greater degree of rationalization of its resources for the benefit of a better redistribution of wealth, and more fairly.

Rather, areas of knowledge regarded as independent, are now not only touching, but are transposing their borders and leading to the emergence of new areas of human knowledge. More than a mix, we are witnessing a convergence of technologies.

In this context, the objective of the TIE course is to train engineers in the teleinformatics area with a solid and consistent technical and scientific training which will enable them to absorb and develop new technologies, encouraging their critical and creative role in identifying and solving related problems, considering its political, socioeconomic, environmental and cultural, ethical and humanistic vision in meeting the needs of society.

Among the specific objectives of the course, we can emphasize:

- Provide a multidisciplinary knowledge of current technologies used in telecommunications systems and computer systems, including aspects of processing, transmitting and receiving information.
- Provide training in TIE with emphasis in telecommunications engineering and computer engineering, consistent with emerging markets, still in need of skilled labor.
- Enable the professional engineer to carry out assignments in the following technical areas: signal transmission, antenna and switching, transmission systems, data, video and voice by cable, optic fiber, microwave links, satellites, television and radio systems; systems and mobile phone networks, optical communications systems, high-speed networks, internet and mobile computing.

Finally, the course presents daytime and evening classes and the average duration for the completion of the regular TIE course is 5 years for the daytime class and 6 years for the evening class.

2) Characteristics of the Sampling: The research on which this study is based was administered with students in the 3rd and 4th years of the TIE course. The SEEQ instrument was performed in 4 classes of students who were enrolled in the disciplines of Signals and Systems (SS) and Digital Signal Processing (DSP). Students of both disciplines were invited to participate voluntarily in this research, ensuring their anonymity as well as teachers. Students were selected from these two disciplines, because all of these students had already attended the basic disciplines of the TIE first year and also had a prior authorization of the teachers of the four classes for the data collection instrument that was used on students during the classes. During the implementation of SETE some characteristics of the instrument were clarified to the participants, and also a process of awareness to the participants was done, highlighting the importance and necessity of the questionnaires to be answered in the most faithful and true to the reality of events during classes taught in the subjects investigated in the first year.

All data was collected between the last fortnight of April 2012 and the first fortnight of May 2012. Of the total of 120 students who enrolled in four classes, 100 students completed the questionnaire, yielding a participation rate of 83.3%.

B. Measurement Instrument

The SETE questionnaire, adopted and modified from previous studies [2] is divided into eleven different subscales, in this study. This questionnaire is the Students Evaluations of Educational Quality (SEEQ) instrument [4].

The Learning (Lrn) subscale reflects what students learned in the classroom. Four items examine the student's interest, knowledge and skill in the discipline area. The Enthusiasm (Enth) is a subscale made up of four questions about the motivation, dynamism and enthusiasm conveyed by the teacher during class. The third factor is the Organization (Orgn), which also assesses claims by four transmission qualities and clarity of content by the teacher, as if the objectives were achieved and the lessons taught eased the assimilation of the content from reading the classes notes. The next item was the Interaction Group (Grp), which investigates the stimulus that the teacher causes to intervene in the classroom during class and if the students are encouraged to participate with their own ideas or answer questions posed by the teacher. The fifth subscale deals with the relationship between teacher and students and is called the Individual Rapport (Ind). This item explores the relationship between teacher and students in extracurricular activities and their availability to serve them. Another important subscale is Breadth (Brd) that investigates the opinions of students towards teacher's skills and concepts and ideas he develops in class, presenting their views and presenting research results in the content of that particular area. The Examinations (Exam) subscale assesses the availability of the teacher in correcting the assessments and judging if their methods are appropriate. The next subscale is the Assignments (Asgn) that assesses whether the workload of the activities as well of the readings and available texts contribute to learning. The ninth and tenth subscales have the same goal, namely Overall, the first of which refers to the overall discipline (O_Disc) in relation to other disciplines, while the second evaluates the teacher (O Inst) in relation to other teachers at the institution. Finally, the last evaluated indicator with four items is the Student and Course Characteristics (C_Carac) respect to the difficulty of the course in relation to another one, as well as the rate classes and the time required for commitment of the pupil. All 35 items belonging to these 11 factors were evaluated in 5 parts of the Likert-scale, from very poor (1) to very good (5). Item 36 to item 40 of the instrument have been raised regarding the profile information of students and these data will be useful to characterize the participants in this study, although not part of the 11 factors that will be the main target of this research.

