Exploring Students' Learning Behaviour in MOOCs using Process Mining Techniques

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Abstract. Massive Open Online Courses (MOOCs) provide increasing opportunities for skills acquisition. Their widespread use can be justified by a number of critical motivating factors such as the possibility of free courses, the flexibility of the learning process as well as the reputation of some of the world most prestigious universities offering these courses. This level of popularity has created the need for a deep understanding of learning in MOOCs. This has been so far achieved through Learning Analytics (LA) using data mining techniques. Nevetheless, it is difficult to perform a sytematic analysis of learning processes based on students' behaviour using these techniques alone. Therefore, we propose to apply process mining since it provides important techniques for understanding learning processes based on students'activities trails from MOOC platforms logs. In this paper, we analyze a Coursera MOOC dataset using several process mining techniques and provide some indications in terms of useful insights and guidance that could inspire intervention measures to improve both the quality and delivery of MOOCs.

Keywords: Learning Analytics, Mooc, Coursera, Educational Data Mining, Process Mining,Online Learning

1 Introduction

There has been a surge in interests for Massive Open Online Courses (MOOCs) in recent years. More people find in MOOCs a cheap means to acquire new skills and improve their imployability [5]. In the same way, many institutions offer free courses online as MOOCs as part of their marketing strategy. The aura and publicity generated by the use of MOOCs raise critical interests for Learning Analytics (LA) [7,8].

A number of LA studies have attempted to explore MOOCs in general. In [10], a systematic survey of the literature is conducted to give a broad picture in terms of research on MOOCs. It emerges that a number of aspects in MOOCs are investigated including individual case studies, educational theory in MOOCs, technology used as part of teaching and learning, MOOCs participants and MOOCs providers [10]. This study highlights that many MOOC participants do not or keep a very limited participation to forums for diverse reasons. Some of these reasons include background and cultural differences. Such participants then seek support through external communication channels [9]. Furthermore, in studying the identity of and motivation behind MOOC participants, Christensen et al. [5] argue that MOOCs population tends to be young, well educated, and employed. The main reasons for partaking in MOOCs are primarily career promotion and curiosity [5]. Other similar studies investigate MOOC popularity and potential [8] and funnel of participation [6].

Moreover, current literature on LA indicates that the focus has mosltly been on prediction, classification and other classical data mining techniques for students' retention, students' dropout risk modeling etc., almost entirely using attributes such as students' age, previous grades, residency, race, academic qualifications etc. [3,4,7]. Beyond this type of analysis, process mining techniques [1] add a new perspective based on the actual behaviour exhibited by students as they learn.

The need to improve both the contents of MOOCs and their delivery calls for a careful consideration of students' direct behaviour. Therefore, Process mining techniques can be used in exploring students' footprints as they interact with the materials. In this paper, we present some of these techniques and the advantages they provide. We make use of a Coursera MOOC as a case study to demonstrate their applicability and usefulness.

The remainder of this paper is structured as follows. We start with a brief introduction to process mining in section 2. This is followed by a description of our case study section 3. In section 4, we give an overview of the Coursera data structure and a discussion on how the input data can be converted to the process mining format in section 5. In section 6, we discuss the application of process mining techniques to MOOC data and discuss the results. Section 7 concludes this paper and discusses possible future directions.

2 Process Mining

Process mining is an emerging discipline providing comprehensive sets of tools to provide fact-based insights and to support process improvements [1]. Process mining can *discover* a process model that describes the process as contained in the event log(s) [1,11].. Process models can provide critical insights and document procedures [1]. A global overview and positioning of process mining is presented in 1. These process models describe how 'the world', in our case the MOOC students, interact with the information system, in our case the Coursera platform.

Next to the fully automatic discovery of process models, process mining also provides techniques to check the conformance of event log data to a given process model. Additionally, given process models can be enhanced using the event log data. Examples of extension include the projection of time information on the process model, or repairing the process model using the event log data. By using the historical data as recorded by the MOOC platform, process mining techniques are able to analyse the underlying process.

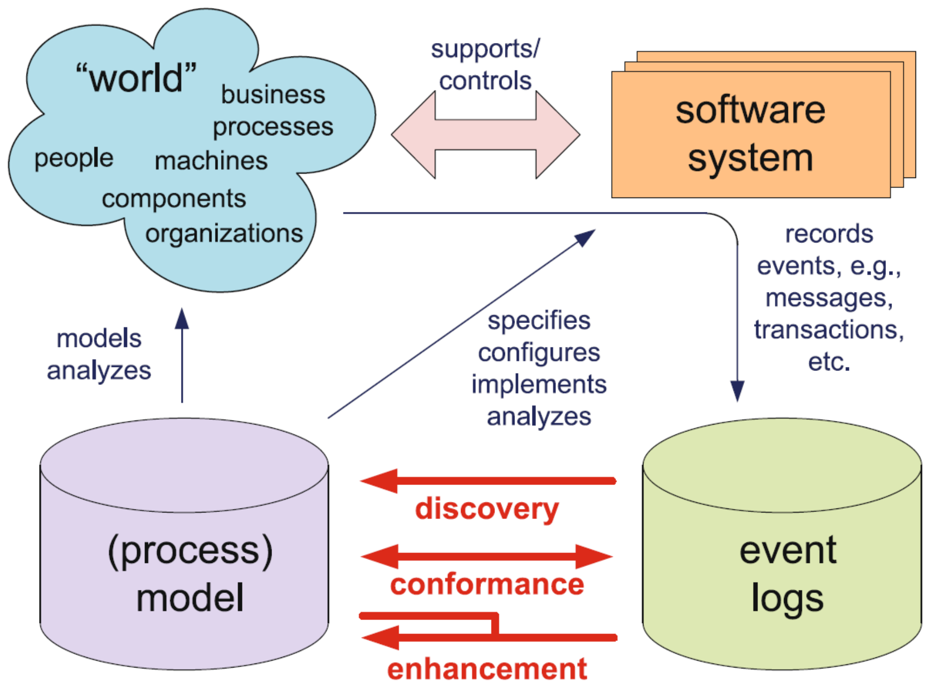


Fig. 1: Overview of Process Mining

Therefore, process mining allows us to answer the following type of questions:

1. What is the learning process that students follow?
   (a) Find distinctive groups of students: (un)successful students, different backgrounds, different learning goals, etc.
   (b) Detect differences in behavior between the groups.
2. Given the process, what is the timing of this process? Do students follow the proposed timing? Do they study in batches/bursts or equally spread over the run of the course?
3. Where do (groups of) students deviate from an ideal or hypothetical learning process?

3 Overview of The Case Study

In this paper, we analyse data obtained from Coursera for the first instance of the course "Process Mining: Data Science in action" which ran from November 11, 2014 to January 8, 2015. Coursera indicates that a total of 43,218 students enrolled for the course, of which 20,868 watched at least one lecture, 5,798 students submitted at least one exercise and 1,688 certificates (either normal or with distinction, and either certified or not) were issued as detailed in Table 1.

Table 1: Global statistics for our Coursera MOOC case study

Start date	**Nov 14, 2014**
# Registered	43,218
# Visited course page	29,209
# Watched a lecture	20,868
# Browsed forums	5,845
# submitted an exercise	5,798
# Certificates (normal/distinction)	1,688
# Normal certificate	1,034
# Distinction Certificate	654
End date	**Jan 8, 2015**

4 MOOC Data: The Coursera Case

Coursera is a large platform that keeps track of all students and staff activities details as they pertain to hosted courses. Coursera subdivises raw data into three categories: general data, forums data and personal identifying data. In total, the standard model comprises 59 tables storing information about users' privileges, announcements regarding the course, all forums details, assessements and evaluation data, course grades, submissions details etc.

