

The PASSt project: predictive analytics and simulation of studies aimed at quality management and curriculum planning

Gabriel Wurzer¹, Shabnam Tauböck¹, Markus Reismann¹, Christian Marschnigg^{1, 3}, Sukrit Sharma², Karl Ledermüller³, Julia Spörk³, Maria Kokovsky³

¹Zentrum für strategische Lehrentwicklung, TU Wien, Austria, ²TU.it, TU Wien, Austria,

³Evaluierung & Qualitätsentwicklung, WU Wien, Austria.

Abstract

Quality management has become a crucial factor for improving student success, with reporting being widely used to scrutinize curricula for possible bottlenecks and resource deficiencies. Predictive capabilities in that context have, however, been often limited to simple regression models acting on historical data, which might not always be available when curricula change often; furthermore, work in curricular planning often demands “what if”-scenarios that are beyond extrapolation, such as determining the influence of changes in procedure on student success, which in itself is based on a multitude of intertwined factors such as social background and individual performance. In the PASSt project, we have been using Machine Learning and Agent-Based Simulation for Predictive Analytics in that sense. As a result, we have been developing an extensive toolset for curriculum planning which we want to outline in this paper, together with some lessons learned in that process. Our work will help practitioners in higher education quality management implement similar methods at their institutions, with all said benefits.

Keywords: *Data modeling; machine learning; agent-based simulation; predictive analytics; quality management; curriculum planning.*

1. Introduction

Reporting is nowadays commonplace in higher education quality assessment: On the one hand, this allows for a guidance of the curricular planning process, on the other hand such assessments are also prescribed by governmental regulation (e.g. the EU “Standards and Guidelines for Quality Assurance in the European Higher Education Area (ESG)”, see ENQA 2015). Digitalization has been long lagging behind requirements in that area, with data repositories primarily serving study administration but not analytics; as a consequence policy makers have explicitly made Digital Transformation in that area a priority (e.g. the EU “Digital Education Action Plan” [EC 2018], especially “Priority 3: Improving education through better data analysis and foresight” [ibid.]).

In the course of the PASSt project, we have been extending the scope of study analytics at the partner universities to prediction using Machine Learning and Simulation while at the same time improving the data basis. This paper reports on the toolset we developed in that course for curricular planning and quality assurance, and gives some lessons learned for people seeking to implement similar measures in their institution. In more detail, we:

- Initially define activity dimensions within curricular planning and quality assessment, both acting as our requirements and context (Section 2, “Background”).
- We then review work that is similar in aim or outcome (Section 3, “Related Work”).
- Next, we describe the data basis that is an outcome of a lengthy discussion process between project partners and a wider field of universities (Section 4, “Base Data”).
- The core of our contribution herein lies in the description of our curriculum planning toolset (Section 5, “Developed Toolset”) on the curriculum and aggregate level.
- Before concluding, we also discuss some lessons learned (Section 6, “Discussion”).

2. Background

Our work is aimed at supporting curricular planning in study committees typically headed by the provost/dean of studies, where work typically happens on the following two design levels:

Curriculum: View of a whole study with strong focus on amount of students (input/output, dropout rates), sequences of courses in different phases (e.g. introductory phase, intermediate phase, finishing phase) and semester-wise view of throughput through this system of these lectures implicitly or explicitly connected by their preconditions.

Lecture: View of an individual course in terms of its location within a curriculum (prescribed vs. actually taken semester), capacity (number of examinations per semester), type (lecture, lab, seminar, etc.; mandatory, elective or optional), success rate (as a function of numbers of times already taken; or curriculum if the course is shared between multiple studies), credits granted for successful completion, periodicity (one-time, every semester, every year, every

two years in seldom cases), temporal view of course utilization by students, rules for accreditation, preconditions for inscribing to a course, and so forth.

Even though many of these factors are beyond planning (e.g. number of students starting their studies), many can be influenced implicitly using the following action dimensions which are, quite interestingly, situated only at the lecture level:

Location within the curriculum and preconditions for lectures. An attribution of study phase (beginning, intermediate, finishing phase) ensured by preconditions is selective with regards to students opting in (or out, e.g. by not continuing a study; while this may seem cruel many of the efforts go towards self-awareness over whether a study is suitable for a student or turns out to be the wrong choice). Another aspect is the semester in which students actually take a lecture (vs. the prescribed semester), since this has to do with the perception of students and the success rate (more in due course for the latter).

Capacity. This dimension is occupied with the capacity of lectures in terms of examinations per semester as well as the capacity for students seeking to enroll; many social and effort-wise questions range into that field and are enforced by specific rules (e.g. not being able to take two large lectures that have project character in one term). Where resources are scarce capacity may also be changed by changing periodicity.

