A Student-oriented Tool to Support Course Selection in Academic Counseling Sessions

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Abstract. Course selection and recommendation are important aspects of any academic counseling system. The Learning Analytics community has long supported these activities via automatic, data-based tools for recommendation and prediction. We contribute to this body of research with a tool that allows students to select multiple courses and predict their academic performance based on historical academic data. The tool is intended to be used prior to counseling sessions in which students plan their upcoming semester at the Ecuadorian university ESPOL. This paper presents the tool's design and implementation and discusses its potential to improve the student-counselor discourse.

Keywords: Learning Analytics · Academic Performance Prediction · Educational Data mining.

1 Introduction

Advising students throughout their educational career is the main duty of any university counseling system [14]. An important aspect of academic counseling is the recommendation of courses to students. This task is usually performed by a designated counselor who assists students in selecting the most appropriate courses at a given point of their degree. This is possible thanks to the counselor's knowledge of the academic program as well as her ability to make good use of historical data. Such data can be used to, e.g., identify successful and problematic academic paths or to characterize the difficulty of the available courses [11,12].

Despite the obvious benefits of academic advising in the mission of universities, course recommendations made by human counselors are not infallible. Recommendations can be inconsistent across counselors (with different counselors providing different advice to the same student), and across students (i.e., the same counselor can give different advice to students with a similar academic history). Recommendations can also be influenced by subjective factors. The perceived difficulty of a given course, for example, may depend on the counselor's personal learning/teaching experience.

To cope with some of these issues, recent research by the Learning Analytics community has proposed solutions to assist counselors in making better decisions [3,7]. Nevertheless, course recommendation remains a time consuming activity that often needs to take place within a short period of time [6]. Each student has a different history, a different set of strengths, and different preferences that make her unique. This implies that, for every new student, counselors will likely be confronted to previously unseen scenarios that require a dedicated analysis. Optimizing this task is of vital importance for universities as it incurs time and financial resources.

This paper reports the efforts made in this direction at the Ecuadorian university ESPOL[4]. We address the aforementioned issues with a tool that supports students in preparation for their academic counseling session and helps them decide which courses to take. We present here a prototype of our tool, which allows students to define arbitrary sets of available courses and predicts the student's performance. We also describe the data-oriented approach we took in designing our tool. This includes a description of how our prediction models take into account a student's own academic history, the performance achieved in the past by other students, and several difficulty estimators of the courses under consideration. We finally discuss the challenges and opportunities we have so far identified and present future research directions.

2 Related Work

Learning Analytics and Educational Data Mining focus on taking advantage of computational tools to collect and analyze educational data [9,15,16]. Learning Analytics research efforts have sought to support academic programs stakeholders through visual interfaces for several purposes [18]: to understand interactions within learning environments, to support instructional design, to explore learning progress, to understand forum discussions, to promote student reflection, and to identify students at risk of dropping out.

Other contributions from EDM and Machine Learning (ML) focus on the development of algorithms that better predict and discover facts from educational phenomena. Building upon these algorithms, a few tools support academic counseling activities (e.g., [1,4,17]). Notable examples that take a visual approach in this category include LISSA [3,13], which assists counselors in planning enrollment of first-year students who have previously failed courses. LADA [7] is another counselor-oriented visual dashboard with planning and prediction modules that uses clustering to estimate a student's risk of failing chosen courses.

Both LISSA [3,13] and LADA [7] pay a lot of attention to the needs of academic counselors and policymakers. Less support has been provided to students within the context of academic counseling. KMCD [19] was a pioneer work in

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this space that sought to help students choose their majors. Our tool shares with the VLA tools and systems mentioned above, the goal of helping people gain insight from educational data. However, it mainly aims at supporting students to make more effective decisions. This objective situates our tool within the area of decision support systems, which seek to "*help people overcome their biases and limitations, and make decisions more knowledgeably and effectively.*" [5, p. 3324]. Our tool, on the other hand, takes a visual approach to expedite the course selection and recommendation aspects of the academic counseling system of an actual higher education institution (HEI). To this end, it makes extensive use of EDM and ML techniques to provide personalized academic performance estimations.