For the purpose of this study, we have limited our analysis to data about direct student behaviour. The datasets we analyse are centered around the *students* participating in a MOOC, and the stream of *click events* they generated on the course webpages. The structure of this dataset is shown in Figure 2.

Clickstream During a course, students visit the course website to, amongst other things, watch lecture videos and make quizzes. As students click through the website to look up these videos and quizzes, they leave a trail of *click events*, collectively called a *clickstream*. Each such event could be associated with, for example, a particular lecture, or a particular quiz submission. In addition to the pages visited by a student (recorded as a *pageview action*), we also know how the students interacted with the lecture videos (recorded as a *video action*).

Student For each student, we have information about when the student registered for the course, and their end course grade. For the registration, we know the exact *time the student registered*, and if they participated in the special (paid) *signature track*, in order to obtain a verified certificate. The course grade consists of two parts: the *normal grade* and the *distinction grade*. In addition, the student is assigned an *achievement level* based on the obtained grades. If the student did not complete the course exams, the achievement level is *absent*. If the student did complete the exams, but his normal grade was not sufficient, the student *failed* the course. On the other hand, if the student did have a sufficient normal grade, but insufficient distinction grade, they get the achievement level *normal*. Finally, if the student both has a sufficient normal and distinction grade, they achieved the level *distinction*.

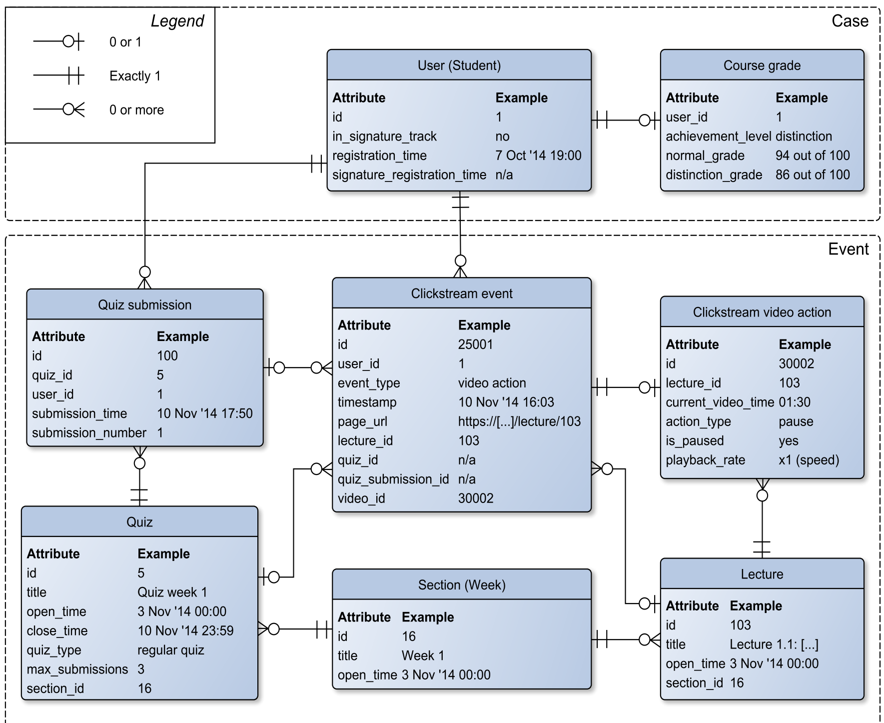


Fig. 2: The structure and type of information used in our analysis, described in an Entity-Relationship Model.

Course structure Lastly, in a Coursera MOOC, lectures and quizzes are grouped into *sections*, (typically *weeks*). Each section is visible to the students at a predetermined time (the *open time*), in order to give structure to the course. Within a section, lectures and quizzes may have their own open time, to further guide students to follow a particular study rhythm. Finally, quizzes an also have deadlines (the *close time*), and quizzes can be attempted multiple times by the student, up to a certain *submission maximum*.

5 Generating Event Logs from MOOC Data

In this case study we are interested in analysing students' behaviours based on the trails of *click events* they generated. Before we can use *process mining* to analyze this behavior, we first need to map the MOOC data to an *event log*. There are two things we must specify for this mapping: what constitutes an *event*, and what makes a *case* (i.e., a sequence of events).

As we are focussing on the behavior of students, we will consider each student as an individual case. The clickstream a student generated will be the basis for the events in this trace. This separation between case and event is also displayed in Figure 2. For this analysis, we will primarily focus on events with the type *pageview action*.

As an example, consider the MOOC data in Table 2. The resulting event log is shown in Table 3. Each student in Table 2 becomes one case in Table 3. For each case, we store the data available about the student, including their course grade data. For each clickstream event, we create an event belonging to the corresponding case (based on the student user_id). In this example, we will only consider lecture pageview actions. That is, we filtered the MOOC data to get a view of the lecture watching behavior of students. For each clickstream event, we store the click event data, including the referenced lecture as event name.

Based on different data attributes we can determine several students groups. First of all, we can group students that failed (F) the course or successfully (S) obtained a certificate, which can be split into a normal (N) certificate or certificate with distinction (D). The second attribute on which we can split is whether a student enrolled in the signature track (T) or not (F). Thirdly we can consider for which weeks events were recorded, e.g. for week one only (1), weeks one and two (2), weeks one, two and three (3), or all.

6 Applying Process Mining to MOOC Data

As part of our exploration, we make use of process mining to model and profile students' behaviour throughout the duration of the course. Before we decide on any process mining techniques appropriate for our analysis, we consider three critical elements as basic dimensions from which we conduct this exploratory analysis. These include the general lecture videos viewing behaviour, quiz submission behaviour as well as a combination of both. The key objective is to

Table 2: Example MOOC data

User (Student)

id	in_signature_track	registration_time	signature_registration_time
1	no	7 Oct '14 19:00	n/a
2	no	9 Oct '14 01:05	n/a
⋮			

Clickstream event

id	user_id	event_type	timestamp	lecture_id ...
25000	1	pageview action	10 Nov '14 16:01	103
25001	1	video action	10 Nov '14 16:03	103
25002	1	pageview action	10 Nov '14 16:42	104
25003	2	pageview action	11 Nov '14 02:05	103
25004	2	pageview action	11 Nov '14 02:15	104
⋮				

Course grade

id	achievement_level	normal_grade	distinction_grade
1	distinction	94 out of 100	86 out of 100
2	failed	35 out of 100	n/a
⋮			

Lecture

id	title	open_time	section_id
103	Lecture 1.1: [...]	3 Nov '14 00:00	16
104	Lecture 1.2: [...]	3 Nov '14 00:00	16
⋮			

Section (Week)

id	title	open_time
16	Week 1	3 Nov '14 00:00
⋮		

Table 3: Example event log based on the data in Table 2

Cases

id	user_id	in_signature_track	registration_time	achievement_level	...
1	1	no	7 Oct '14 19:00	distinction	
2	2	no	9 Oct '14 01:05	failed	
⋮					

Events

id	case_id	clickstream_id	event_name	timestamp	...
1	1	25000	Lecture 1.1: [...]	10 Nov '14 16:01	
2	1	25002	Lecture 1.2: [...]	10 Nov '14 16:42	
3	2	25003	Lecture 1.1: [...]	11 Nov '14 02:05	
4	2	25004	Lecture 1.2: [...]	11 Nov '14 02:15	
⋮					

understand how students study and what impact such behaviours have on their involvement in the course. Therefore, we make use of process discovery algorithms, dotted charts and conformance checking to accomplish this.

We divide students into separate groups in order to enrich our analysis. This grouping is predicated on the assumption that similar group of students exhibit common beaviours. The first criteria for grouping is the type of certificate students enroll for. In order to acquire a signature track certificate, one is required to pay a fee and this motivation can translate into the exhibited level of commitment to learning. The second criteria is the achievement level or final grade. By clustering students according to their performance, we can point out common characteristics and inherent patterns that can shed lights into learning behaviour exhibited by these students.

