Correlations between Syllabus Schedule and Academic Achievement, a Case Study

Rodolfo Bojorque[1], Fernando Moscoso-Merchán[2], Fernando Pesantez-Avilés[3]

Universidad Politécnica Salesiana, Ecuador[1,2,3]

Abstract

There is a lot of literature about syllabi importance but does not exist studies than measure the impact of the syllabi, some studies asses the degree to which a syllabus achieves a learning-centered orientation other studies analyze its design. A syllabus can be useful in engaging students, yet discussions of their effective use rarely appear. The function of syllabi has seven purposes: It sets the tone for a course, motivates students to set lofty but achievable goals, serves as a planning tool for faculty, structure students' work over the course of the semester, helps faculty plan and meet course goals in a timely manner, serves as a contract between faculty and students about what students can expect from faculty and vice versa, and is a portfolio artifact for tenure, promotion or jobs applications. Nowadays, the information technology allows collect data from the educative process, this work analyzes the correlations between syllabi schedule and grades obtained by students in an Ecuadorian technical university. We analyze data of four semesters over an information system for register and follow syllabus progress. Our results show that good scheduling of the activities, at least one per class, has a direct correlation with grades, in conclusion, while more activities were scheduled, the students grades increase.

Keywords: *Academic Achievement, Syllabus, Learning Analytics.*

1. Introduction

A syllabus is generally defined as a plan that states exactly what students at a school or college should learn in a particular subject [1]. However, there is a lot of literature about syllabi importance in other scopes [2-3], especially about higher education; but does not exist studies than measure the impact of the syllabi, some studies asses the degree to which a syllabus achieves a learning-centered orientation other studies analyze its design [4-5]. A syllabus can be useful in engaging students, yet discussions of their effective use rarely appear. While the scholarship of teaching and learning literature has made great advances in our understanding of how learning might best occur, the syllabus as a teaching and learning tool appears to have been almost completely left out of the developmental conversation [6]. Our study gathering information about syllabi at Salesian Technical University. We collect data from 4700-course groups in four semesters. Approximately 450 courses of different kinds of subjects, grades of 185000 students and syllabi scheduling of 760 lecturers. Nowadays, the information technology allows collect data from the educative process, this work analyzes the correlations between syllabi schedule and grades obtained by students. To understand how our information system gathering information, the educative process at the university is as follows: a) When a lecturer has been assigned to a course, it is necessary to plan the syllabus activities in the information system, each lecturer can plan his/her activities as he/she considers pertinent, for instance, hour by hour, or to bunch topics in many hours. b) The activities include grade activities or assessments with their respective values. c) Along the semester the lecturer has to register finished activities in the information system. Lecturers and students can verify the syllabi progress at any time.

Our Information System allows us to perform the learning analytics process, as we sill se besides, so we can execute more sophisticated artificial intelligence techniques [7], all of them are part of our Academic Quality Management System.

The remainder of this work is divided as follows: Section two is a review of essentials concepts, section three shows and explains the methodology used, in section four we outline the results and finally in section five we present the work conclusions.

2. Review

In this section, we focus on the syllabus utility and fundamentals of learning analytics.

2.1 Syllabus

The function of syllabi has seven purposes: It sets the tone for a course, motivates students to set lofty but achievable goals, serves as a planning tool for faculty, structure students' work over the course of the semester, helps faculty plan and meet course goals in a timely manner, serves as a contract between faculty and students about what students can expect from faculty and vice versa, and is a portfolio artifact for tenure, promotion or jobs applications [2].

The syllabus should delineate the responsibilities of students and of the instructors for various tasks, including attendance, assignments, examinations and other requirements [4]. It is important to highlight that a syllabus is a learning tool. Students usually receive the course syllabus at the first class meeting, the syllabus is often the first contact a student has with a faculty member, one way to assess learner-centeredness is through the syllabus [8]. A good course and syllabus need not be rigid in providing this structure but should be flexibly responsive to student concerns and external events [9]. Our Information System allows any change at any time.

In our case, the Information System for each syllabus activity saves activity detail, kind of activity, duration, resources, and grade if exists. Each lecturer has to plan his/her syllabus and record in the Information System before course beginnings.

