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Original Paper

A Mathematical Model of a Course Performance Index to Measure Improvements in Students' Soft Skills

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Abstract

In this paper, a method to assess engineering students' performance after humanity course is introduced. Mathematical model for a student improvement index is derived to quantify a student's improvements in some learning parameters related to the course. Input to the index is the data obtained from a survey given to students before the end of the course. Statements in the survey can be given different weights according to their importance. A numerical example on how to calculate improvement index is represented. A course performance index is introduced as well to measure how all students in the course achieved in comparison with previous or target performance. A case study in which a survey can be given to undergraduate engineering students before the end of a course about oral presentation skills is introduced as an application for the proposed models. The second index can also be used by the institution to measure the quality of the learning process through the course in certain semester. The proposed approach has the advantage of being of almost no additional cost and can be modified and applied to other courses as well. Also, this approach needs moderate use of Microsoft Excel and doesn't need sophisticated academic analytics or learning management system to be owned by the institution.

Keywords

engineering education, learning analytics, learning outcomes, course performance index, communication skills

1. Introduction

After finishing any undergraduate course, students, instructor, and institution may need to know how successful was the course. Obviously, a measure of this success is the performance of students in all summative assessments. Another measure of success is how students improved their soft skills or gained new ones. In such a case, informative assessments such as surveys can be used. Generally, any method to evaluate performance of students should include some measurable parameters. Actually, there are many parameters that contribute to the success of the learning process and can be included. Some parameters are important to evaluate the achievements of students while others, for example, are important to evaluate the performance of the instructor through the whole course. Considering some parameters more important than others depends on how the institution define the learning process as effective or successful. Once the definition of effective or successful learning process is well established by the institution, related parameters can be considered more important and need to be evaluated and other parameters of less importance can be neglected. Therefore, a criterion of weighting parameters according to their importance should be established.

Engineering students should satisfy the recent requirements of the local and global markets after graduation. For example, an engineering student should be equipped with necessary communication and presentation skills to cope with the dynamic change in technology and industry (Rimer, 2002; Gover & Huray, 2007; Wulf, 2000; Ghazy, 2017). Sometimes the score in the final exam can be considered as a measure of improvement. In this case, the grades in the mid-term exams can be used to predict the outcome in the final exam (Huang & Fang, 2010). After that, the actual grades can be compared with the predictions to check if students achieved the expected targets of the learning process or not. Quantification methods of measurements usually depend on the nature of the data being measured. Multivariate regression analysis was used to formulate an outcome function based on some predictor or independent variables (Alexopoulos, 2010). Palmer used the logistic regression to predict engineering student performance and improve retention rates (Palmer, 2013). Students' retention rates and other applications necessitate using tools of academic analytics (Campbell et al., 2007). By analyzing the data related to students programming behavior, their performance in introductory programming course could be predicted (Watson, Li, & Godwin, 2013). Results from this approach were then compared to the error quotient method introduced in (Jadud, 2006). Actually, quantification of behavior is originated back at the Grounded theory (Glaser & Strauss, 1967).

Evaluation of technical courses may be simpler when compared to humanity courses. Exams and quizzes can measure students' gains in technical engineering knowledge and skills. In humanity courses, the soft skills can't be measured through examination only. Surveys and group discussion with live feedback from students can be used to measure gains in such skills. Therefore, in humanity courses, sometimes special seminars, surveys, and workshops are necessary to explore all parameters affecting students' perception to the course material and their class interaction (Kazamia, 2012). Data obtained from learners can benefit instructor and department and can also be implemented in academic analytics on institution level (Long & Siemens, 2011). On the other hand, when tools of learning analytics are available for instructors they can be used for instructional purposes (Long & Siemens, 2011; Conde & Hernández-García, 2016; Buendía-García & Benlloch-Dualde, 2017). However, sometimes, these tools may not be available or the institution doesn't want to change its evaluation system. In such a case, a simple approach like the one we introduce in this paper, with minimum requirements of programming knowledge and based on Microsoft Excel with some flexibility, can be used by the instructors and departments.

In this paper, we introduce a simple method to measure a student's performance in a humanity course. Thus, mathematical models for two indices are established. The first index is used to measure individual student improvement while the other is used to measure performance of all students over the whole course. To show how to apply the two indices in a specific course, a survey that can be given to engineering students before the end of a course about oral presentation skills, to solicit their feedback in some parameters related to the learning process, is introduced. A rare situation in which a student got zero improvement in all parameters is discussed and analyzed. Our findings will be discussed and future extensions of the idea of the student and course indices will be suggested. An obvious extension is to include a student's previous experience in the course material, before even registering the course, into his improvement index.

