A latent class approach for advising in learning statistics: implementation in the ALEAS system

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Abstract

Over the years, several instructional methods have been employed to support students in learning Statistics. Among them, intelligent tutoring systems deserve particular interest, personalizing the learning activities according to individual characteristics. Generally, students enrolled in human and social sciences degrees exhibit a high level of Statistical anxiety and severe math shortcomings that negatively affect their success in Statistics. In this framework, the present paper reports the description of ALEAS (Adaptive LEArning in Statistics) ERASMUS+ Project, which is aimed to implement an adaptive system for advising these students in learning Statistics. The ALEAS system includes a knowledge structure for the introductory statistics course, accounting for three of the five Dublin descriptors (i.e. knowledge, application, judgement). Dublin descriptors refer to the dimensions defining students' ability, they allow to detect homogeneous sub-populations of students and to select the most appropriate learning path accordingly. Students' learning process is also supported by learning materials, cartoons, and formative and motivational feedback. Some examples of how students can interact with the ALEAS system are illustrated in the last section of the paper.

Keywords

Intelligent tutoring system, Multidimensional latent class IRT model, Dublin descriptors, Statistical anxiety,

1. Introduction

Statistics is an essential topic in most Higher Education (HE) curricula. However, the discipline remains among the most "frightening" for students, making them feel anxious. Statistical anxiety refers to apprehension to the statistics content or the evaluative contexts dealing with statistics [1]. It is also described as an enduring and persistent type of anxiety [2, 3], distinguished from mathematics anxiety [4, 5]. This kind of concern seems to mainly affect students enrolled in social and human sciences courses like Psychology, Health Sciences, Medicine, Political Science, and Social Science [2, 6]. Many studies have suggested that the anxiety encountered when taking a statistics course may play an essential role in predicting academic achievements (for a

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review, [7]). Specifically, several studies showed the negative relationship between statistical anxiety and achievement in statistical exams [8, 9, 10].

Despite the broad literature that studies the link between statistical anxiety and achievement, no studies consider the dimensions that contribute to the definition of the student's ability. The student's ability is a multidimensional quantity grounded on the typical expectations of achievements and skills, as defined by the Dublin descriptors [11].

In this framework, the ALEAS project partnership proposed developing a system for advising in learning Statistics that considers this multidimensionality that characterizes the learning process of statistics. The system is part of the ALEAS (Adaptive LEArning in Statistics) ERASMUS+ Project [1]. According to the Dublin descriptors, the ALEAS project is conceived to evaluate and to improve student's knowledge to: *knowledge and understanding*, *applying knowledge and understanding*, *making judgments*.

The so-called Dublin descriptors have been developed to provide a general statement of qualifications that students should have acquired at the end of each cycle of HE (bachelor, master, and doctoral degree). The Dublin descriptors qualify the expected learning outcome. Learning outcomes refer to what a learner should know, understand, and do at the end of a learning path. The Dublin descriptors serve as the basis for the framework for qualifications of the European HE area. They are used to assess the knowledge a student has achieved within a specific knowledge state.

In ALEAS, the Dublin descriptors can be defined as competence levels in statistics on the following elements: *Knowledge and understanding*, *Applying knowledge and understanding*, and *Making judgements*. Knowledge and understanding refers to the ability to demonstrate knowledge and understanding, including knowledge about the range of theoretical, practical, conceptual, and critical perspectives on the statistical topics. Applying knowledge and understanding ability refers to the proficiency to apply the knowledge identifying, analyzing, and solving problems sustaining an argument. Making judgements refers to the ability to gather, evaluate, and present information exercising appropriate judgement. These three domains require different skills to be deployed in the learning process. The Dublin descriptors allow unpacking the achievement of the student's that approaches statistics. The knowledge descriptor concerns theoretical concepts, such as central tendency measures, Gaussian random variable, Central Limit Theorem. For the application descriptor, the student is required to do calculations to solve simple statistical problems. Instead, the judgement descriptor refers to students' ability to make decisions about situations of the course of studies, such as Psychology and Political Sciences.

