



# Assessing the Impact of Exam Preparation Process on Students' Careers

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**Abstract.** Educational Process Mining techniques leverage educational data to gather relevant insights on the corresponding processes, ultimately supporting the development of evidence-based strategies for their improvement. In this work, we analyze students' exam preparation process to i) uncover process patterns describing students' behaviors and ii) develop predictive models capable of predicting students' performance regarding graduation times. The results of the analysis can be employed both to formulate improvements to the study curricula and to enable the early detection of students who are likely to struggle in their career, to support them at an early stage of their studies.

**Keywords:** Educational process mining · Curriculum Mining · Student performance analysis

## 1 Introduction

A major challenge for today's universities is enhancing their educational programs. This effort is especially crucial for Italian universities, where around 40% of students do not complete their studies on time, and of those, only 20% graduate within a year of the expected timeframe<sup>1</sup>. The increasingly widespread use of digital platforms to support university processes boosted the development of evidence-based techniques to support this effort in recent years. Among those, a discipline which is gaining increasing attention is *Educational Process Mining* (EPM). The goal of EPM is to uncover patterns and trends within educational data to understand how educational processes are carried out and identify improvement opportunities [4]. In this study, we focus on a specific branch of EPM, the so-called "curriculum mining", whose goal consists in analyzing data related to students' *careers*, i.e. the sequence of registrations of credits-bearing

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<sup>1</sup> <https://www2.almalaura.it/cgi-php/universita/statistiche/visualizza.php?anno=2023&corstipo=tutti&ateneo=tutti&facolta=tutti&gruppo=tutti&livello=tutti&area4=tutti&classe=tutti&postcorso=tutti&isstella=0&presiu=tutti&disaggregazione=&LANG=it&CONFIG=profilo>

**Table 1.** Percentage of early and late students for each academic year

Year	Early	Late
2010	0%	100%
2011	37.14%	62.86%
2012	35.71%	64.29%
2013	38.36%	61.64%
2014	47.54 %	52.46%
2015	40.00%	60.00%
2016	42.86%	57.14%
2017	50.60%	49.40%
2018	64.21%	35.79%
2019	69.23%	30.77%
2020	100%	0%

activities, to determine valuable insights on the curricula chosen by students. Previous studies show how these techniques can facilitate understanding behaviors that characterize students’ academic performance, e.g., graduation times.

Our study showcases the application of these techniques to answer the following research question: “How does a student’s exam-taking behavior in the first year impact their graduation performance?” The “exam taking behaviour” consists of the sequences of activities modelling each exam’s successful or unsuccessful taking. This task is inherently challenging due to the heterogeneity of the pathways followed by students, which stems from the lack of constraints in the examination process, as will be elaborated upon later in this paper. Nevertheless, our goal is to investigate whether there exists some regularities or patterns in the exam-taking behaviour among different students, which may provide a reliable estimate of whether a given student is likely to graduate on time or not. Identifying these behaviours is beneficial both to develop improvements in the overall study curricula and to spot-on students who are expected to struggle at an early stage of their career, to support them and mitigate the probabilities of graduation delays or dropping.

The rest of this manuscript is organized as follows. Section 2 describes the case study and the research design. Section 3 illustrates the obtained results. Section 4 provides an overview of relevant related work, while Sect. 5 draw some conclusions and delineates future work.

## 2 Study Design

### 2.1 Case Study: Bachelor Program of an Italian University

Our study focuses on a 3-year Bachelor’s Degree program from an Italian university. The dataset comprises over 700 graduated students spanning 11 academic years (from 2010/2011 to 2020/2021). Table 1 reports the percentage of