3 Case Study: Academic Counseling at ESPOL

The Escuela Superior Politécnica del Litoral (ESPOL) is an engineering-oriented university in Guayaquil, Ecuador with over 10 000 students in its 32 undergraduate programs. Academic counseling was first established in ESPOL in 1991 with the purpose of helping students detect their strengths and needs, but it was not until 2013 that a formal, systematic academic counseling system was deployed.

Counselors are lecturers chosen by workload availability who are assigned, on average, twenty five students. Counseling sessions take place twice every semester: right before the semester begins for course-recommendation purposes and in the middle of the semester to monitor the student's progress. Each counseling period lasts about two weeks and students must meet with their counselors for a 15-minute session.

A common issue that we have identified through in-house observations at ESPOL is that counselors complain about the duration of the counseling session. They claim sessions hardly take under 15 minutes as students often need more time to decide on the courses they want to take. This is exacerbated when the students face particular issues that need to be addressed during the meeting.

Counselors have also reported that students seldom prepare themselves for the meetings in which they plan their upcoming semester. This lead to rushed decisions made on the fly, while talking to the counselor. These observations suggest that a system aimed to be used by students before they attend their counseling session could alleviate the counselor's workload. Ultimately, this would place more agency on the students' side regarding their academic choices.

4 Data-oriented Academic Advising

This work makes extensive use of Machine Learning (ML) techniques to generate models that can accurately predict the performance of a student in a given course. To this end, we consider the student's own academic history, her progress and followed academic path, and her target workload. We first describe the data used for our analysis (Sec. 4.1). This is followed by a description of the features that characterize students (Sec. 4.2) and the models we generated (Sec. 4.3).

4.1 Data

We analyzed a dataset containing the academic history of 2 543 Computer Science (CS) undergraduate students from ESPOL. This data spans the period 2002–2012. We worked with a simplified version of the CS curriculum previously studied in [11] and [12]. This academic program is composed of 26 core subjects: seven basic science courses, sixteen of professional instruction, and three from the humanities category.

4.2 Feature Selection

Feature selection is the task of selecting the "signals" that provide most information about the variable we aim to predict. An example of a feature in our context is the grade of a student in a given course taken in a previous semester.

Based on our knowledge of the study program and the way students plan their semesters, we tested a set of features that provide information about the performance of students in a course. The list shown below describes the final set of features with which we characterize students:

- **Previous Grades:** If course A is a pre-requisite of course B, it is natural to assume that the topics covered in A are necessary to understand the topics of B. This implies that if a student has performed well in A, she will likely succeed in B. On these grounds, to predict a student's grade in a given course, we used as input features her grades in all the corresponding pre-requisites[5] as well as in previous trials of the target course. Since students may have multiple grades associated to a course (in case of failure), we always use the latest obtained grade as features. The only exception to this rule is the target course: if the student has grades from previous trials, we take the most recent of those grades, otherwise we do imputation by considering the average grade among all students that have passed the target course.
- **Course and Semester Difficulty Estimators:** Some courses are more difficult or demanding than others, which means that for some of them, students are more likely to obtain lower marks. Our model considers the difficulty of a course j through three different features. First, it characterizes the course's grading standard (α) and its grading stringency (β) as proposed by Caulkins et al. [2]. These values are computed according to Equations 1 and 2, where GPA_i represents the overall academic performance of student i; r_{ij} is the student's grade in the course; and N_s^j is the total number of students that have taken the course. In general, the bigger the α_j (> 1), the more difficult the course. On the other hand, β estimates how much on average the course j shifts all students' grades up or down. Therefore, the smaller the β is, the easier the course can be considered.

$$\alpha_j = \frac{\sum\limits_i {GPA_i}^2}{\sum\limits_i (r_{ij} * GPA_i)} \qquad (1) \qquad\qquad \beta_j = \frac{\sum\limits_i (GPA_i - r_{ij})}{N_s^j} \qquad (2)$$

[5] Our results confirm this intuition: The best grade predictor of the performance of a student in a given course is typically her grade in the course's closest pre-requisite.