6.1 Vizualizing Viewing Behaviour

This dimension provides hints to the degree of commitment and general watching behavior exhibited by students throughout the course. The idea is to understand the path followed by students while viewing videos. This also provides a broad representation of students' migration and evolution throughout the course as depicted in Figure 3.

In Figure 3, the dotted chart depicts the lecture video viewing sequence behavior for all the students having registered for the course. The information is sorted according to the last event in order to have a picture of dropout rate. The x axis depicts the time expressed in weeks, while the y axis depict the cases (students). Seven different colors depict different events at a given time. The white dots show the timing when students viewed the first two videos on course background and introduction to disco and prom tools. All videos for week 1 are

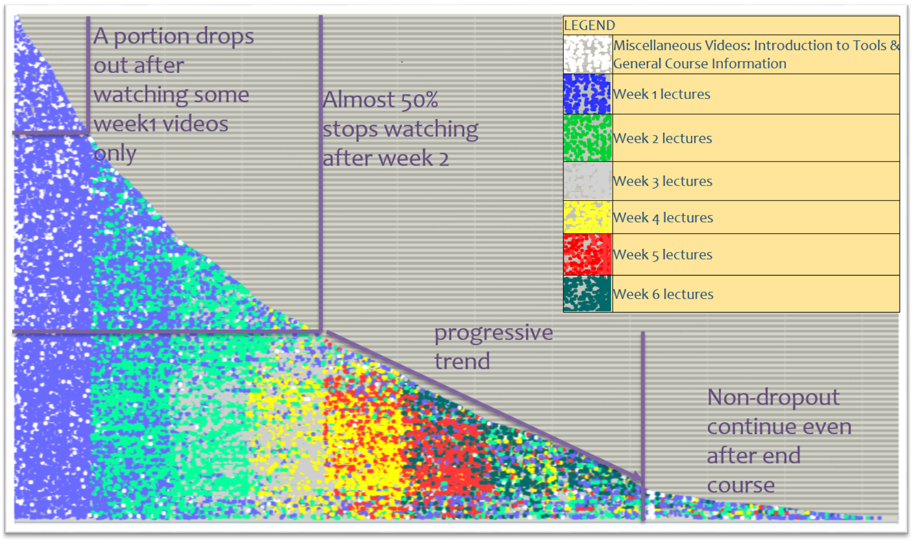


Fig. 3: Dotted Chart depicting a general viewing behaviour throughout the duration of the MOOC

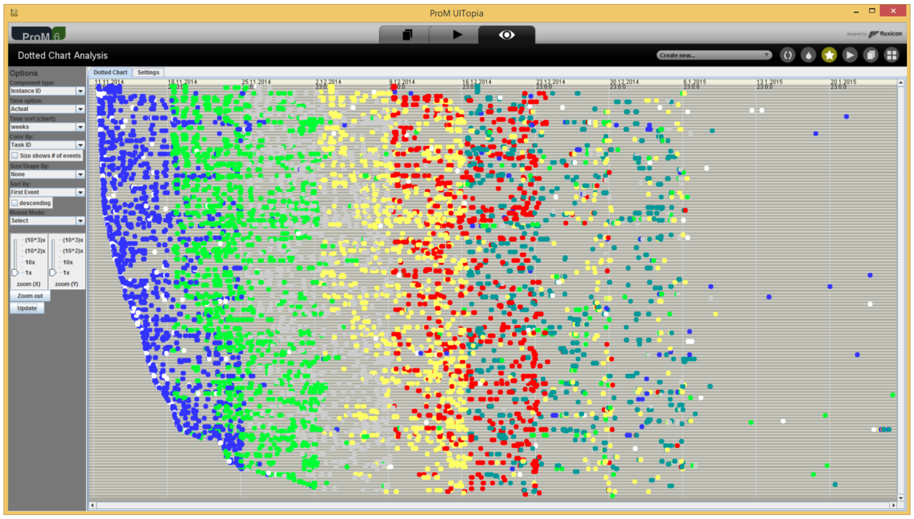
depicted with the blue dots; green dots represent lecture videos for week 2, gray dots show the distribution for lecture in week 3, all yellow dots show lecture views for week 4, week 5 lectures are seen in red while the last week (week 6) lecture videos are viewed through dark green dots.

Based on this visualzation, we can observe that:

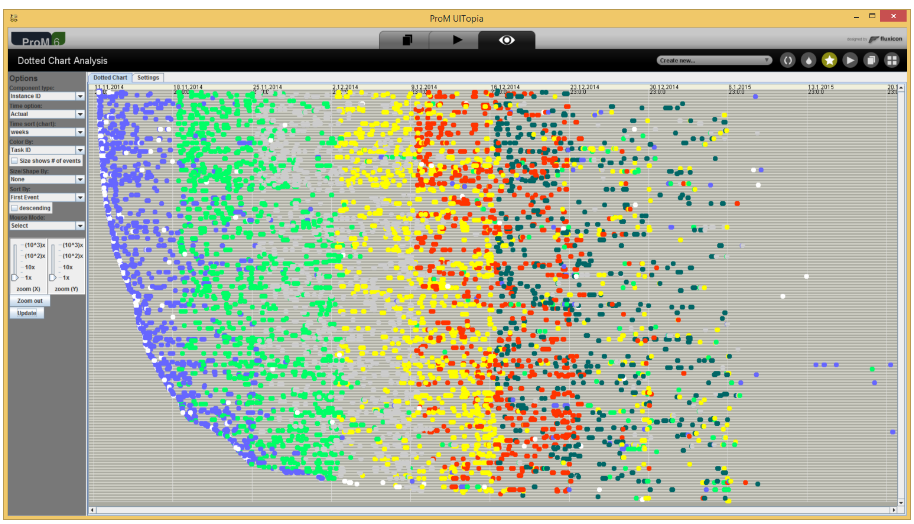
- A significant number of students drop out throughout the duration of the course.
- Many stop watching after the first week but about 50% of students drop out after the second week of the course. Some actually even quit after watching the introductory videos (a handful of them).
- Not all students watch the videos in sequence. Although all of them watch week 1 before watching week 2, the picture also demonstrates that even towards the end of the course, many still watch week 1 and go back and forth.

Lecture Viewing Per Group Over Time In order to get deeper insights of the viewing habit, we group the students into subgroups based on their respective profiles. We consider their final performance (achievement level) and the type of the certificate they sign up for. We have 4 achievement levels including distinction, normal, absent and fail. These students could sign up for a signature track certificate or not.

These students show that they follow a sequential pattern as they watch the videos. Some join a little late at week 2 or week 3, although some videos are



(a) Signature Track



(b) Non-Signature Track

Fig. 4: Dotted Charts for Distinction Students

rewatched in weeks later but the general trend remains that most of them watch videossequentially as they are made available. This can be seen by looking at the demarcation imposed by respective lecture videos colors.

In Figure 5, we observe the behaviour of those successful students that pass the course without a distinction. This can happen because of 2 things. If students decide not to submit the project (assignment) or if their overall mark is below the threshold for distinction pass. Figure 5, shows that these students watch videos almost in the same sequence as distinction students. Although some start a bit later, but the general behaviour is that from Week 3, the majority of videos are watched in sequence with a few exceptions when some videos from earlier weeks are rewatched.