*early* students, i.e., students who took their degree within the standard duration of the degree programme, and *late* students who experienced one or more years of delays in their graduation. For the year 2010, we only have a small portion of students, all of whom graduated late. As for the students enrolled in 2020, since we have information up to 2023, we only have those who took less than three and a half years and, therefore, are considered early. While Table 1 shows a consistent improvement in students’ performance over time, we observe that at least 30% of students graduated later than expected. As mentioned in Sect. 1, our analysis aims to assess the impact of students’ exam-taking behaviors on their graduation performance. This question can be modeled in terms of a classification problem. Namely, we aim to develop a robust classifier that can learn the relation between a set of input features modeling different characteristics of students’ exam-taking behaviors in the first year and a target variable corresponding to students’ graduation performance. Note that we are interested in studying both the impact of students’ overall performance (e.g., the average grades of passed exams) and the impact of *process-related* features, modeling the order in which exams have been taken by students. The latter enables the development of evidence-based recommendations on *when* students should strive to take one or more exams, as well as to identify which (combinations of) exam(s) have a critical impact on students’ careers. Given the high variability of students’ careers, we focus on extracting patterns (or subprocesses) modeling relevant combinations of exam-taking events.

Consequently, we identify the following sub-questions that must be addressed to answer the overarching one.

- **RQ1** Which common patterns in exam-taking behaviors arise from the students’ career paths?
- **RQ2** How do exam-taking behaviors patterns in the first year affect students’ graduation performance?

*Dataset.* We merged the information from two datasets that record the students’ academic pathways to create the event log. In the first dataset, each row corresponds to an exam passed by a student, and the following information is provided: the student’s identification code, the name of the exam, the date when the exam was passed, the grade obtained, the weight in CFU, and whether the exam is mandatory. The second dataset extends the information found in the first dataset by including unsuccessful exam attempts for each student together with reasons for not passing the exam, such as student absence, failure/withdrawal, or an insufficient mark. The resulting event log consists of one trace for each student, where each event tracks the outcome of an attempt for a specific exam, enriched with the corresponding attributes. To gain a better understanding of when activities are carried out w.r.t. the academic year, we have inserted in the log four artificial activities as a time reference to indicate the end of each semester and year: “End first semester”, “End first year”, “End third semester” and “End second year”.

The next subsection delves into the methodology applied for each subsection.

## 2.2 Methodology

*RQ1: Extracting Exam-Taking Patterns.* Several techniques have been proposed in the literature to extract process patterns from an event log. Our analysis employs the strategy devised by [10], since it considers the potential *concurrency* among process activities. They propose a pipeline where first, each sequential log trace is converted in a so-called *Instance Graph* (IG), which is a direct acyclic graph where each graph corresponds to an event in the trace and edges model dependency relation among the corresponding process activities. Then, they apply *subgraph mining* techniques to extract the most important subgraphs from the IG set which, in this setting, correspond to the most important process patterns.

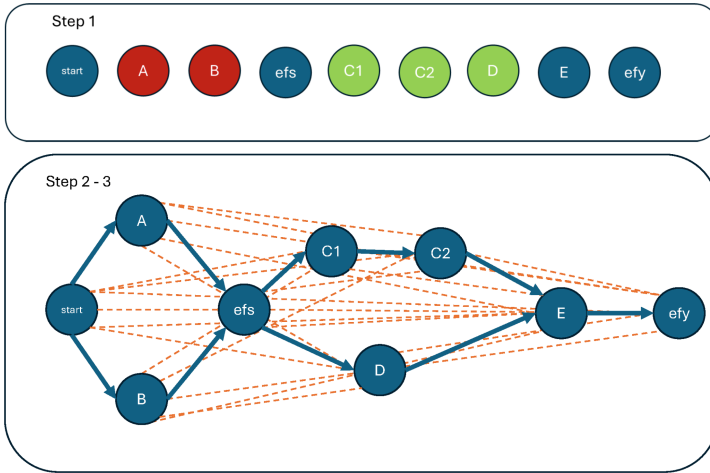
We applied an ad-hoc procedure to build the IG set to reflect the concept of concurrency in our case study. From our discussions with stakeholders from the University, we derived the assumption that two different exams for which an attempt is made within one month can be considered concurrent, intended as exams that the student is preparing simultaneously.