Our model resorts also to the skewness of the distribution (denoted by γ) produced by the distances between the GPAs of all the students that took a given course and their corresponding grade in that course. This estimator is part of the definition of β and has been used in data-driven curricular analyses [11,12]. All these scores are computed from the academic history.

- **Failing History:** The failing history of a student may convey hints about her skills or attitude towards the topic of a course. Hence, our model defines the *repeating frequency* of a student in a given course as the number of times the student has taken the course before passing it. This feature is equals to zero when the student intends to take the lecture for the first time.

4.3 Generated Models

We built training sets using the aforementioned features for different courses in the study program. For courses with few training points, we built training sets at the level of semesters. We did so by merging the records from courses usually taken together by students (i.e., they have common features) and adding an additional feature that identifies the course the record belongs to.

After testing different models such as linear regression, random forests and gradient boosting trees (GBT), we picked GBT for two reasons. First, it exhibits the best accuracy. Second, it allows us to deliver lowers and upper bounds for predictions by means of quantile regression [8]. On the downside GBT models are not interpretable: one cannot know the exact effect of the input signals on the model's answer. This limitation supposes a problem in our scenario because a mere prediction does not suffice for proper counseling. Counselors always provide explanations for their predictions in order to support their arguments.

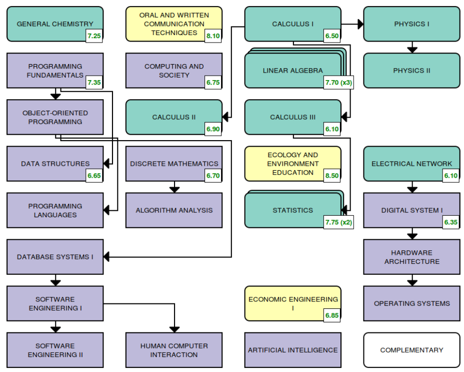
To overcome this shortcoming, we resorted to a post-hoc interpretability module. SHAP [10] is a explanation layer for ML models that relies on game theory to calculate the contribution of each feature (called the Shapley value of the feature) to the answer of a black-box model. SHAP is based on linear attribution, i.e., if we denote by δ_y the difference between the grade predicted by a model and the average grade, the Shapley value of a feature x measures the contribution of x to δ_y. Our prototype uses SHAP on top of our GBT prediction model to show the features that contributed the most to a predicted grade.

5 Our Prototype

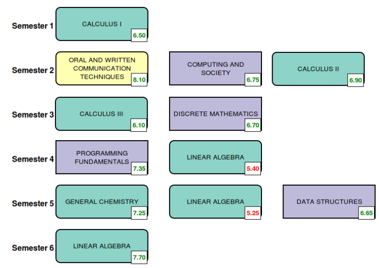
We integrated the outcomes of our data mining analyses within an interactive interface that enables students to plan out their upcoming semesters. The tool allows to compose sets of courses interactively and predicts for each the range the student's grade would fall in.

5.1 Program and Semesters Views

On opening the tool, the *Program view* shows the student's career program with courses organized into a grid and linked to their corresponding pre- and co-requisites (Fig 1a). Courses appear color-coded according to their type (green



(a) Program view



(b) Semesters view

Fig. 1: Program and semesters view of a student's academic history.

for basic science, yellow for humanities, and purple for professional training). The grade of the courses that the student has taken appears in green if the course has been passed and in red otherwise. This view also shows the number of times the student took a given course (if greater than one). Courses that have been repeated are depicted as a group of stacked rectangles.