Success rate. Students are sometimes impeded by lack of previous knowledge, in which case additional lectures on basics (“introduction to ...”) or shifting lectures from one semester to the other can be used to raise success rates; on the other hand, there might be reasonable doubts on fair assessment by lecturers, which must be further addressed in the process of quality management.

Clearly there is also a *social dimension* in all of this; for example, taking one’s mouth too full will result in a danger of dropping out, and therefore the aim must also be on ensuring that a curriculum is adequate in the light of different target groups which must be empowered to study at their own pace. Even though the project is not focused on individual feedback, we have the option to simulate individual study performance [in credits] based on different (also: *social*) characteristics, which gives a more realistic model of maximal effort invested.

3. Related Work

As said, our work is targeted at curricular planning rather than student self assessment or individual feedback which a lot of approaches seek to facilitate. Some of the examples of the latter include the Ingram (2020) agent-based classroom lessons model, which is an example of Agent-Based Simulation on the individual level, but does not offer general insight for further study analytics. In fact, we are convinced our Agent-Based Simulation is the first of its kind, from having researched the literature to the best of our knowledge. Research

analytics with the intended goal of curriculum planning is also novel; there are a handful of approaches which try to understand curricula in higher education – e.g. De Silva et al. 2021 – however there is lack of a tool approach as novel methods proposed but not implemented.

4. Base Data

Universities are very different in terms of what they assess in their administrative processes on which study analytics builds; therefore it was necessary to negotiate, in view of this project’s goals, what data should be included in a “common data structure” serving as base data for further analysis among all project partners. The outcome (also compare with Figure 1) is structured as follows:

Base Entities. *Students* (sid) and *Lectures* (lid, title, name, type, credits) with their metadata. Several *Curriculums* (cid, ...) are also present, which are to be outlined in due course.

Linking Relations. *Lectures* are assigned to a *Curriculum* by the presence of a *Curriculum Assignment*; this is, however, a theoretical assignment; the actual realization of that relation is the *Study*, which links a *Student* to a *Curriculum*. In this course a student takes an *Examination* for a *Lecture*. The outcomes and semester of this examination are further taken by us to infer additional data (semester actually taken; distribution of semesters taken; success rate; periodicity and base semester [winter or summer term]; capacity of a lecture).

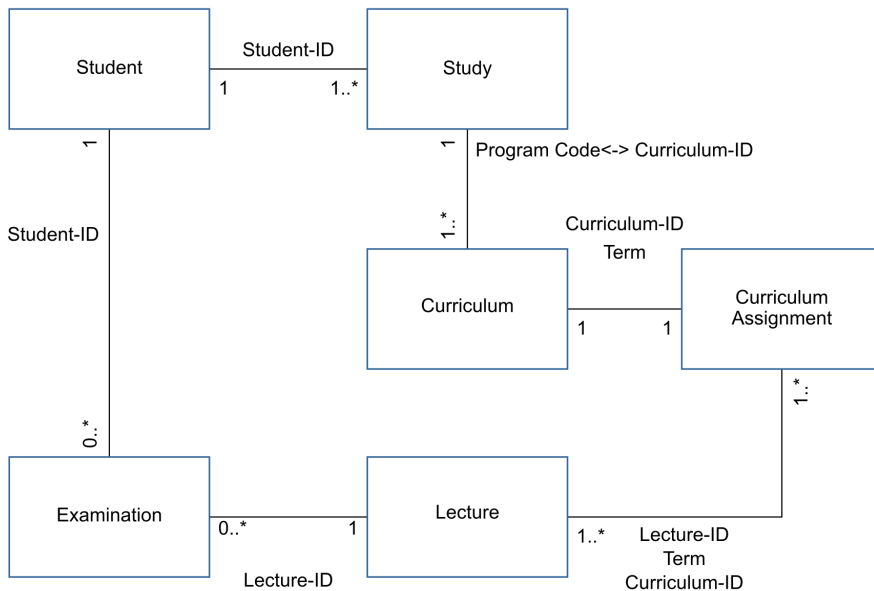


Figure 1. Base data structure for the PASSt project.

5. Developed Toolset

Based on the *Examinations* within the base data, we can infer the actual semester distribution of *Lectures* within a *Curriculum*. The most frequent semester (see red bar in the left part of Figure 2) is then used to build up replica of a curriculum (lectures in semesters, see background table in the left part of Figure 2) that can be simulated by use of Agent-Based Simulation, where each agent represents an individual student. The student numbers are inferred from *Study* within the base data, and can be altered to simulate “what-if” scenarios (see right part of Figure 2). Likewise, capacities of lectures (examinations/semester), type (mandatory, elective or optional), success rates (likelihood of students successfully taking a lecture), periodicity (one-time, every semester, yearly, every two years) and anchor semester (winter or summer) are inferred from *Examination* and *Study*. Student performance (maximal effort in credits/semester) can either be inferred from the mean credits of all students per semester (see again right part of Figure 2), or using a Machine Learning prediction of credits based on individual factors such as (ordered by importance) credits in previous semesters, education background, existence of multiple studies, gender and citizenship (more details cf. Spörk et al. 2021 [in German]).