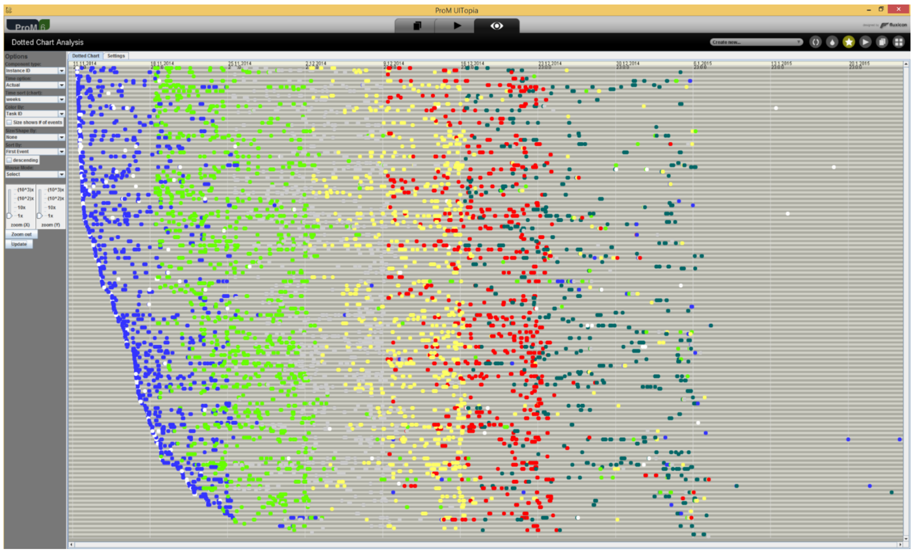
Finally, we consider unsuccessful students. These are those who did not obtain either a distinction or normal grade. We can observe in Figure 6that most of these students join the course as just curious users who join even in the last week of the course and only view some videos from week 1.

Moreover, Figure 6 gives an indication that many of the students that fail join the course significantly late, and do not watch all the videos. We can see that blue dots (week 1 videos) are visible throughout the entire weeks of the course demonstrating that many students who join late probably do so out of curiosity. These students watch mostly the first 2 weeks videos.

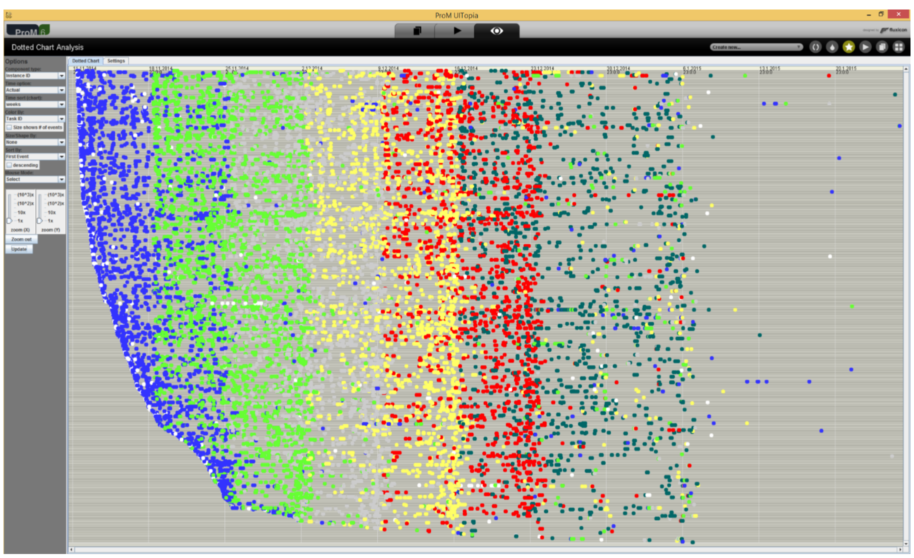
Conformance Checking In process mining, conformance checking allows to verify how accurately a normative model, such as the model in Figure 7 , can be replayed on event logs. Having a sequential model encompassing sequential steps which represent the different tasks executed in the process, we make use of conformance checking to verify whether event logs comply to such a model [1,2].

We perform conformance checking to quantify the watching behaviour for these groups over the duration of the course. Making an assumption that all students follow the course in sequence, we designed a model to represent this hypothesis. This idealised model, given as a BPMN model, is depicted in Figure 7 . It is an aggregated version of the real model that shows only succession and flow between videos from weeks 1 to 6. The main reason for not showng all videos in a chain is the high number of videos in the MOOC. With over 60 videos, the model would not be readable in this paper. The model used in the experiment therefore specifies the first lecture in the series "Lecture 1.1: Data Science and Big Data (17 min.)" as the first task and the last lecture "Lecture 6.9: Data Science in Action (9 min.)" as the last task in the model.

The general assumption is that students start watching videos as they are made available online and hence, exhibiting a watching behaviour as depicted by Figure 7. The results of conformance checking will enrich and provide more insights pertaining to the real behaviour of students in the MOOC. The conformance checker provides detailed statistics regarding the conformance between the normative model we developed regarding an idealized viewing behavior and



(a) Signature Track



(b) Non-Signature Track

Fig. 5: Dotted Charts for Normal Students

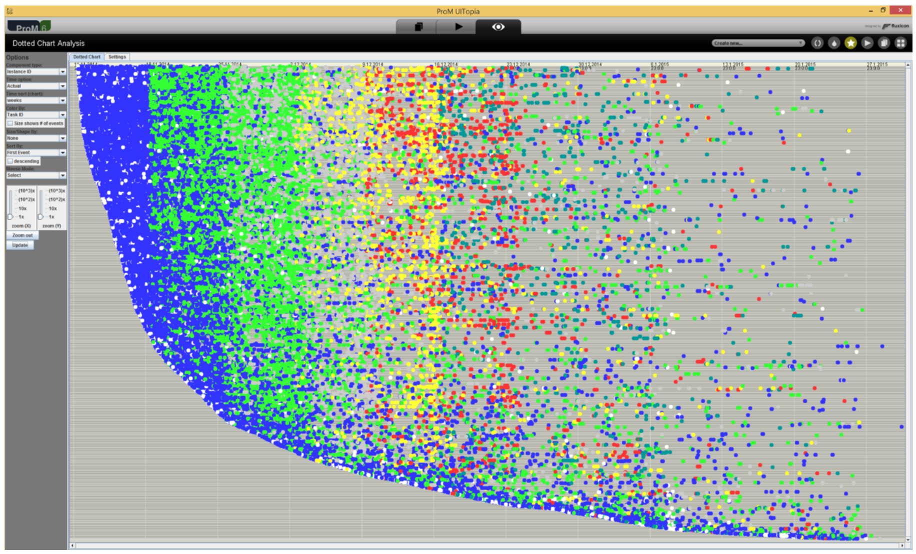


Fig. 6: Dotted Chart for both Signature and Non-Signature Track fail Students

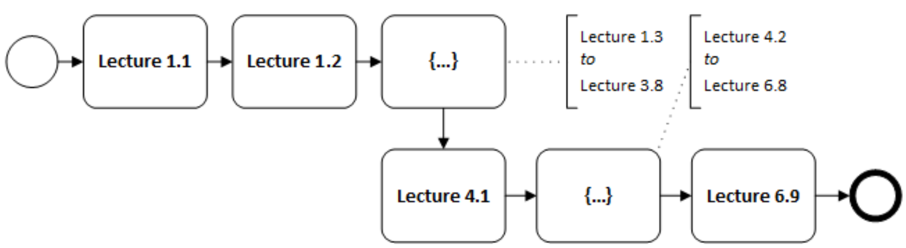


Fig. 7: BPMN Model for Sequential viewing of videos from Lecture 1.1 in Week 1 to Lecture 6.9 in Week 6

the event log. Primarily, we consider the trace fitness. This is a measurement expressed between 0 and 1 to determine the level of conformance.

Figure 8 shows that sucessful students (distinction and normal) are more likely to study sequentially than unsuccessful students(fail and absent). This seems like an obvious observation but a confirmation with conformance checking can help provide even more diagnostic details. Such details provide insights and/or identify deviations between tasks (activities) that were thought to occur (as per model specification) but did not occur as specified based on the evidence from the log and vice versa. We include a part of the normative model annotated with diagnostic information for illustrative purposes.