The *Semesters view* reorganizes the elements of the *Program view* to show individual enrollment instances. This view uncovers the elements of the stacks that represent repeated courses and depicts when, within her own academic history, the student took each course. Figure 1b shows the academic history of the student of Figure 1a, which spans a period of six semesters.

5.2 Prediction Mode

The interface provides a button to enable the prediction mode. Upon activation, courses in the *Program view* that the student has already passed are disabled. This also happens to those courses that the student would not be able to take because of missing requisites (Fig. 2.A). In the prediction mode, students can select (or deselect), via clicking, courses they may be interested in taking. Each new course selection or deselection triggers the execution of our prediction algorithms. In turn, this updates the content of the *Prediction Results* view, which shows the performance prediction for each selected course as a range on a horizontal range between 0 and 10 (Fig. 2.B). The range corresponds to the confidence interval of our GBT prediction. We decided against showing here the exact value predicted by our model as a single point. We wanted to convey the fact that the provided prediction is an estimate and, as such, it carries some uncertainty. We also felt that depicting a single value could mislead students and bias their expectations, which would be counterproductive for the goals we pursue.

The tool shows the prediction results in a red-yellow-green divergent color scale with a zero value of 6. This is the minimum grade required to pass a course in ESPOL. Figure 2.B shows the predictions results for a set of four courses.

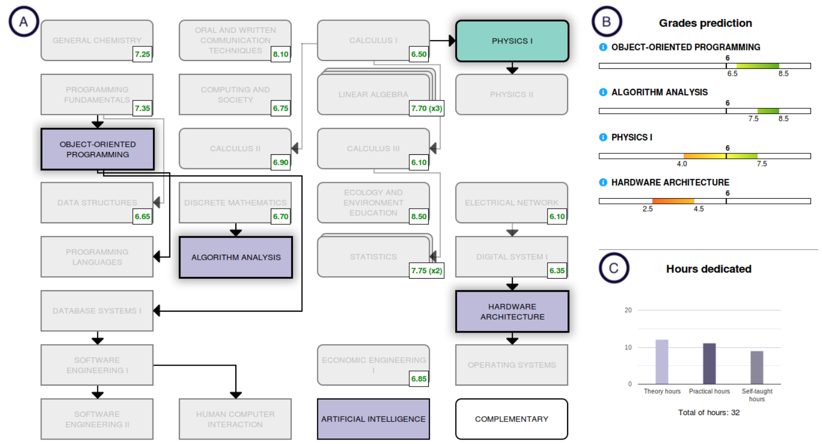


Fig. 2: Prediction mode. Selecting courses on the Program view (A) results in the performance predictions shown in (B). The weekly workload is shown in (C).

These results are quite optimistic for two of these courses (shown in the green part of the range), regular for one course (shown in between orange and green) and pretty pessimist about another (shown in a redish tone).

An additional view shows a breakdown of the the weekly workload the student would face due to their current course selection (Fig. 2.C). The load decomposition is shown as a bar chart with three categories: theory, autonomous work, and practicals. This visualization is also updated by the user's interactions on the *Program view* when in the prediction mode.

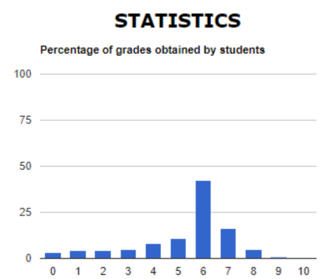
5.3 Supporting Understanding of Predicted Results

In addition to predicting the performance that a student could achieve in a given set of courses, an important goal of our tool is to provide insights on the reasons behind its predictions.