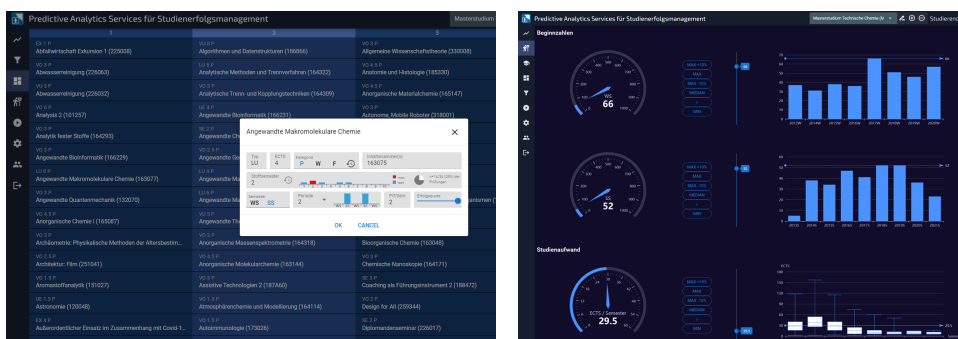


Figure 2. Simulation Input. (left) Curriculum with one lecture being currently edited, (right) number of students in winter and summer cohort, number of credits taken per term

Given their maximal performance, students seek to enroll in lectures and take examinations (subject to maximal capacities = lectures as servers with queues; examinations governed by the aforementioned *success rate*). As outcome, we can observe the semester-wise utilization of a curriculum where most prominent lectures are highlighted in tabular form (left in Figure 3) or visualized as a sim “semester tunnel” (right in Figure 3).

In addition, we have been developing a portal that lists aggregate measures for a whole curriculum (see Figure 4): There we depict student beginner numbers, performance in credits, and status (active, completed and aborted per semester). Furthermore, we have the regulatory measure of “examination-active” students (i.e. more credits than a certain credit threshold).

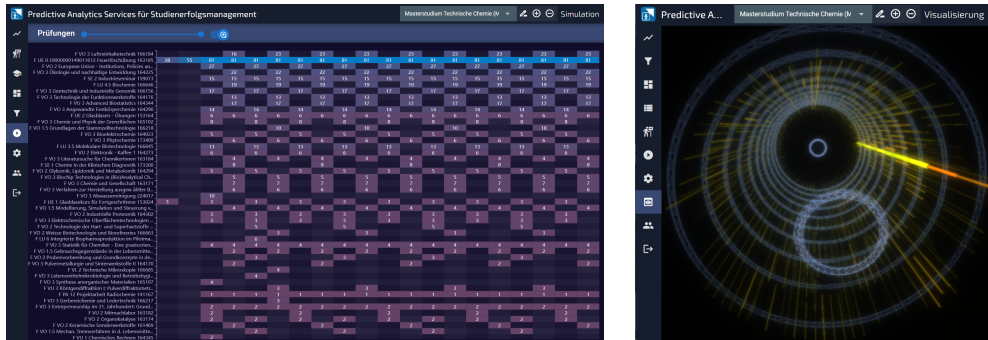


Figure 3. Simulation results. (left) Tabular depiction of utilization, (right) visualization as “semester tunnel”



Figure 4. Portal depicting aggregated view per curriculum.

6. Discussion

The developed curriculum simulation is a queuing system with servers = lectures and clients = students with individual amounts of credits (mean credits or determined by Machine Learning). The question is whether that is “realistic” or not. Analysis of actual examinations show that there is a Poisson-curve-like utilization of lectures, where students take less than their maximal amount of credits in the first semester followed by more than the maximum before the performance decreases based on study success and remaining credits to be made. This behavior can be modelled in the simulation, however not as emergent outcome but as a prescribed utilization curve; the cause for this is still an open question, or is this effect because of examinations being taken one semester too late (and thus it would appear that students

have more effort in the second rather than in the first semester). Regardless, one sure take-away is that it would make sense to reward studying uniformly, since no resources are wasted.

It would seem that our approach results in a “recommendation engine” that automatically proposes the best way to increase student success and studyability; however, this is not the case; the most important contribution of our work lies in bringing the numbers to the table; a discussion is always needed since each study commission knows its “problematic” areas, and solutions are based on many factors (but we are contributing some ground truth, of course). In this context, we also wish to emphasize the role of the aggregate views available in the portal (see again Figure 4), which add an overview of the base data per curriculum (filterable also per semester) as well as a prediction component (e.g. predicted ECTS/semester).