In Figure 9, we illustrate a part of the normative model representation distinction students' behaviour as well as the corresponding legend depicting sll the meanings to the corresponding colors as found in the model. The model is annotated with diagnostic information depicting possible deviations as a result of conformance checking.

Process Discovery Process discovery entails learning a process model from the event log. In section 5, we explained how the event log is generated from the MOOC dataset. This log can be used as an input to a number of process mining algorithms in order to visualize and eanact the real behaviour of students. We consider the fuzzy miner to mine our dataset. While we could mine all of our subgroups and their corresponding logs, we consider for illustrative purposes 2 extremes: the distinction students on signature track and failing students not on signature track.The resulting models are displayed in Figure 10.

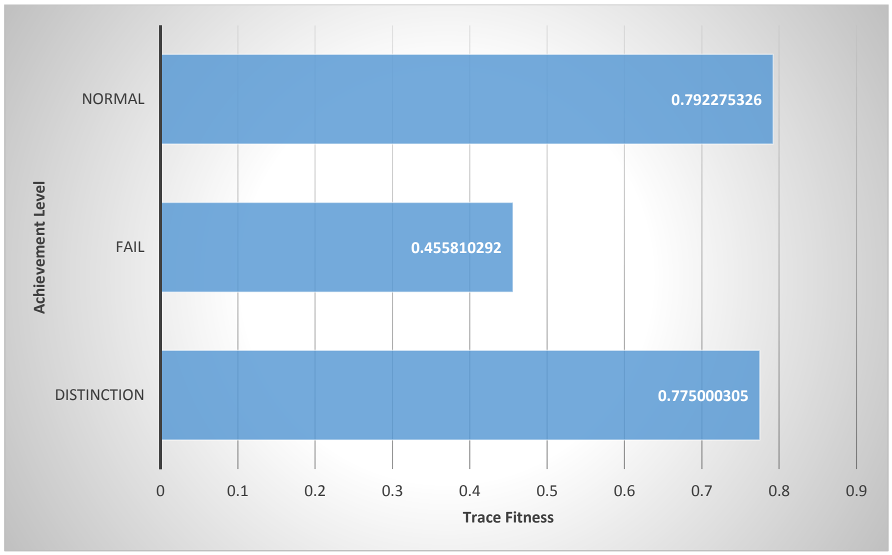
Figure 10 supports the findings observed in Sections 6.1.1 & 6.1.2 (dotted chart and conformance checker). The models indicate that distinction students tend to have a more structured learning process in contrast with the students who failed. The failing students follow a very unstructured learning process that exemplifies the volatitlity and unpredictability of the majority of participants.

6.2 Quiz Submissions

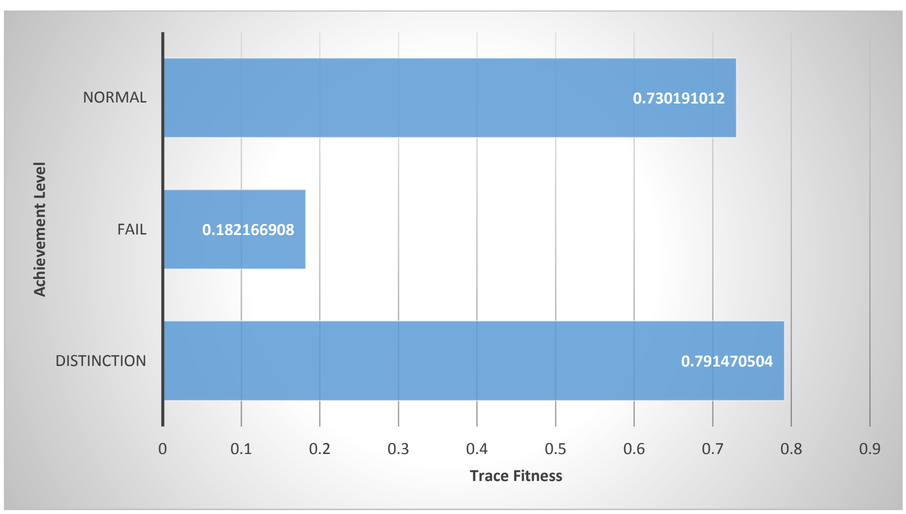
In order to enrich the exploration of students' behaviour, one can also look at the way they submit their quizzes. Some participants can register and even watch videos consistentely without taking the assessment. Some might not watch all videos in any particular order but take the quizzes and perform well. Therefore, it is helpful to also focus on quizzes separately and observe how these groups of students behave.

We can follow the same steps as in the previous analyses using process mining. However, we only mine the process model using the fuzzy model and consider the dotted chart visualisation.

Figure 11 shows that students who passed follow a structured process in submitting their weekly quizzes until the final quiz. With the exception of quizzes

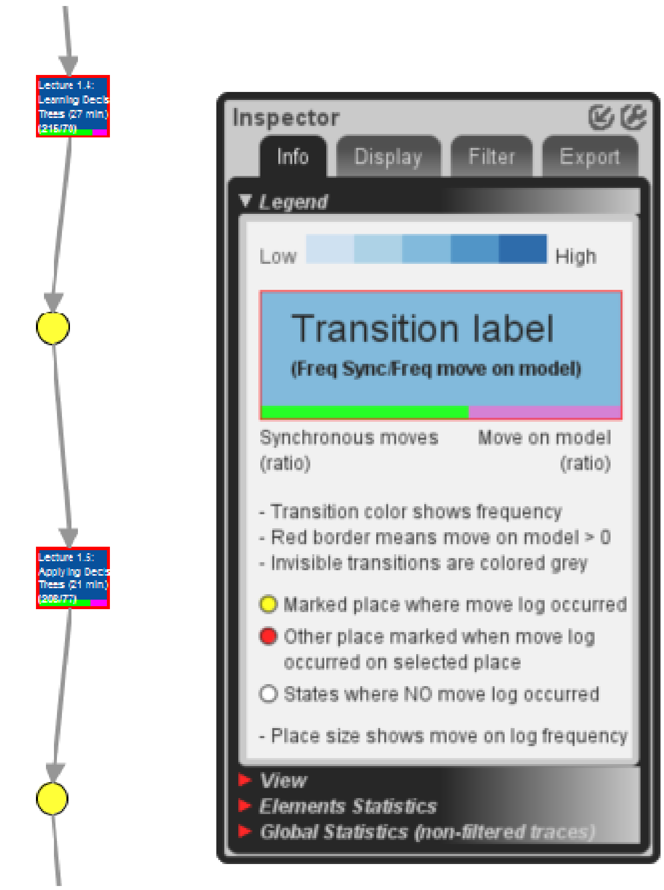


(a) Signature Track Students



(b) Non-Signature Track Students

Fig. 8: Trace Fitness for MOOC viewing behaviour



(a) Diagnosed

(b) Legend explaining meaning of colorings on annotated normative models

Fig. 9: Sample conformance diagnostics for Lecture view Model by Distinction Students