This paper aims to describe the ALEAS system and its engine to classify students according to their ability level measured according to the above mentioned learning descriptors. The contribution consists of the following sections: Section 2 introduces the ALEAS system, Section 3 reports examples of the ALEAS system, Section 4 consists of final remarks and research perspectives.

[1]https://aleas-project.eu/

[1]http://ecahe.eu/w/index.php/Dublin_Descriptors/

2. ALEAS system

Over the years, several instructional methods have been employed to support students in Statistics (e.g., [12, 13]). Among them, intelligent tutoring systems deserve particular interest, personalizing the learning activities according to individual characteristics [14].

In this framework, ALEAS represents a novel tool for both teachers and students to complement traditional statistics courses. Indeed, ALEAS offers customized learning paths helping students to cope with statistical anxiety and lack of motivation. On the other hand, teachers can take advantage of the data analytics provided at the end of each learning session. They offer several indicators of students' level of knowledge to fine-tune their future teaching strategy.

The ALEAS system includes a knowledge structure for the introductory statistics course, consisting in ten main Topics: basic concepts, statistical graphical representation, central tendency, variability, empirical and theoretical distribution, bivariate categorical data, correlation and simple linear regression, basic probability, random variables and distributions, hypothesis testing. In turn, each Topic contains several Units that represent the most specific matter of knowledge distinction (e.g. mode, median and arithmetic mean for the central tendency topic). One or more Topics constitute a more general classification of statistical subjects, named Area. Several experts in teaching Statistics specified a set of possible relationships among the topics exploiting the Knowledge Space Theory (KST; [15]), which allows organising the full knowledge required to master into a directed acyclic graph structure. Thus, users can progress in their learning route once they mastered all the required Topics according to the paths on the knowledge structure.

It is worth noting that each learning Unit in ALEAS considers three of the five Dublin descriptors (i.e. knowledge, application, judgement) to assess and improve students' statistical knowledge. In particular, ALEAS includes a set of single-choice questions with a different level of difficulty to evaluate theoretical knowledge and critical judgement in coping with situations involving statistical issues, and exercises requiring simple computations to assess the ability to apply statistical knowledge. On the other hand, ALEAS provides students with learning materials (slides and readings) for all the Units, supporting each step of the learning process. The ALEAS system also includes cartoons and vignettes to facilitate the learning of some essential statistical topics, as several studies have demonstrated that graphical device can have a considerable effect on the aptitude and on the motivation for learning [16, 17]. A tutoring agent named "Ronny McStat", reminiscent of the famous statistician Ronald Fisher, welcomes the students and follows them during the learning process, giving feedback on the progressive achievement. Ronny McStat also takes part in the animated videos that address some difficult topics of the course, intending to present them by merely telling a story.

Moreover, since students who attend non-mathematics programs generally exhibit a high level of statistical anxiety and severe math shortcomings, ALEAS includes the assessment of these two features affecting students' performance in Statistics. After the first log-in, students' statistical anxiety is assessed using the Statistical Anxiety Scale [18], whereas the scale for Mathematical Prerequisites for Psychometrics [19] is used to evaluate math background. Data collection allows ALEAS to define different typologies of students and select the most appropriate learning path accordingly. It is worth noting that statistical anxiety can be assessed several times during the learning process to understand whether students' use of ALEAS has had an effect on their level of anxiety.

Students receive feedback regarding their general performance at the end of each Area according to the considered Dublin descriptors. As discussed in [20], feedback needs to be clearly defined and directly related to the assessment criteria. Thus, it should summarise learning outcomes and point the attention towards the gap between the performance and the expected achievement, enabling students to identify their strengths and weaknesses.

Besides, students are also provided with more in-depth Topic-level feedback allowing them to identify the arguments they need to repeat. This formative feedback has a developmental focus [21], defining goals and suggesting learning strategies.