C. Multivariate Data

The data obtained from this research is multivariate and is the field of sensory analysis there is no theory that describes when individuals have different preferences. In this regard, the application of chemometrics methods is an elegant way of exploring data of this nature [12], [13].

In general, students' data has the following form: K students x I disciplines x with respect to J attributes, the set of 11 factors that SEEQ (adapted) [4]. The values obtained were transformed from a 3D array to a 2D array performing an average of students' responses (Fig. 1).

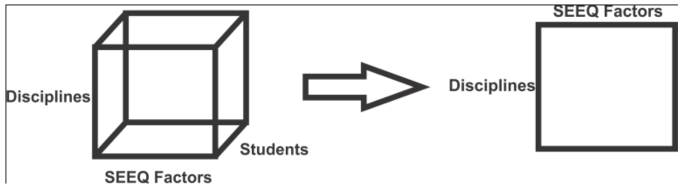

Figure 1. Data organization.

The matrix **X**m with the dimensions (I disciplines x J SEEQ factors) obtained from the average of the scorings per student, a two-dimensional array is explored by PCA through an average configuration matrix, where the average information about the students is considered. The disciplines that have been analyzed: Fundamental Physics (FP), Experimental Physics (EP), General Chemistry (GQ), Engineering Design (ED), Elementary Calculus (EC), Linear Algebra (LA), Programming Techniques (PT) and Digital Logic Project (DLP).

V. Results and Discussion

A. Reliability of Dataset

In this study, Cronbach's α was calculated to estimate the reliability of the SETE scales, and the results revealed high internal consistency. The α-coefficient of the dataset was high at 0,9536. The reliability analysis showed the scales to be highly reliable.

B. PCA Analysis

The principal component analysis in terms of a change made formal basis for the vector space data set after the application of SETE. PCA was applied to the matrix X_m with dimensions (8 x 11), obtained by calculating the average of the students answers that was describe in section IV-C.

Due to I < J, by the spectral decomposition theorem we find only 8 distinct eigenvalues witch is associated with 8 linear independent eigenvectors.

TABLE I. Variance Explained

Components	Eigenvalues	Variance %	Cumulative %
1	7,859	71,449	71,449
2	2,152	19,563	91,011
3	0,411	3,735	94,747
4	0,273	2,503	97,250
5	0,203	1,850	99,100
6	0,083	0,751	99,851
7	0,016	0,149	99,901
8	4,3E-16	3,9E-15	100

Each discipline that was then represented in the M dimensional space defined by SEEQ factors has now to be represented by the N principal components. Table I shows the variance explained and cumulative variance for each of the 8 major components. As can be seen, the first two principal components corresponding to most of the variance explained (91,011%).

Fig. 2 shows the loadings for the first two principal components representing the relationship between the 11 variables analyzed, we can infer an interpretation for the main components. It is interesting to note that the arrangement of the variables along the PC1 modeling contains 71.449 % of the variance of the data matrix. We can see high loading values for the attributes that are related to the characteristics of the disciplines and their difficulty with the others, this behavior is seen in both PC1 and PC2. Characteristics related to the teacher are clustered in one area of Figure 2, thus forming a clustering only related to behaviors of teachers in the disciplines.