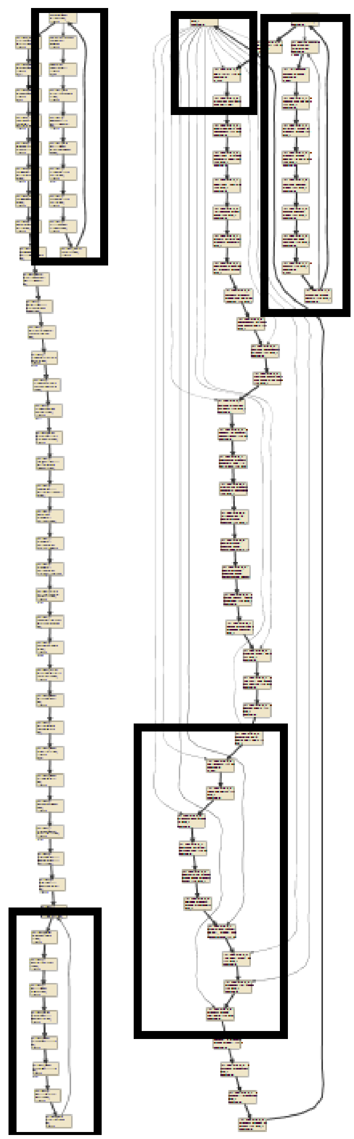


Fig. 10: Process Models for Signature-Track Distinction Students with possible "Loopbacks" signaled vs. Non-Signature Track Fail students with "bottlenecks and deviations" signaled

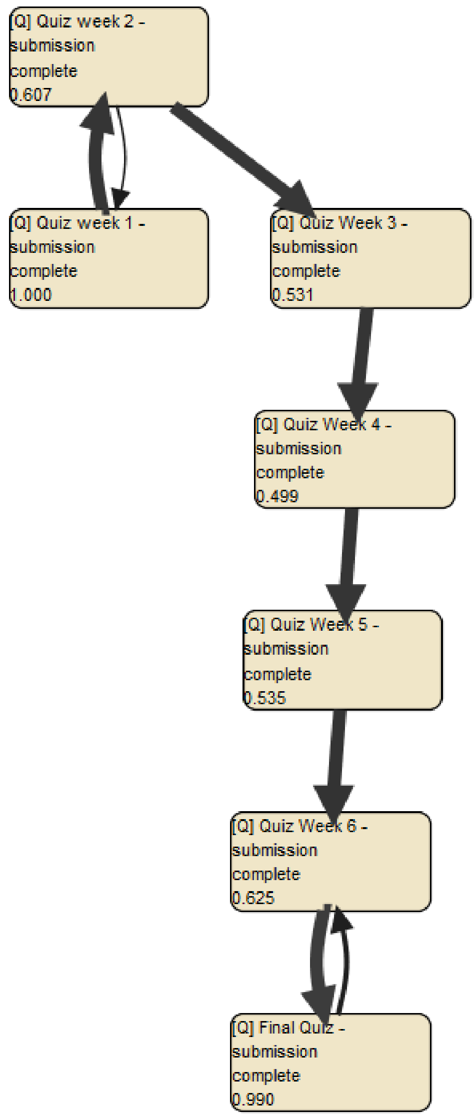


Fig. 11: Quiz Submission Behaviour for Signature Track Normal Students

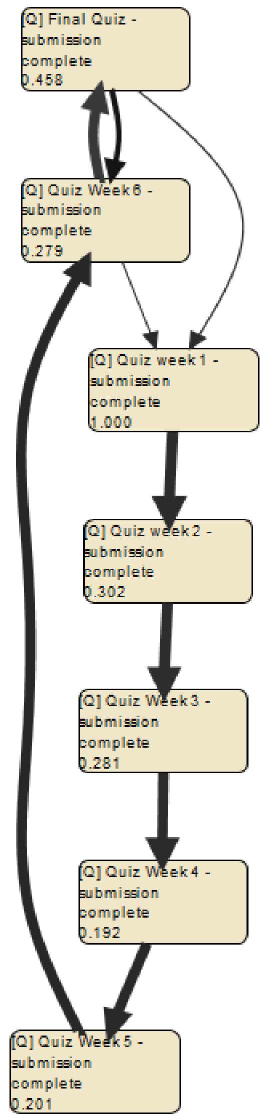


Fig. 12: Quiz Submission Behaviour for Non-Signature Track Fail Students

1 and 2, a small number of students do any of them in no particular order. The same happens with quiz 6 and the final quiz. However, some of the failing students take even quiz 1 after taking quiz 6 and final quiz as seen in Figure 12. Although both groups maintain mostly the same process, the completion rates differ. To visualize these relative proportional differences, we make use of the dotted chart for all the subgroups as seen in Figures 14, 15 and 16. Figure 13 provides detailed explanations of all the elements (dots) representing quizzes as well as the relative deadlines.

MOOCs allow for students to submit a quiz a number of times. However, there are two deadlines to a quiz: a soft and hard deadline. When students submit after the soft deadline, they still get a mark but get penalized for a late submission while a quiz submitted after the hard deadline does not count as seen in Figure 13. Considering this information, we filtered the event log to capture only quizzes for the 6 weeks including the tool and final quiz.

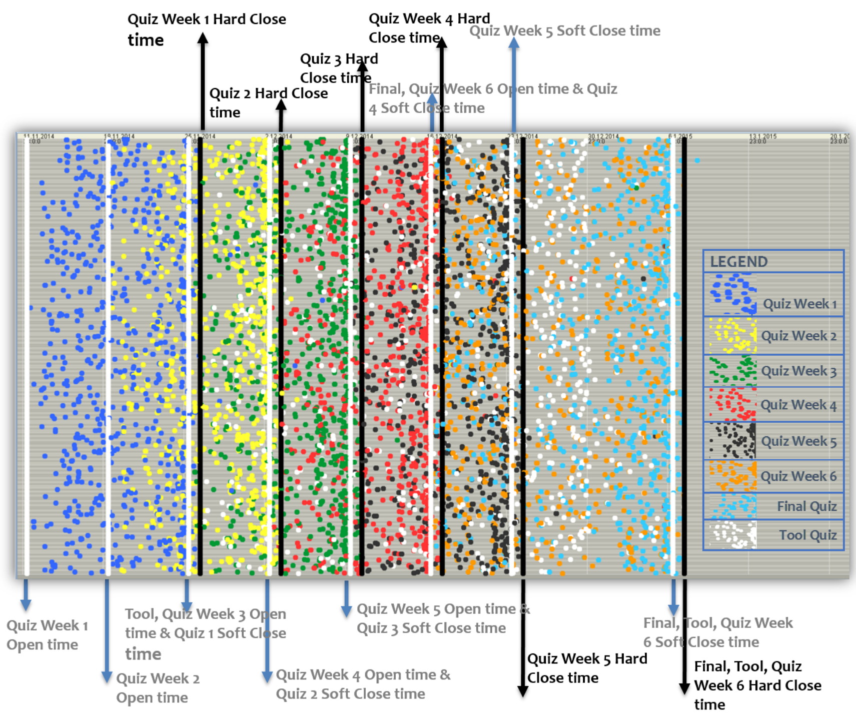


Fig. 13: A visual description of quizzes submission

MOOC students exhibit different behaviours as they interact in forums, watch lecture videos and take quizzes. In analyzing the quiz submission behaviour, we can observe our initial remarks observed in Figures 11 and 12.