Nevertheless, research has highlighted that students often do not collect formative feedback (see [22], among others). Reasons can be mainly found in students' lack of motivation, and the feedback's communication method [23]. Different tools can be used in this vein to engage students in the feedback process, such as humour, cartoons, and motivational feedback [20]. In particular, motivational feedback aims to encourage students, recognizing effort, acknowledging achievements, and giving hope about their future outcomes. Thus, motivational feedback plays an important role, especially when students feel unconfident, discouraged, and anxious.

In ALEAS, the formative feedback is displayed along with motivational feedback given by the mascot Ronny McStat, who appears in animated GIF files with congrats, indifferent, or disappointed expression, according to the level of evaluation. Motivational feedback has the primary purpose of reducing the level of statistical anxiety, especially for low performance.

2.1. Methodological framework

Regarding the learners' classification, which is used to assess their ability level and track their progress, ALEAS system exploited the multidimensional latent class IRT models [24], where Dublin descriptors refer to the dimensions defining students' ability.

The latent class IRT models represent a semi-parametric formulation of the traditional IRT models, in which the latent trait is defined through a discrete distribution with $\xi_1, \dots, \xi_k$ support points defining k latent classes with weights $\pi_1, \dots, \pi_k$. Thus, the latent class approach allows detecting sub-populations of homogeneous students for their ability level where class weight π_c (with $c = 1, \dots, k$) represents the probability that a subject belongs to that sub-population. More formally, let Θ_s be the discrete random variable of the latent trait of the subject s, the class weight can be expressed as $\pi_c = P(\Theta_s = \xi_c)$ with $\sum_{c=1}^{k} \pi_c = 1$ and $\pi_c \geq 0$.

Since the ability is defined as a multidimensional latent trait, we adopted the between-item multidimensional extension of the model, dividing items into different subsets I_d (with $d = 1, 2, 3$), according to the three Dublin descriptors we considered. The probability that the student s, with the ability vector $\boldsymbol{\Theta}_s = (\Theta_{s1}, \Theta_{s2}, \Theta_{s3})'$, correctly answers the dichotomously-scored item i (with $i = 1, \dots, I$) is formalised according to the two-parameter logistic (2PL) parametrisation, so that:

$$\mathrm{g}[P(X_{si} = 1|\theta_s)] = \log \frac{P(X_{si} = 1|\theta_s)}{P(X_{si} = 0|\theta_s)} = a_i(\sum_{d=1}^{3} \delta_{id}\theta_{sd} - b_i), \tag{1}$$

where $\mathrm{g}(\cdot)$ is the logit link function; X_{si} is the response of the subject s at the item i with realization $x_{si} \in [0; 1]$; δ_{id} is a dummy variable equal to 1 if the item i measures the latent trait d; a_i and b_i are the item discrimination and the item difficulty parameter, respectively.

According to the semi-parametric formulation, the manifest distribution of the response vector $\mathbf{X} = (X_1, \dots, X_I)'$ can be expressed as:

$$P(\mathbf{X} = \mathbf{x}) = \sum_{c=1}^{k} P(\mathbf{X} = \mathbf{x} | \boldsymbol{\Theta} = \boldsymbol{\xi}_c)\pi_c, \quad (2)$$

where

$$P(\mathbf{X} = \mathbf{x} | \boldsymbol{\Theta} = \boldsymbol{\xi}_c) = \prod_{d=1}^{3} \prod_{i \in I_d} P(X_i = x_i | \Theta_d = \xi_{cd}), \quad (3)$$

due to the assumption of *local independence*.