In the following, we illustrate our procedure to build an IG for a trace in the event log, using the trace  $\sigma = \langle \text{start}, A, B, \text{efs}, C_1, C_2, D, E, \text{efy} \rangle$  as an example.  $A, B, C, D, E$  correspond to an exam;  $C_1$  and  $C_2$  correspond to two attempts of taking the exam  $C$ , indicating that the exam has been failed the first time. The artificial activities have been marked as “start,” “efs” (end first semester) and “efy” (end first year). First, we create one node for each exam and each artificial activity (Step 1 in Fig. 1). The colors in Fig. 1 (Step 1) illustrate the concurrency between the activities under the assumption previously introduced. To connect the nodes, we iterate through each pair of nodes, and we create an edge connecting them as follows:

- a) If the pair contains at least one artificial activity, the pair is connected based on chronological order. In Fig. 1 (Step 2), “start,” “efs,” and “efy” are connected to every node.
- b) If the pair does not contain artificial activities but the nodes are concurrent, no edges are added unless the pair represents two attempts for the same subject. For example, in Fig. 1, even though  $C_1$  and  $C_2$  were concurrent, they are not considered as such.
- c) If the pair does not contain artificial activities and the nodes are not concurrent, edges are created based on chronological order.

Once the graph is created, we apply a transitive reduction to remove superfluous edges while maintaining reachability. In our example, edges removed by the transitive reduction are the dotted ones (Fig. 1 Step 3).

Once the IG set has been created, we leverage the SUBDUE algorithm [15] to derive the most important subgraphs. SUBDUE iteratively analyzes the input

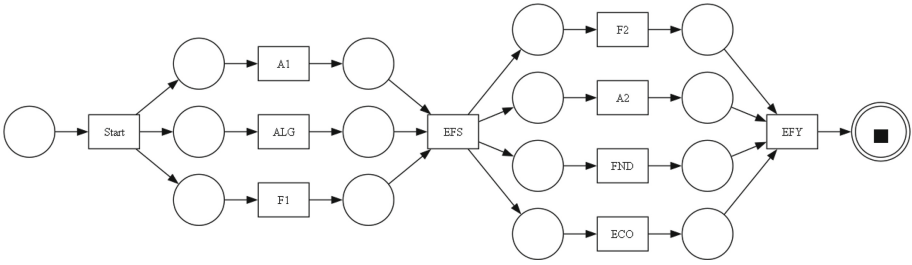


**Fig. 1.** Steps for Instance Graphs creation

graphs to extract at each step the subgraph that best compresses the graphs set. This subgraph is then used to compress the graph set by replacing each occurrence of the substructure with a single node. The compressed graphs are presented to SUBDUE again to repeat these steps until no more compression is possible. The algorithm returns a hierarchy of subgraphs with different levels of abstraction. Top-level subgraphs are defined only through elements belonging to input graphs (i.e., nodes and arcs). Lower-level subgraphs contains also upper-level subgraphs as nodes, defining a lattice structure. Descending the hierarchy, we pass from subgraphs that are very common in input graphs (i.e., frequently occurring, with a high support) to subgraphs specific of few input graphs (i.e., with low support). Since the top-level subgraphs are the most relevant, we used those for our analysis.

*RQ2: Assessing the Impact of the Exam-Taking Patterns on Students' Graduation Performance.* To evaluate the usefulness of subgraphs in predicting student performance, we first develop different predictive models using a set of variables extracted from the original event logs: **High school grade**, **First year mean grades**, **Consistency in votes**, **Exam passed first year**, **Credits given first year**, **Exams given first semester**, **Credits given first semester**, **Exams given second semester**, **Credits given second semester**, **Replayed fitness**, **Aligned fitness**, **Mean temporal interval between exams**, **Temporal consistency** and **First year failures**, which is the amount of times the student failed an exam in the first year. **Consistency in votes** and **Temporal consistency** correspond to the standard deviation of, respectively, the exam grades and the temporal intervals between consecutive exams.