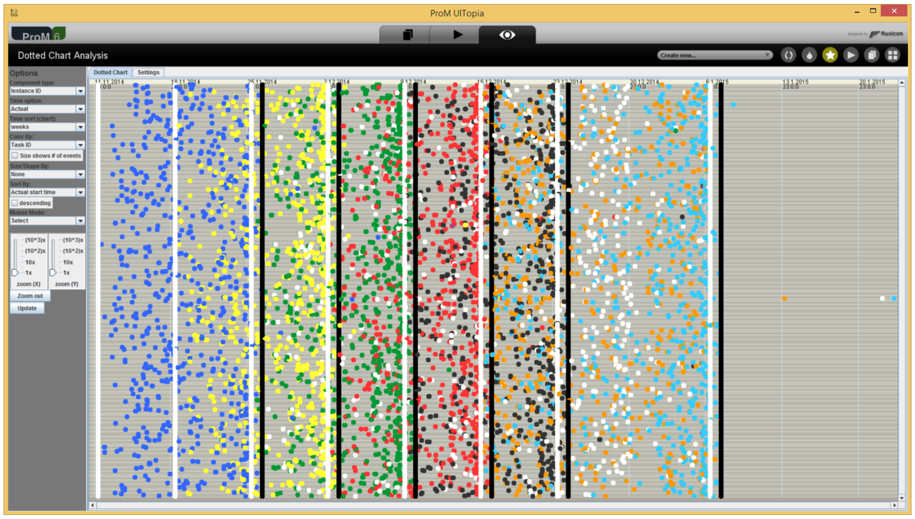


Fig. 14: Dotted Chart for Quiz submissions by Distinction Students

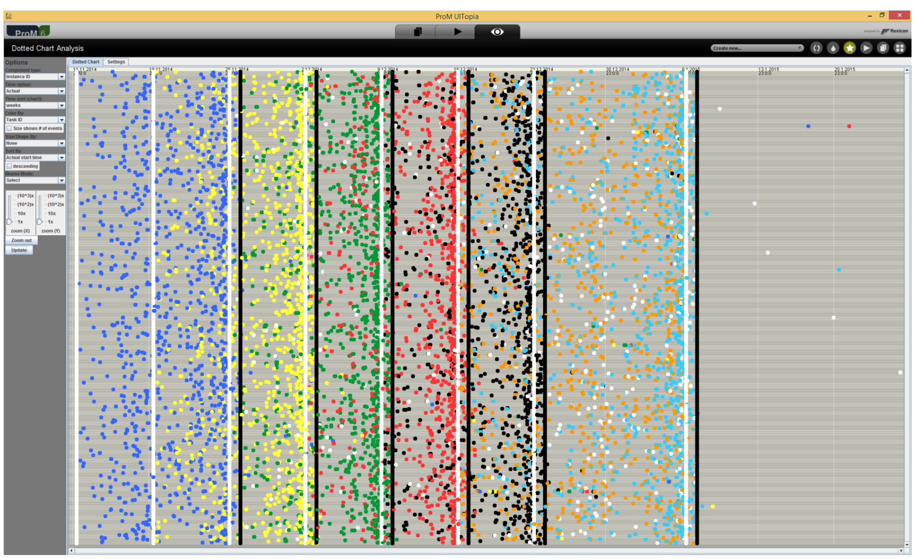


Fig. 15: Dotted Chart for Quiz submissions by Normal Students

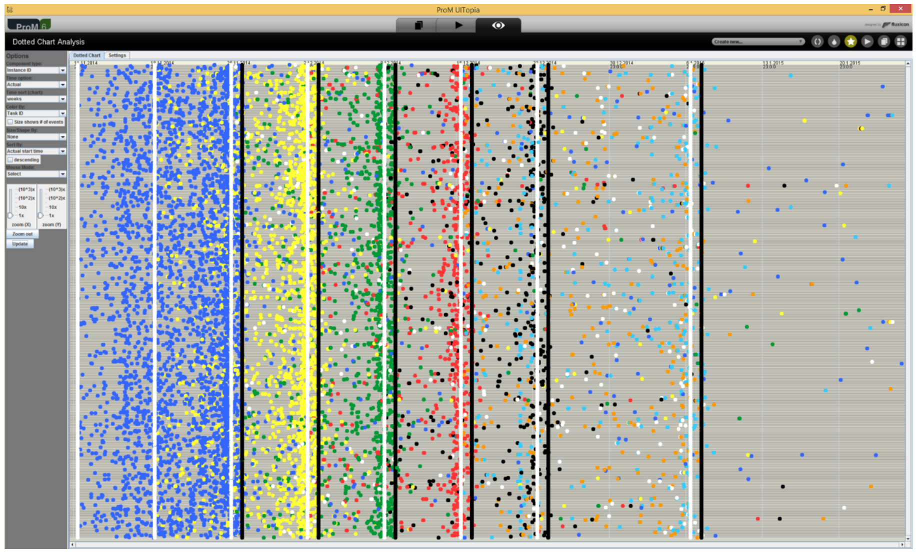


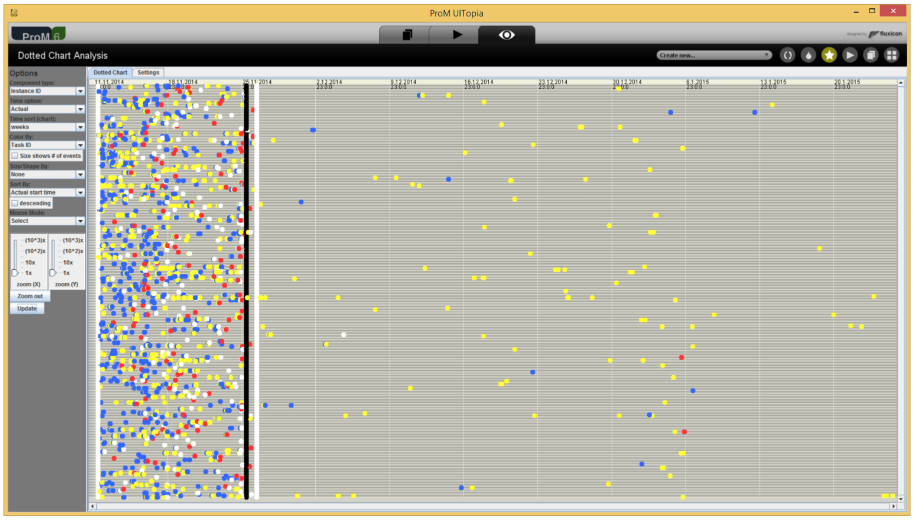
Fig. 16: Dotted Chart for Quiz submissions by Fail Students

With sucessful students (distinction and normal), there are less initial weeks' dots in later weeks. Every time we spot a dot of similar color after the hard close time, we know it did not count and this has an impact on the final grade. This happens a lot with failing students. We observe a number of blue dots (quiz 1), yellow and even green spreading throughout the remaining weeks. Moreover, the dropout rate can be observed here as there are less final quizzes submitted in comparison to the first quizzes.

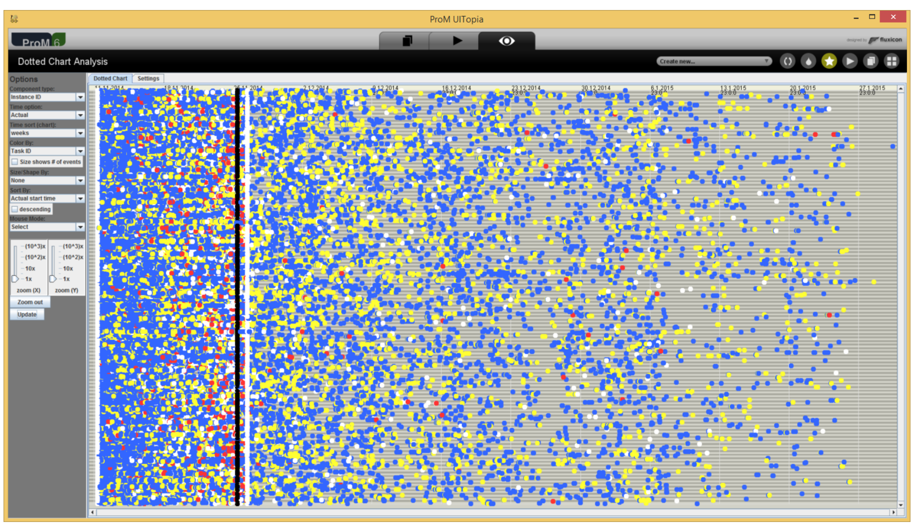
Lecture Views vs. Quiz Submission At this point, we consider both the video watch and re-watch as well as the weekly quiz submissions and re-submissions within the boundaries of the respective deadlines. This last analysis aims at giving insights on how committed to knowledge students can be. We visualize both weekly lecture videos and the corresponding quizzes. Sometimes, students still watch videos even after submitting a quiz (re-watch). For illustrative purposes, we consider only two weeks (1st and 4th) for selected subgroups.