The estimation of the model parameters is based on the Maximum Marginal Likelihood (MML) approach [25]. In particular, we need to maximize the following log-likelihood:

$$\ell(\boldsymbol{\eta}) = \sum_{\mathbf{x}} n_{\mathbf{x}} \log[\mathrm{P}(\mathbf{X} = \mathbf{x})], \quad (4)$$

where the vector $\boldsymbol{\eta}$ contains all the free model parameters, $n_{\mathbf{x}}$ is the frequency of the response vector $\mathbf{x}$, and $P(\mathbf{X} = \mathbf{x})$ is defined according to the equation 2. In order to maximize $\ell(\boldsymbol{\eta})$, the Expectation-Maximization (EM) algorithm is used [26]. The EM algorithm alternates two steps, named E-step and M- step, until convergence. In particular, the Expectation step estimates the individual's conditional probability belonging to one of the latent classes given her/his response configuration, whereas the Maximization step maximizes the expected value of the complete data log-likelihood based on the posterior probabilities computed in the E-step.

The estimation process is performed through the R package `MultiLCIRT` [25]. For more details about the ALEAS methodology see [27].

3. Examples from ALEAS environment

This section aims to illustrate how students can interact with the ALEAS system. First, Ronny McStat welcomes the student and asks her/him to complete the preliminary diagnostic assessment regarding demographic characteristics, statistical anxiety, and math background (see Figure 1). According to the knowledge structure, the student begins her/his training process through the learning program, after receiving the first feedback on math background skills. At the beginning of some learning Topic, an animated video with Ronny McStat and his grandchild Alice introduces the topic highlighting the advantages and the drawbacks of a statistical method. For example, the story *Passed and Failed* focuses on the arithmetic mean and sheds light on how average evaluations flatten the differences leading to a biased description of a phenomenon. In the story, Alice complains about her teacher that gave the best class award to another class, although her class had achieved the same average grade, and she and some of her classmates achieved the highest grade. Ronny McStat explains to his grandchild that even though no one reached the highest grade in the other class, more students achieved a suitable performance level. Figure 2 shows a scene of the *Passed and Failed* story (on the left) and the statistical explanation behind the story appearing at the end of the video (on the right). Afterwards, for each Unit, students were required to administer fifteen test items, five for each of the three considered

Figure 1: Ronny McStat welcomes students and asks them to complete the demographic questionnaire, the statistical anxiety test, and the math test.

Figure 2: *Passed and Failed* story introducing the arithmetic mean topic.

Dublin descriptors (knowledge, application, judgement). Figure 3 presents an example question for each Dublin descriptor for the central tendency topic, whereas Figure 4 shows some slides belonging to the learning materials for this topic. Users are provided with both a formative and motivational feedback, at the end of each Area, taking into account the learning goals. For example, let us consider the descriptive statistics Area and a student who reported a good performance in the Knowledge domain. Still, low performance in Application and Judgement in the descriptive measures will receive the following formative feedback: *"Your theoretical*