The fitness measures presented earlier were calculated by implementing conformance checking with the first event log, which contains only exams passed, on the Petri net representing the ideal process model for the first year. This model



**Fig. 2.** Path defined by Univerity’s manifesto

**Table 2.** Classification models and their corresponding parameters

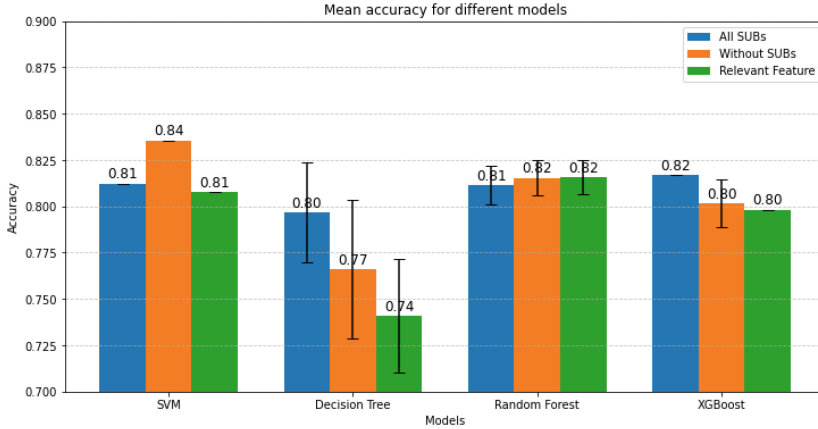
Model	Parameters
SVM	‘C’, ‘gamma’, ‘kernel’
Decision Tree	‘criterion’, ‘splitter’, ‘max depth’, ‘min samples split’, ‘min samples leaf’
Random Forest	‘n° estimators’, ‘criterion’, ‘max depth’, ‘min samples split’, ‘min samples leaf’, ‘bootstrap’
XGBOOST	‘colsample bytree’, ‘learning rate’, ‘max depth’, ‘n estimators’, ‘subsample’

is considered the standard path defined by the university’s manifesto, with the addition of “artificial” activities, as illustrated in Fig. 2. A value between 0 and 1 is assigned to each student based on their level of conformance to that ideal path.

All categorical variables were encoded through one-hot encoding, while the numerical variables were normalized using a standard scaler, that subtract to each value the mean and divide it by the standard deviation, transforming the data to have a mean of 0 and a standard deviation of 1. Four classifiers frequently mentioned in the literature were used for prediction: SVM, Decision Tree, Random Forest, and XGBoost. We used 70% of the dataset for the train set, and 30% for the test set.

For all classifiers and feature sets (i.e., without and with subgraphs), we performed hyperparameter tuning using Grid-Search with 5-fold cross-validation and maximizing accuracy. The parameters we combined for each model through grid search are shown in Table 2.

After finding the best hyperparameters, we evaluated the model on the test set. Due to the inherent randomness of Decision Tree, Random Forest, and XGBoost we trained these models 20 times using the same dataset and parameters while iterating the random seed every time. For these stochastic models, we evaluated 20 different values for accuracy to enhance the robustness of the results and then calculated the mean accuracy and the standard deviation of the accuracy. To evaluate performance, we considered accuracy because the two classes are balanced. After comparing the results of the models with all the sub-



**Fig. 3.** Classification results

graphs and without them, we implemented a feature selection wrapper method for each model to identify the best set of features specific to each model and observe if the results improved.

Once we identified the best classifier, we employed Explainable AI (XAI) techniques to elucidate which features had the most significant impact among those used in our model. In particular, we employed SHAP (Shapley Additive exPlanations) [17], a widely used XAI technique based on game theory that uses Shapley values to fairly distribute the “credit” for a model’s prediction among its input features.