2.2 Learning Analytics

Learning analytics is an emerging field in which educators and researchers are using data to improve their students' educational experiences [10]. According to [11], the most dramatic factor shaping the future of higher education is data. Learning analytics is the evolution of social networks (Web 2.0) and previously of learning management systems.

The learning analytics process includes data collection, analysis, model selection, and intervention treatment [12]. There are lots of techniques to analysis data, in our case, we only use a correlation coefficient among different syllabi features. In addition, we apply similarity measures to the lecturers' features, our aim is trying to find out hidden patterns in the data like lecturer's clusters. Fig.1 shows the interaction among stages of the learning analytics process, double arrow lines indicate that the process can go back to the previous stage, and single arrow lines indicate that the process has to pass the next stage. The "Choose model" stage is a generic representation since we choose among different techniques. The main and most useful are:

- Data visualization: it is the graphical representation of information and data, the main idea is provided an accessible way to see and understand trends, outliers, and patterns in data.
- Prediction: It is a data analysis to try to predict future data trends, there are two kinds of prediction. The first one is a regression when the goal is to predict a real number. The second one is classification when the goal is to predict class membership.
- Clustering: It is a technique to group similar objects in sets named clusters. When the groups are formed, we can explain details about the data like hidden patterns or relationships.

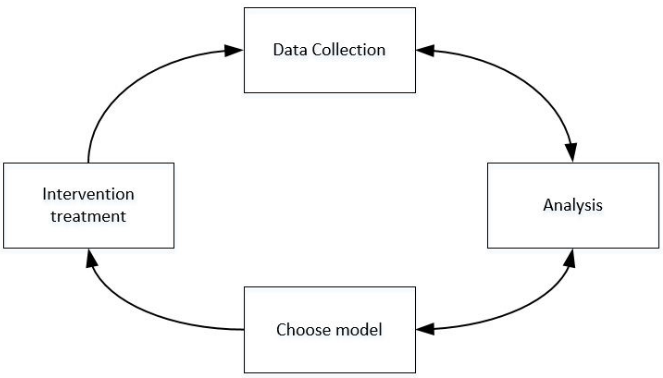

Fig.1. Learning analytics process.

3. Methodology

The data collection stage is performed by the information system. The syllabi data is ranked by campus, career, subject, and lecturer. For each rank, we summarize the data features like the number of students, number of groups, academic achievement and several more. Our aim is to make a multidimensional vector, that represents the features of this rank level. The set of multidimensional vectors by rank is a matrix. Fig.2 shows a matrix example; with this structure we can probe different learning analytics models.

	#students	#promoted students	average hours	Average Activities
Career 1	13086	5550	3.30	13129
Career 2	645	172	3.70	843
Career 3	644	388	2.24	516
Career 4	220	0	2.75	116
Career 5	11426	4001	3.60	7676
Career 6	15103	7127	4.03	12380
Career 7	18846	7423	3.48	13749
Career 8	653	0	3.19	482
Career 9	9195	2906	8.12	8196

Matrix representation

Multidimensional vector

Fig.2. Matrix representation example for data analysis.

Once we had matrixes, we apply two techniques: a) Correlation coefficient, and we proceed to make data visualization of relevant results. b) K-means clustering algorithm, to try to find out lecturer's clusters. There are a lot of variations of the k-means algorithm, [13] shows a comparative analysis of similarity metrics that we can apply in the k-means algorithm.

4. Results

Below we present the most relevant results, Fig.3. shows the relationship between the number of activities planning and students' grades. As we see, while more activities were planned by the lecturer, the average course rate approval increase. We scale between 0 and 1 the activities, where a value near to one means that the lecturer planning his/her class hour by hour, and values near to zero means that the lecturer planning is not per class or hour, maybe the syllabus planning is by topic. Since the average class has two hours, we expect that values near to 0.5 (50%) mean an adequate syllabus scheduling. Nowadays, the average of activities is 40%. Hence, the syllabus scheduling at Salesian Technical University is near to the target of at least one activity per class. Maybe, 1% of increment in syllabus scheduling, sounds no enough, but this 1% is a very hard goal, we are working between 100 and 1400 groups per semester.