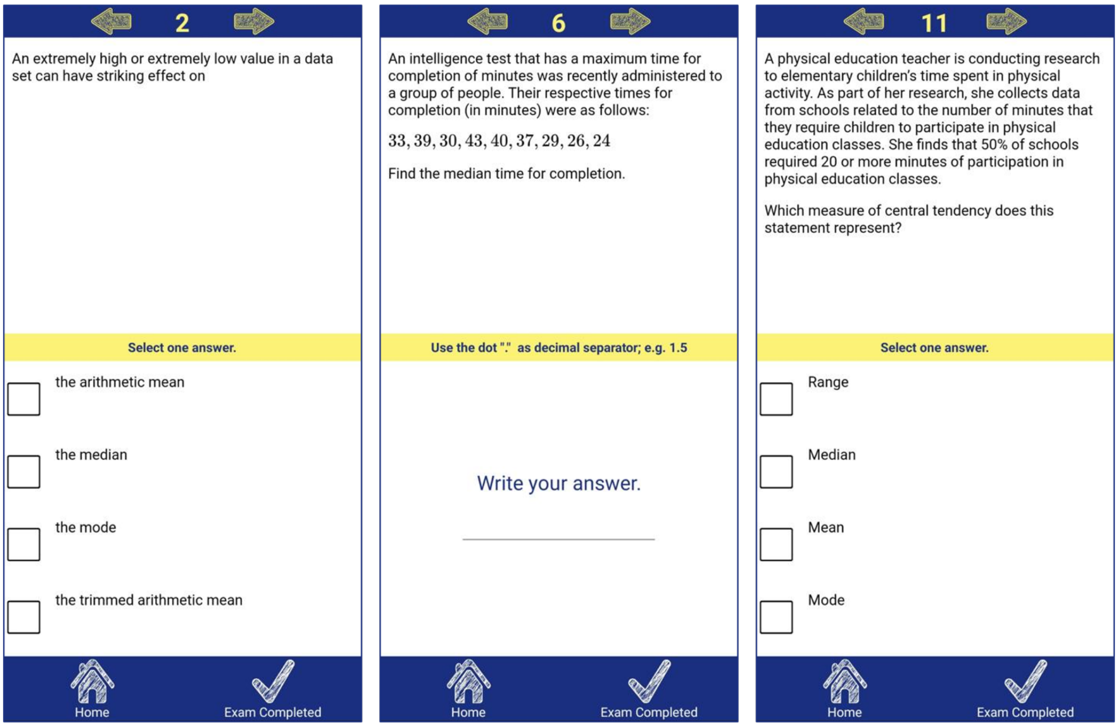

Figure 3: Examples of question for the central tendency Topic according to the Dublin descriptors: Knowledge (number 2), Application (number 6), and Judgement (number 11).

knowledge of the topics belonging to the descriptive measures Area is good! You seem to have understood the theoretical perspective and learned well the formal definition of the concepts. On the other hand, your ability to apply knowledge and make judgements is very lacking. I strongly advise you to do more exercises to improve your calculation skills and your ability to gather and evaluate information to reach an appropriate judgement in any situation. In particular, I recommend a more in-depth study of...".

Analogously, the student will be provided by Ronny McStat with motivational feedback as the following: *"Good for trying! You learned the topics of the descriptive measures Area, but not entirely. Practice more, and you could do better!".* As shown in Figure 5, Ronny McStat appears with an expression of congrats, indifference or disappointment, and give a medal to students properly accomplishing the learning Area. Moreover, during the learning process, several humoristic vignettes, like those in Figure 6, are displayed to the students to capture their attention and enhance their motivation.

4. Final remarks

The Adaptive LEArning system for Statistics (ALEAS) aims to provide an adaptive assessment of social and human sciences undergraduate students' statistical abilities. According to the Dublin Descriptors, thanks to this personalized assessment based on a Latent Class approach, ALEAS