Figure 17 and Figure 18 depict the typical behaviour exhibited by these groups of students in weeks 1 and 4 respectively. The blue dots identify a first time watch for lecture video, while the white dot symbolises a quiz submission on first attempt. The yellow and red dots depict a reoccurence of the same activity respectively for watching lectures and submitting a video.

We note that in both these weeks, distinction students tend to watch videos first and attempt quizzes before the hard deadline. After the deadline, they can rewatch videos from the same week in later weeks. On the other hand, fail students do not stick to deadlines as the behaviour depicts a volitile and

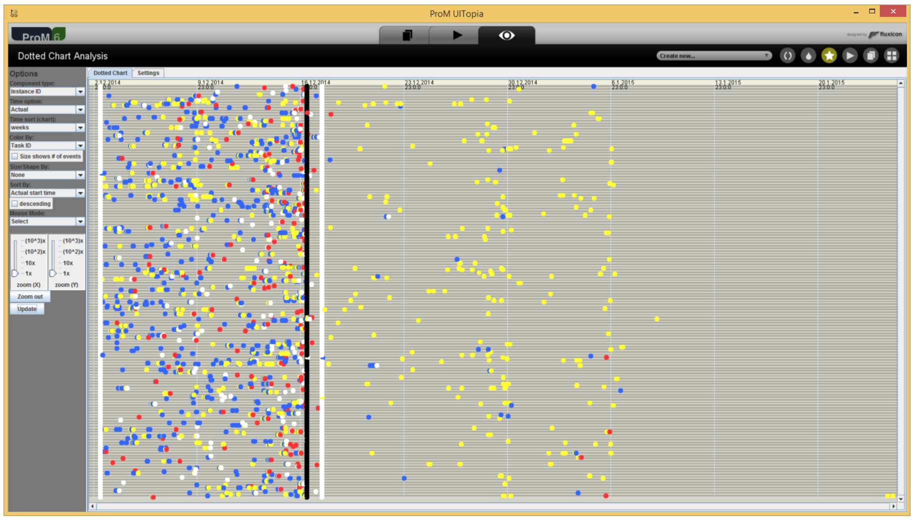


(a) Distinction students

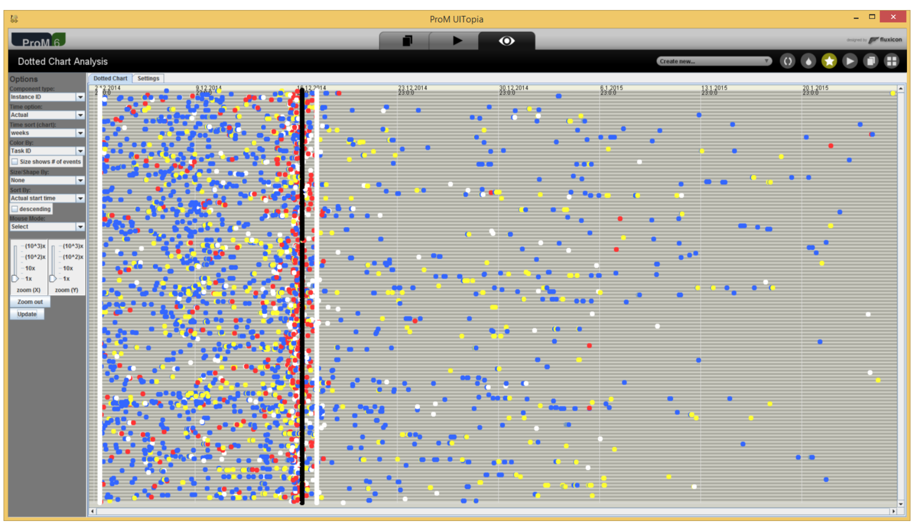


(b) Fail students

Fig. 17: Lecture and Quiz Submission Behaviour for Signature-Track Distinction Students vs. Non-Signature Track Fail students in Week 1



(a) Distinction students



(b) Fail students

Fig. 18: Lecture and quiz submission behaviour for Signature-Track Distinction Students vs. Non-Signature Track Fail students in Week 4

unpredictable behaviour. They watch videos even after the related quiz is closed (many blue dots after the white line) suggesting that there probabaly is no interest in getting any results.

7 Conclusion

In this paper, we modeled and analyzed MOOC students' learning behaviour using a case study from TU/e. Given the popularity of MOOCs, issues of content quality and delivery mode ought to be carefully studied.

While there is a plethora of individual and collective factors influencing students' performance, by focusing on what is observable, one can forge an opinion of students' study patterns and trigger appropriate actions. Process mining helps replay and visualize students' footprints as they interact with the MOOC portals through watching lecture videos and submitting quizzes.

We demonstrated that using the dotted chart, process discovery and conformance checking, we can locate and categorize behavioural differences among different groups of students. Our observations indicate that succesful (distinction and normal) students perform better because they follow the videos and submit quizzes in a more structured way than unsuccessful (fail) students. Knowing that the way students follow videos can have a direct impact on their final performance is paramount to organizing the course contents and the overall structure.

Furthermore, dotted charts provide a glipmse of watching behaviour that can be tracked. One can study the most interesting parts of the course or even the most skipped or most repeated videos in the series simply by looking at the spread on the dashboard. Consequently, appropriate actions can be taken or even further studies triggered in order to enhance behavioural studies.

References

1. van der Aalst, W.M.P.: Process Mining - Discovery, Conformance and Enhancement of Business Processes. Springer (2011)
2. Adriansyah, A., Munoz-Gama, J., Carmona, J., van Dongen, B.F., van der Aalst, W.M.: Alignment based precision checking. In: Business Process Management Workshops. pp. 137–149. Springer (2013)
3. Arnold, K.E., Pistilli, M.D.: Course signals at purdue: using learning analytics to increase student success. In: Proceedings of the 2nd International Conference on Learning Analytics and Knowledge. pp. 267–270. ACM (2012)
4. Baker, R.S., Inventado, P.S.: Educational data mining and learning analytics. In: Learning Analytics, pp. 61–75. Springer (2014)
5. Christensen, G., Steinmetz, A., Alcorn, B., Bennett, A., Woods, D., Emanuel, E.J.: The mooc phenomenon: who takes massive open online courses and why? Available at SSRN 2350964 (2013)
6. Clow, D.: Moocs and the funnel of participation. In: Proceedings of the Third International Conference on Learning Analytics and Knowledge. pp. 185–189. ACM (2013)

7. Ferguson, R.: Learning analytics: drivers, developments and challenges. International Journal of Technology Enhanced Learning 4(5-6), 304–317 (2012)
8. Kay, J., Reimann, P., Diebold, E., Kummerfeld, B.: Moocs: So many learners, so much potential... IEEE Intelligent Systems (3), 70–77 (2013)
9. Liyanagunawardena, T.R.: Information communication technologies and distance education in Sri Lanka: A case study of two universities. Ph.D. thesis, University of Reading (2012)
10. Liyanagunawardena, T.R., Adams, A.A., Williams, S.A.: Moocs: A systematic study of the published literature 2008-2012. The International Review of Research in Open and Distributed Learning 14(3), 202–227 (2013)
11. Verbeek, H.M.W., Buijs, J.C.A.M., van Dongen, B.F., van der Aalst, W.M.P.: ProM 6: The process mining toolkit. In: Proc. of BPM Demonstration Track 2010. vol. 615, pp. 34–39. CEUR-WS.org (2010), `http://ceur-ws.org/Vol-615/paper13.pdf`