2. Method

2.1 Mathematical Modeling

In this section, two functions will be constructed to represent the student improvement index and the course performance index respectively. These indices are thought of as non-binary decimals taking any value between zero and unity. Assume that n is the number of statements in a survey that is given to students. Let x_i denotes the change or improvement in the i^{th} statement, where $i = 1, 2, 3, ..., n$. Variables from x_1 to x_n will constitute the vector of independent variables $\mathbf{x}$. Where x_i takes any value from zero to four, so that $x_i = 0$ means no improvement at all, $x_i = 1$ means small improvement, $x_i = 2$ means medium improvement, $x_i = 3$ means big improvement, and $x_i = 4$ means very big or huge improvement. As statements in a survey may have different importance and consequently different weights, we need to define the vector of weighting values $\mathbf{w}$. Now, we have the following vectors

$$\mathbf{x} = \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{pmatrix}, \quad \mathbf{w} = \begin{pmatrix} w_1 \\ w_2 \\ \vdots \\ w_n \end{pmatrix}. \tag{1}$$

The student improvement index II_s is the outcome or response variable and will be a function of the independent variables and the weighting values, i.e. $II_s = f(\mathbf{x}; \mathbf{w})$. Using the maximum value of the independent variable, we can introduce normalized independent variables $v_i = x_i / x_{\max}$, where $i = 1 \to n$ and $v_{\max} = 1$. Actually, using normalized independent variables allows adapting any number of choices corresponding to each statement in the survey. For five choices $x_{\max} = 4$ and for eleven choices $x_{\max} = 10$ ...etc. It also eliminates the effect of data formats and units. The student improvement index can then be written as

$$II_s = f(\mathbf{v};\mathbf{w}), \ \mathbf{v} = \begin{pmatrix} v_1 \\ v_2 \\ \vdots \\ v_n \end{pmatrix} \tag{2}$$

Where $f(\mathbf{v})$ is a scalar valued function of the normalized independent variables.

Assuming that m is the number of students and $(II_s)_k = f_k(\mathbf{v})$ is the k^{th} student index, where $k = 1 \to m$, another index can be formulated to measure the performance for the whole course as follows

$$PI_c = g\{\mathbf{f}(\mathbf{v};\mathbf{w})\}, \ \mathbf{f}(\mathbf{v}) = \begin{pmatrix} f_1(\mathbf{v};\mathbf{w}) \\ f_2(\mathbf{v};\mathbf{w}) \\ \vdots \\ f_m(\mathbf{v};\mathbf{w}) \end{pmatrix}, \tag{3}$$

where, $g\{\mathbf{f}(\mathbf{v};\mathbf{w})\}$ is a scalar valued functional and $\mathbf{f}(\mathbf{v};\mathbf{w})$ is the vector of individual improvement indices. The forms of the function $\mathbf{f}(\mathbf{v};\mathbf{w})$ and the functional $g\{\mathbf{f}(\mathbf{v};\mathbf{w})\}$ are not fully determined yet. They might be linear or nonlinear depending on many parameters including, but not limited to; the nature of the course i.e., how much of its content technical and how much humanity, the level at which the course is offered, the academic environment, and the importance of each statement…etc.

The elements of the weighting vector are arbitrarily chosen and, theoretically, each element can take any real numerical value. To complete our model, we enforce the condition $\sum_{i=1}^{n} w_i = 1$ to be satisfied when choosing the elements of the weighting vector. The improvement index can simply be considered as the summation of the weighted normalized independent variables

$$\begin{aligned} II_s(\mathbf{v};\mathbf{w}) &= \mathbf{w}^{\mathrm{T}}\mathbf{v} = \frac{\mathbf{w}^{\mathrm{T}}\mathbf{x}}{x_{\max}} = \sum_{i=1}^{n} \frac{w_i x_i}{x_{\max}} \\ &= \sum_{i=1}^{n} w_i \frac{x_i}{x_{\max}} = w_1 \frac{x_1}{x_{\max}} + w_2 \frac{x_2}{x_{\max}} + \dots + w_n \frac{x_n}{x_{\max}} \\ &= w_1 v_1 + w_2 v_2 + \dots + w_n v_n = \sum_{i=1}^{n} w_i v_i \end{aligned} \tag{4}$$