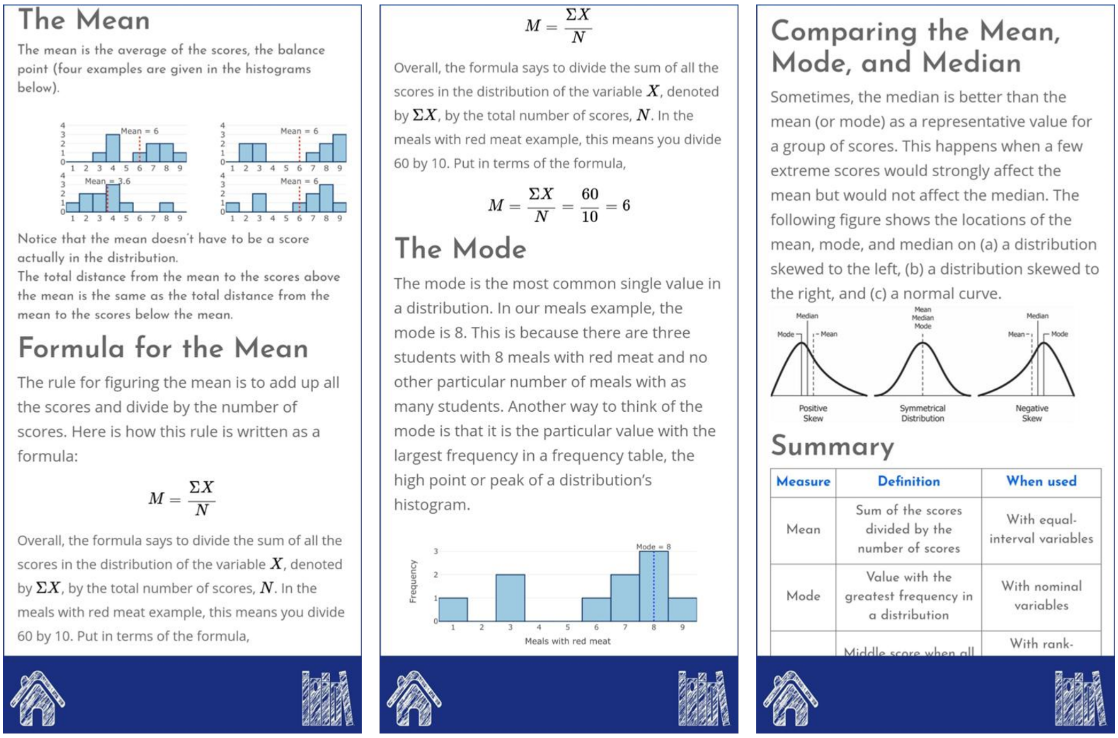

Figure 4: Learning materials on the central tendency Topic.

a b c

Figure 5: Motivational feedback: Ronny McStat's expression of congrats (a), indifference (b) and disappointment (c).

defines the most appropriate learning path. Through personalized learning paths and tools such as feedback, videos and humoristic vignettes, ALEAS helps students cope with statistical anxiety and lack of motivation. Formative and motivational feedback can be used to engage students in their progressive achievement and encourage them to define goals, suggest learning strategies, and encourage their efforts. In conclusion, the environment provided by ALEAS is a useful tool to improve Statistical learning strategies, as a complement to the traditional HE courses.

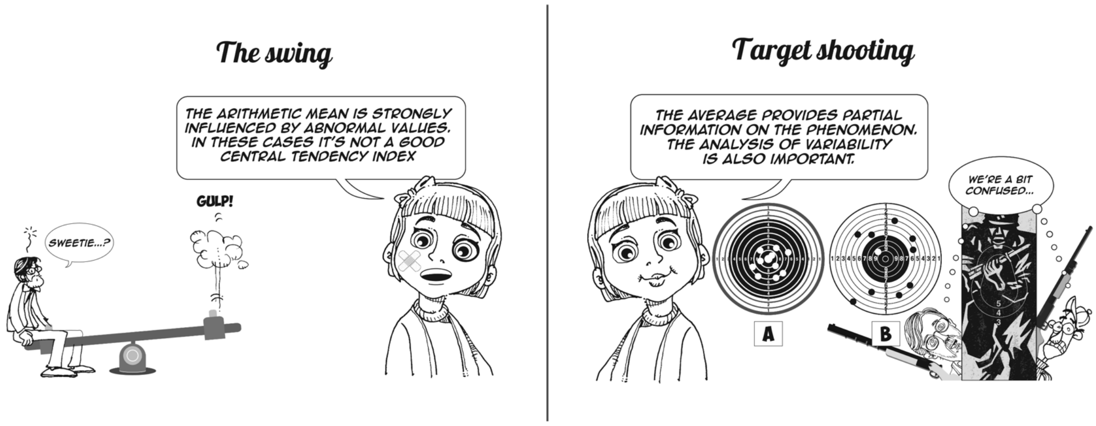

Figure 6: Humoristic vignettes that aim to facilitate the understanding and the interpretation of the arithmetic mean.

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