Fig.4. shows clusters of lecturers, we probe clusters from 2 to 20, and k=5 obtains the best cluster quality results. The magenta samples are the lecturers who more plan their syllabus. The blue samples are the lecturers who do not plan enough their syllabus and their approval rates are low. Both, black and red samples are lecturers who are in transition to improve their syllabus scheduling. Finally, the green samples are special cases, because the majority of their approval rates are very high and their syllabus scheduling is under the mean. These results are used in the final stage "intervention treatment" of learning analytics and allow support desitions about awareness of correct syllabus scheduling.

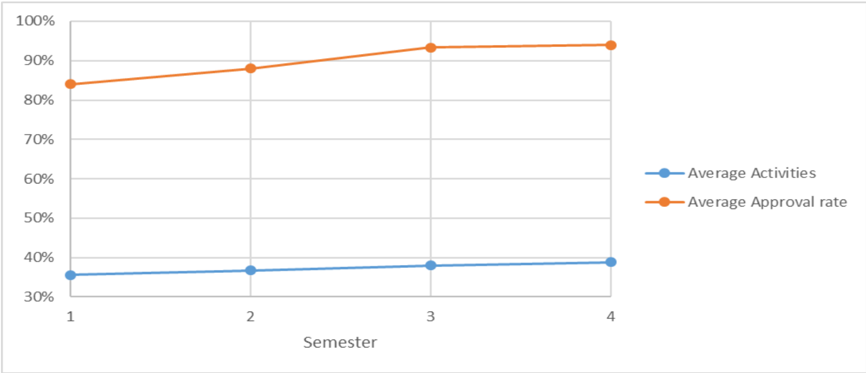

Fig.3. Relationship Activities-Approval rate

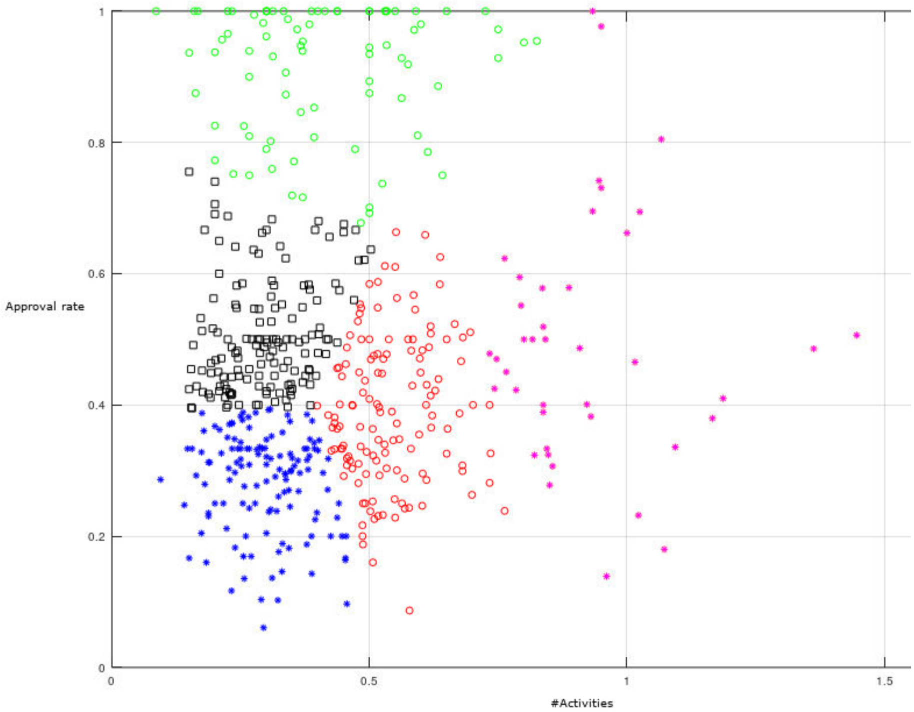

Fig.4. Clusters of lecturers

5. Conclusions

Our results show that good scheduling of the activities, at least one per class, has a direct correlation with grades, in conclusion, while more activities were scheduled, the students grades increase. Besides, we use a clustering model to detect how good is the syllabus scheduling per each lecturer. We show only a little application of our learning analytics process. This work summary four semesters of data. The Salesian Technical University tries to take advantage of the daily generated data. We consider that share information is necessary to start an understanding of new opportunities. Nowadays, people believe that learning analytics is possible only for online studies maybe they think that an online platform collects lots of information and they do not see their data sources, we consider that learning analytics is possible in any scenario where there is data.

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