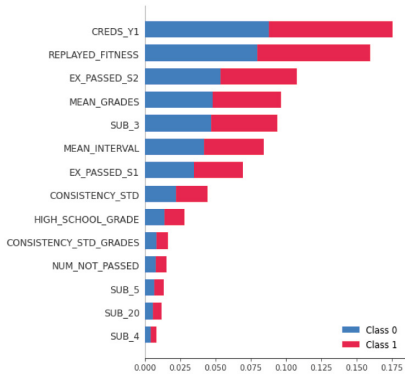
### 3 Results

This section discusses the results of our study. First, we compare the results obtained with and without including the exam-taking patterns. Then, we show results obtained applying wrapper methods for each classifier. Finally, we discuss the importance of different features obtained with SHAP.

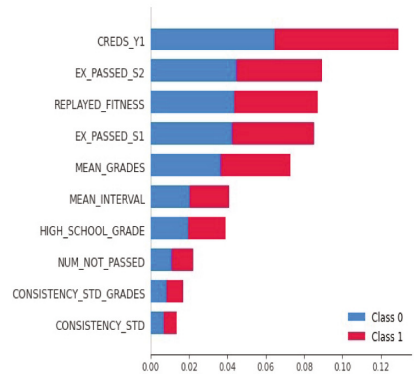
#### 3.1 Impact of Exam-Taking Patterns on Classification Performance

First, we made predictions using a feature set composed only of the initial variables listed in Sect. 2.2. The results, in terms of accuracy for each classifier, are represented by the orange bars in Fig. 3. The most performant classifier is the SVM, which is also the most consistent with respect to the varying seed.

The blue bars show the accuracy obtained when all the exam-taking patterns are considered. Overall, including the patterns lead to the same or worse classification performance. This is possibly due to the increase in dataset features and, therefore, the sparsity of the obtained data.



(a) Features importance with SHAP for best model with subgraphs(RF)



(b) Features importance with SHAP for the best overall model (SVM)

**Fig. 4.** Features importance with SHAP

After comparing the results of the classifiers with and without subgraphs, we proceed to calculate the accuracy using only the relevant features. These features are identified for each classifier based on wrapper methods of feature selection specific to each classifier. The results are presented in Fig. 3, in green. The SVM performs similarly to the situation with all subgraphs, thus also lower than the case without subgraphs. The decision tree keeps obtaining the worst performance, with a low average accuracy and high variability. The random forest remains the best among the stochastic models, with a stable average accuracy across all three scenarios and a much lower variability compared to the decision tree. Finally, XGBoost’s performance remains similar to the situation where the dataset contains only the initial variables, and consequently, it is inferior compared to when we also consider all subgraphs.

### 3.2 Importance of Subgraphs

The results show that the model that best predicts student performance based on first-year information is the SVM, which considers only the initial variables. Although other models improve their accuracy by utilizing student behavior patterns, the results do not provide evidence supporting the usefulness of these features in the predictive model.

To delve deeper into the relation between the occurrence of the extracted subgraphs and the student’s performance, we applied SHAP to the Random Forest model since it is the best-performing model when subgraphs are considered. The results are illustrated in Fig. 4a.

After selecting the best features for the Random Forest, only 4 of the 18 subgraphs features were retained. In Fig. 4a, we can see that only SUB\_3 significantly impacted the model’s output. This subgraph represents the absence of exam attempts in the first semester, which is reasonable to consider important

as it indicates a total lack of engagement, thereby predicting a negative outcome due to this behavior. However, no other exam-taking patterns have shown a significant impact on students' performance. Instead, the figure suggests that the amount of credits gained during the first year and the compliance with the student manifesto have the strongest impact on students' graduation performance.

We employed SHAP to highlight the impact of the features for the best overall model as well, that is the SVM when subgraphs are not considered. The results depicted in the Fig. 4b indicate that the most impactful features are similar to those previously highlighted for the random forest when considering subgraphs. The credits earned in the first year remain the most important feature, significantly outpacing the second feature, which is no longer replayed fitness but rather the exams passed in the second semester.