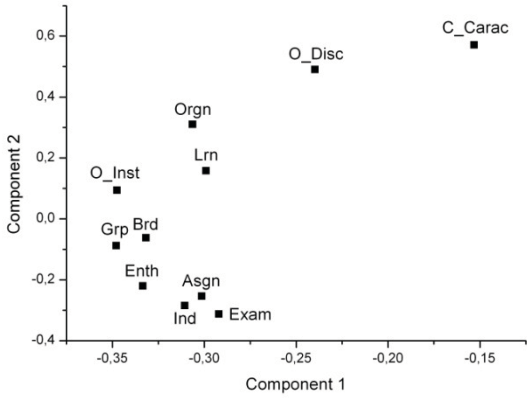

Figure 2. Loadings plot.

Fig. 3 shows the scores for the first two principal components, relating to the eight disciplines analyzed. As can be seen that the right most elements can be classified as a group. These scores are for the disciplines of Programming Techniques and Digital Logic Projects which belong to the same course curricular unit referring to the cycle of computer systems. In another group observed in the left are for the basic cycle disciplines of TIE, they are core disciplines of the sciences and mathematics that will theoretically support students for the more applied disciplines.

Analyzing Figure 2 and Figure 3 simultaneously, we see a consistency in the arrangement of the points in both figures. We highlight in Figure 2 that PC1 has a strong relationship with the general characteristics of the subjects, which confirms the picture presented in Figure 3. These high load values in the PC1 can be explained because the analysis has been made in different disciplines with very different contents and methodologies.

Given that the factors Overall Disciplines and Student and Course Characteristics have higher loading on PC1, we can infer that the discipline's workload and its difficulty in relation to other disciplines [4]–[9] are the most relevant factors to be analyzed. This analysis allows checking, for example, if the workload of the discipline and its difficulty in relation to the other is taken into account in the formulation of the curriculum of the course, considering that students recognize the workload and difficulty. The use of PCA helps to understand better these relationships between disciplines through the student's perspective.

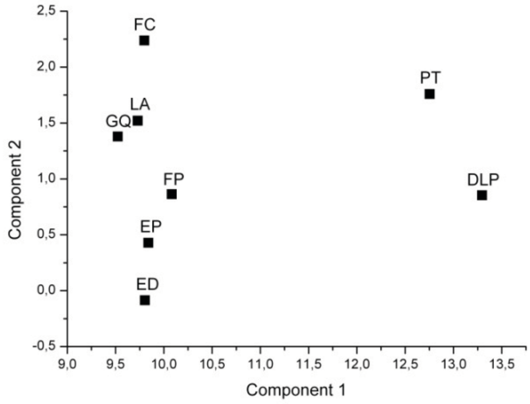

Figure 3. Scores plot.

This study presents limitations. First of all, we used a small number of disciplines belonging to the curricular unit of TIE course and a panel composed of 100 students, a number that is not representative of the population. Secondly, we do not analyze information regarding the year of study that were collected in the SEEQ instrument. However, our findings are valuable since they report several correlations among SETE data collected, such as the relationships between distinct disciplines.

VI. Conclusion and Perspectives

The PCA method seems to be a potential tool for data analysis related to assessing the teaching effectiveness. Its use provides intrinsic perception information of students on subjects related to the factors that relate to the SEEQ instrument.

According to this model, the disciplines PT and DLP (Figure 3) have similar characteristics in view of the effectiveness of teaching, as well as the disciplines FP, EP, GQ, ED, EC and LA also have such similarities (Figure 3). This may suggest that students have a greater receptivity to disciplines more related to the area of technology than the basic science related disciplines. Furthermore, the discipline Engineering Design showed more similar characteristics related to basic science disciplines than the technology disciplines, because the subject of ED is more related to analytic geometry and non-technological issues related to the computer or electronic area.

Considering the complexity of the data matrix evaluation and intrinsic and extrinsic factors evaluated in SETE, our results are useful and deserve consideration in the educational assessment area, because we propose the use of a multivariate technique analysis of factors related to the subjective evaluation of the effectiveness of education, which we shall call Educametrics [22].

An important topic for future research is applying new multilinear methods in an educational dataset. We are currently investigating the multilinearity of data applying mathematical tools of tensor decompositions that take into account this multiway aspect [13].

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