From (4), the boundary values of the student improvement index correspond to maximum improvement or zero improvement respectively of the student in the course are

$$II_s(\mathbf{x}_{\max};\mathbf{w}) = 1\,,\;\; II_s(\mathbf{0};\mathbf{w}) = 0 \tag{5}$$

For example, in a survey with seven statements, the weighting vector of the statements is chosen to be

$$\mathbf{w}^* = \begin{pmatrix} 0.2 & 0.2 & 0.1 & 0.1 & 0.1 & 0.1 & 0.2 \end{pmatrix}^T \tag{6}$$

Assuming that each statement has five choices and based on certain student's selections, the vector of independent variables was found to be

$$\mathbf{x}^* = \begin{pmatrix} 4 & 3 & 3 & 3 & 2 & 4 & 2 \end{pmatrix}^T \tag{7}$$

the improvement index for this student, calculated using equation (4), will be $II_s(\mathbf{v}^*;\mathbf{w}^*) = 0.75$. The value of the improvement index for this student can, for example, be compared with the average index of the class to give more indication about improvement of this student relative to his classmates.

Assume that $\mathbf{V}$ is the matrix of improvements of all students in all statements with a number of columns equal to the number of students and number of rows equal to number of statements. The row vector of individual improvement indices for all students will be

$$\mathbf{f}(\mathbf{v};\mathbf{w}) = \mathbf{w}^T\mathbf{V} = \begin{pmatrix} w_1 & w_2 & \dots & w_n \end{pmatrix} \begin{pmatrix} v_{11} & v_{12} & v_{13} & \dots & v_{1m} \\ v_{21} & v_{22} & v_{23} & \dots & v_{2m} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ v_{n1} & v_{n2} & v_{n3} & \cdots & v_{nm} \end{pmatrix} \tag{8}$$

The course performance index PI_c can be any function, such as mean, standard deviation…etc., of the vector of individual indices $\mathbf{f}(\mathbf{v};\mathbf{w})$. If, for example, we give a survey to students and obtain their evaluations to all statements we then have the matrix $\mathbf{V}$ fully determined. For this survey, by defining the vector $\mathbf{w}$ we can use equation (8) to generate $\mathbf{f}(\mathbf{v};\mathbf{w})$. If we change $\mathbf{w}$ for any reason we can iterate to generate another $\mathbf{f}(\mathbf{v};\mathbf{w})$.

2.2 Single Statement Mode

In the previous example we were interested in all improvements. But sometimes for some reasons, the instructor or institution may neglect or cancel one or more of statements inside the survey and the weights of these statements inside the vector $\mathbf{w}$ will be set to zero. In a very special case, we may be interested in improvement in one parameter only. For example, if we are interested in improvement in the i^{th} statement in the survey, the weighting vector will have only one non-zero element $w_i = 1$ to satisfy the condition $\sum_{i=1}^{n} w_i = 1$. In this case, the student improvement index in equation (4) reduces to

$$II_s(\mathbf{v};\mathbf{w}) = v_i \times 1 = v_i \tag{9}$$

and (8) simplifies to

$$\mathbf{f}(\mathbf{v};\mathbf{w}) = \begin{pmatrix} v_{i1} & v_{i2} & \dots & v_{ik} & \dots & v_{im} \end{pmatrix} \tag{10}$$

In this case, the idea of weighting the improvements vanishes from the mathematical model. Actually, such a case is a limiting case for the model of the improvement index.

2.3 Survey

A descriptive analysis based on data from a survey given to undergraduate engineering students at the beginning of a course about academic oral presentation skills was carried out (Ghazy, 2017). In this survey, nine statements were given to students to measure some parameters including students' perception to the course importance, objectives, and other parameters. Since, it was interesting to know how these parameters will change after finishing the course, a second survey can then be given to them at the end of the course to measure the improvements in some of the aforementioned parameters. But, for these measurements to be useful a quantitative analysis is required in addition to a descriptive analysis. The number of statements in the second survey was reduced from nine to seven so that only statements in which improvements can be realized and estimated by a student were kept.

The form of a survey to be given to students at the end of the course is shown in Figure 1. The outputs of this survey will be analyzed statistically through the mathematical models of indices which we derived previously. The survey should be given to all students attending the course and the number of students who participate in it should be sufficient so that the results will be accurate and reflect real students' perceptions. The survey includes seven statements with five choices correspond to each statement. The number of statements can be increased to include other factors when instructor, institution, or even students feel necessary. A student can fill the circle that represents how much improvement or change he realized or achieved. Though a student is required to keep himself anonymous he can add comments about any other improvement that is not addressed in the survey. This part of the survey dedicated to students' comments is not included in the mathematical models of improvement and performance indices.