In practical terms, our toolset offers an unprecedented data density for *evidence-based curriculum planning*, as we would call it: We have *reporting* based historical data, *prognosis* based on Machine Learning and/or extrapolation of the former (e.g. linear regression); we also support “what-if” type of capacity planning using our *simulation*. The intended audience of such tools ranges from study commissions over provosts/deans to the university management, at which level benchmarking and goal-setting is important not only because one wants to improve studyability but also since may be connected to financing (e.g. via objective agreements set by the state).

“*The ultimate goal is to help HEIs quality management processes and procedures*” summarizes what we aim for best (thank you to reviewer 3 for that perfect one-liner). However, as also noted by the same reviewer, care must be taken as to not employ these methods in order to single out lectures with adverse intents, or (as we would also add) to give a negative prognosis on an individual level. Therefore, an integral part of the PASSt project is to also look at the ethical and legal implications when applying that technology, resulting in a legal guide (e.g. pseudonymization as requirement) as well as a *Code of Practice* document which states what computations may or may not be performed on the base data.

7. Conclusion

We presented a curriculum planning tool based on the individual lecture level that is simulated in an agent-based manner, plus an analysis tool that shows aggregated student data for students of a curriculum; both approaches are supplemented by a machine-learning prediction that can predict student performance based on individual factors. The outcome is that many levels of inquiry are needed (and: possible, with our approaches) in order to increase student performance; however most analysis results demand a post-hoc discussion with the stakeholders.

Acknowledgments

The PASSt project is funded by the Austrian Federal Ministry of Education, Science and Research under the call “Digital and Social Transformation”. This paper builds on two previous articles in the Journal for Higher Education Development [Zeitschrift für Hochschulentwicklung], Spörk et al. 2021 as well as Tauböck et al. 2023 [in press] as well as one conference paper in MathMod 2022 [Wurzer et al. 2022]. The paper has been written from scratch with the focus on tool support for curriculum planning and QM, leaving out legal and ethical aspects which form yet another basis (kudos go to Johannes Kepler University Linz - especially to Anna Schöfecker, Gerhard Mühlbacher, Günther Gruber, Florian Gundl and Stefan Pittner).

References

- De Silva, L.C., Rodríguez-Triana, M., Chounta, I.-A., Pishtari, G.. (2021). An overview of analytics for curriculum understanding and optimization in Higher Education. *Proceedings 11th International Conference on Learning Analytics & Knowledge (LAK21)*, 270-285.
- EC (2018). *Commission Staff Working Document on the Digital Education Action Plan*. EUR-LEX Document 52018SC0012, Retrieved from: <https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A52018SC0012&qid=1647943853396> (accessed Jan 19, 2023).
- ENQA (2015). *Standards and Guidelines for Quality Assurance in the European Higher Education Area (ESG)*. Brussels, Belgium. ISBN 978-9-08-168672-3. Available from https://www.enqa.eu/wp-content/uploads/2015/11/ESG_2015.pdf (accessed Jan 19, 2023).
- Ingram, F. (2020). *An Agent-based Classroom Lessons Model and Simulation*. Doctoral Thesis, Lancaster University. Available from: https://www.researchgate.net/publication/354625019_An_Agent-based_Classroom_Lessons_Model_and_Simulation (retrieved 16th Jan 2023).
- Spörk, J., Tauböck, S., Ledermüller, K., Krikawa, R. and Wurzer, G. (2021). Analysis of studyability by means of prediction and simulation models, in *Journal for Higher Education Development [Zeitschrift für Hochschulentwicklung]*, 16(4), 163-182.
- Tauböck, S., Schöfecker, A., Ledermüller, K., Krakovsky, M., Sharma, S., Reismann, M., Marschnigg, C.G., Mühlbacher, G., Spörk, J., Schadler and Wurzer G. (2023 [in press]). PASSt - Predictive Analytics Services für Studienerfolgsmanagement. *Journal for Higher Education Development [Zeitschrift für Hochschulentwicklung]*, Special Issue “Sonderausgabe Hochschullehre - Digitalisierung der Hochschullehre – Projekte österreichischer Hochschulen 2020–2024”.
- Wurzer, G., Reismann, M., Marschnigg, C., Dorfmeister, A., Tauböck, S., Ledermüller, K. and Spörk, J. (2022). PASSt-A: Agent-based student analytics aimed at improved feasibility and study success. *Proceedings of MathMod 2022*, IFAC PapersOnLine, 55 (20), 361-366.