*Discussion.* The results show that the exam-taking process does not demonstrate a predictive capacity that confirms its usefulness. This may be due to several factors. The first factor concerns the variability in student behavior. Each student can choose which exams to take, the order to take them, and how many times to retake them. This results in the creation of behavior patterns that pertain to a small number of students, compared to the total population. Another factor is that the common behaviors analyzed are only the “root” subgraphs, meaning they are the subgraphs that do not contain other subgraphs. Consequently, some potentially relevant behaviors were not considered in our analysis. Nevertheless, our analysis was able to derive robust and well-performing classifiers leveraging aggregated indicators of students' behaviors, such as the total number of credits earned in the first year, the level of conformity with the standard path, the grade point average, and so on. Such classifiers can be used to spot students' in need of help early in their careers, when there is still time to intervene and support them to improve their performance.

## 4 Related Work

Educational Data Mining (EDM) is an emerging discipline that aims to understand and improve students' learning process [19, 22]. Our work is mainly related to EDM approaches that analyze students' academic performance and their failure. A popular trend in this respect consists in modeling students according to predefined features and applying machine learning to predict student's performance [9, 11–13, 16, 23]. Many of these studies provide a perspective complementary to the one provided by our analysis, taking into account factors external to the graduation process itself. Even studies centered on the graduation process usually perform a data-oriented analysis, in which students' behaviors are encoded in terms of features without considering the study program's underlying structure. In this respect, our work is similar to the one in [8], which proposes to model and analyze students' careers. They introduce the notion of *ideal career* that corresponds to the career of a graduated student who took each exam just after the end of the corresponding course. Different metrics are used to measure

the distance between each student's career and the ideal one (e.g., the Bubblesort distance). Compared to our approach, the work in [8] does not exploit the potentialities of process-based analysis in modeling students' behaviors. In particular, they do not infer any model representing the overall students' behaviors. In contrast, we exploit process formalisms to model the manifesto of study programs that explicitly accounts for parallelisms, thus allowing us to obtain a more accurate evaluation of the difference between single careers and the ideal path.

The application of process mining techniques to educational data, referred to as *Educational Process Mining* (EPM) [4], is a subject that has been recently gaining increasing interest. EPM has been applied to deal with different educational problems, such as on-line learning environments [5,18,25], computer-supported collaborative learning tools [3,21], professional training [2,6]. However, only a few works investigated the applications of EPM to curriculum mining. [24] propose a set of patterns modeling typical constraints of academic curricula and use these patterns to analyze the graduation process. However unlike the present work, they do not infer the process model representing students' careers and do not focus on delay analysis. Our approach is similar to [14], in analyzing the exam-taking process and program study compliance. However, [14] do not consider differences between early and late students.

In [1], authors apply process mining techniques to analyze event log data generated within educational information systems, with the purpose of understanding students' behavior during online learning. The work differs from ours in two main ways: (i) it is based on the concept of digital twin for the representation of students' activities and (ii) its focus is on the single course while ours is on the entire career. To the best of our knowledge, [7,20] are the only work considering the entire student's career. The former applies process discovery techniques to curriculum event logs with the purpose of characterizing behaviors of students that performed best/worst in terms of years required to complete the graduation process and final grade. The latter shifts the focus to classes of early and late students, similar to our study. However, they did not consider the potential impact of exam-taking patterns on students' performance in their analysis.

## 5 Conclusion and Future Works

This study focused on the analysis of the students' behaviors during their first year. The goal was to determine if and how these behaviors influenced graduation times. Our results show the feasibility of leveraging these properties to estimate students' performance early during their careers, though the extracted exam-taking pattern behaviors did not show a significant impact on the classification performance. These results call for additional research on the subject. In future work, first we intend to investigate the use of alternative process pattern discovery techniques, as the kind of extracted patterns are likely to have a strong influence on their predictive capabilities. Furthermore, we aim to explore how

to transform the insights gained from this analysis into practical recommendations. These recommendations will help students identify the best career paths at various stages, considering their current progress.

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