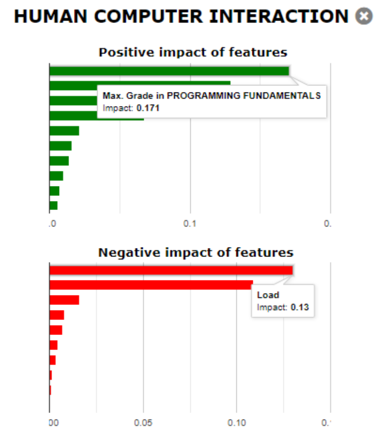
To this end, our current prototype provides access to the historic distribution of grades obtained by all the students that have passed a given course (Fig. 3a). This is possible by moving the mouse pointer onto a course of the *Program view* when the prediction mode is active. This visualization allows users to get an overall impression of a course's difficulty as it shows how other students from the same academic program usually perform.

The tool also provides an explanation of the factors that may have a critical impact in the student's performance. We provide a visualization of the Shapley values output by our interpretability module discussed in section 4.3. These visual explanations are available through the light blue icon shown to the left of each course on the *Prediction Results* view (Fig. 2.B).

An example of such visualization for the Human-Computer Interaction (HCI) course is shown in Figure 3b. Two horizontal bar charts show the ten features that have the more positive (green) and negative (red) impact on the predicted



(a) Grades historic distribution



(b) Relative impact of features

Fig. 3: Additional views available in the Prediction mode

performance. The features are sorted by their contribution to the prediction outcome and their name and relative contribution are available through a tooltip that appears on hovering the bars of the visualization. In the depicted example, the feature that most contributes positively to the performance in the HCI course is the grade of Programming Fundamentals. That is, students with a good grade on the latter course are likely to perform well in HCI. On the other hand, the total weekly load of the semester assessed is the main factor that could negatively impact the student performance.

6 Open Questions and Future Work

Designing and implementing our tool posed several questions. In this section, we discuss some of them and outline directions for future research.

- **Dealing with curricular modifications:** Academic programs are dynamic by nature. Often, courses are split or merged, some are created by the needs of the market and others disappear for similar reasons. Tracing these changes is vital to generate models that are consistent for all the students of an academic program. Some curricular modifications, however, can be particularly problematic. Consider the removal of an important predictor course. Estimating the performance of students who do not have a grade for this course will require a different model. However, the number of students to whom this change applies will be small right after the curricular modification is done. This, in turn, can lead to over-fitting.
- **Improving explanations of predicted performance:** Explainability is crucial to produce predictions that can be understood by humans. While we account for this by showing the relative contribution of the features used in our models, our current implementation is far from being explainable. These visualizations are not enough to fully open the AI *black boxes* we use.

One of our goals in this regard is to provide explanations of the predicted results in natural language. Ideally, this should consider not only the impact of the most prominent features, but also data on what makes a feature more or less understandable. This is a promising venue for future work that we will consider. However, the question of how to translate the models' output into fully human understandable language is out of the scope of this paper.

- **Beyond a simplified program:** Our prototype is part of an ongoing effort to improve and optimize the process of academic counseling at ESPOL. As reported in this paper, our tool works with a simplified version of the CS academic program that was valid between 2000 and 2012. Before and after this period, many curricular modifications took place at ESPOL. So, this limitation is mainly due to the unavailability of consistent data. Our immediate plans include to generate prediction models from more recent data. This, however, is not a trivial task as mapping courses among different versions of the curriculum can be challenging. We thus plan to ask for expertise on the transition rules that were applied between the performed curricular modifications.
- **Need of empirical evaluation:** Our research aims at supporting a human decision process via automatic prediction. Thus, assessing the perceived benefits of our prototype both on the students' and the counselors' side is of paramount importance. We plan to run several observational studies to gather users' impressions on the system and its usefulness. Pilots in more realistic settings will also be performed. These steps, however, require prediction models that can be used by current students.

7 Conclusion

This paper presented the design and implementation of a tool that supports students in preparation for the counseling sessions where they plan their upcoming semester. Given a selection of courses, the tool estimates the student's performance on each course. We described the data-driven approach used to generate the prediction models based on several factors such as the student's own academic history, the performance of other students, and several features that characterize the difficulty of courses. This research aims at improving and optimizing ESPOL's academic counseling system.

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