Please complete this arbitrary survey, choosing how much you improved your skills after finishing the course in each of the following topics

No	Statement	No improvement 0	Small improvement 1	Medium improvement 2	Big improvement 3	Very big improvement 4
1	You found the course important for your career	○	○	○	○	○
2	You knew clearly the objective of this course	○	○	○	○	○
3	Your level in English allowed you to understand the contents in the course	○	○	○	○	○
4	You gave oral presentations in the faculty	○	○	○	○	○
5	You gave oral presentations outside the faculty	○	○	○	○	○
6	The instructor encouraged feedback from the class	○	○	○	○	○
7	This course helped you improve your English	○	○	○	○	○

Please write any additional notes you may like to strengthen this course

Figure 1. A Survey Given to Students at the End of the Course

3. Discussion and Future Work

Though the case of zero improvement in all of the statements are not considered in formulation of the improvement index, it may be noteworthy that zero improvement may not necessarily give negative meaning, neither means that a student has no knowledge in one or all of the statements in the survey. Actually, a student may have some prior knowledge about the course contents or partial knowledge related to one or more of the statements. Thus, the initial knowledge or proficiency IP_s of a student can also be considered as one of the parameters that should be included in the improvement index. The previous knowledge may be very important in education systems which accept students based on their qualifications, i.e., systems other than competition-based systems. In this case, the total proficiency TP_s of the student should have initial part in addition to the improvements. Thus, if a student has no improvement, he or she still has some proficiency or simply knowledge. The model of proficiency index should be written as follows

$$TP_s = IP_s + II_s(\mathbf{v};\mathbf{w};IP_s) \tag{11}$$

According to the previous analysis, the zero improvement may not bother a student if he has a previous knowledge about the course material. For example, some students who work part time in companies in human resources or sales departments may have very good presentation skills as they may gave tens of presentations. The job of some of them is to evaluate presentations given by new applicants. Such students register the course to complete their degree plan requirements and they don't expect big improvements after finishing the course. However, the institution requires the course to make some difference and supply students with new skills or even improve their previous skills. An instructor who understands this situation will work continuously on adding new skills or improving skills students already had before registering the course as indicated. In order to enable instructor to achieve this goal, he should have a chance to modify the course specifications or even the course learning outcomes. Therefore, even in such a special case of zero improvements, the course improvement index is still important.

The results in the vector $\mathbf{f}(\mathbf{v};\mathbf{w})$ can be compared with nominal values predetermined by the institution. These nominal values may be obtained from average performance in the course over years or any other benchmarking. Moreover, the results in the vector $\mathbf{f}(\mathbf{v};\mathbf{w})$ can be plotted against their normal distribution to see if the improvements of this class are naturally distributed among students. The improvement index is not unique. Once a new set of weighting values in vector $\mathbf{w}$ is chosen, a new value of the improvement index can be generated. One way to choose some weighting values in this model is to satisfy the intended learning outcomes. This approach has the advantage of updating $\mathbf{w}$ from time to time whenever the learning outcomes are updated. But still the way to choose values inside the weighting vector $\mathbf{w}$ needs more investigation and represents a potential extension to this research in the future.

4. Conclusion

Performance of a student in terms of improvements in his soft skills after a humanity course can be quantitatively measured. A mathematical model for a student improvement index can be formulated as a simple mathematical function. Consequently, performance over the whole course can be measured using another index which is the course performance index. Thus, a primary mathematical model of a course performance index can be established. The derived models are not mathematically difficult and have the flexibility to be reformulated or modified. Another advantage is that the indices can easily include any number of parameters of interest by the instructor in the future. In addition, these models allow using weighting values for different learning parameters according to their importance and contribution to the learning process. Our approach shows extra flexibility as it can be applied to any humanity course after modifying the survey which is given to students to get estimation of the learning parameters. More importantly, departments and institutions can use these indices to compare achievements in the same course over years, as the course performance index has one numerical value weighted to be less than or equal to one.

The idea of having the performance in a whole course as one number could facilitate the periodic, or specifically the annual, evaluation of the instructor and the course done by the institution. It makes the comparison of the performance in the course in one semester with previous semesters a quick and easy process. As the model of the index depends on normalized values, it can be applied to courses of different nature. Thus, it can be used to compare the whole performance in technical as well as humanity courses. Finally, it facilitates the archiving process of the periodic evaluation reports done by the institution to build its learning analytic system.

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