Identifying Styles and Paths toward Success in MOOCs

Kshitij Sharma[1], Patrick Jermann[2], Pierre Dillenbourg[1]
1. Computer Human Interaction in Learning and Instruction
2. Center for Digital Education, École Polytechnique Fédérale de Lausanne, Switzerland
<firstname>.<lastname>@epfl.ch

ABSTRACT
Current schemes to categorise MOOC students result from a single view on the population which either contains the engagement of the students or demographics or self reported motivation. We propose a new hierarchical student categorisation, which uses common online activities capturing both engagement and achievement of MOOC students. A first level is based on the online engagement with the course structure, i.e., whether they take part in graded activities or not. Based on this criterion, we divide students into two major categories: *active students* and *viewers*. The second levels are based on the different activities typically performed by the students in these two categories. For the "active students" we categorise them based on their final result. For the "viewers", we further divide the category based on their engagement quotient, i.e., how much of the course content they follow and whether they involve with the non-mandatory exercises in the course or not. Further, in this contribution we analyse the behaviour of the students in different categories to highlight the basic differences among them.

Keywords
Student categorisation, Student achievement, Massive open online courses, Student engagement

1. INTRODUCTION
The global wave of free, large and virtual courses attracts an incredibly diverse student population. With this diversity comes a huge variety of online behaviours. For data scientists it is a challenge to find categories that are suitable for sampling the whole population. It is also important to keep the categorisation scalable and robust.

To the best of our knowledge, there exist only a few categorisation schemes, mostly based on what emerges as a pattern of behaviour from MOOC students. These categories are based on the students' motivation [10] or engagement patterns [6, 7, 9, 4, 3, 5] or demographics [2, 1].

Based on student motivation (their "stated intent") of the students, [10] categorised the students, No-shows, Observers, Casual Learners and Completers. Where No-shows only register, Observers want to know about how a MOOC looks like, Casual Learners want to learn a few things only, and Completers want to earn a finishing certificate.

There are many categorisation schemes depending on engagement patterns. [6] categorised students in Completing, Auditing, Disengaging and Sampling students based on their activities which range from watching majority of lectures and submitting all the assignments (Completing) to watching only one or two lectures and no assignment submissions (Sampling). In a connectivist MOOC setting, [7] categorised students into Active (students who adapt well to the connectivest pedagogy), Passive (frustrated ones) and Lurkers (who actively follow the course but do not interact with anyone). Phil Hill first categorised MOOC students into Lurkers (ones who only enrol or sample the course), Active (fully engaged with the course material, quizzes and forums), Passive (only consume the content, did not participate in forums) and Drop-ins (consumed only a part of the course as an Active student) [5]. Later he revised his categories and divided the Lurkers into No-shows and Observers [3, 4].

Petty and Farinde [9] used the engagement categories from [8] to categorise students in an online mathematics course. These categories, based on the students' engagement patterns into critical thinking, were Clarification, Assessment, Inference, and Strategies.

The other dimension used to categorise students is to look at the demographics. For an electrical engineering course [2] categorised students based on their country of origin, education qualifications and backgrounds. Looking at the demographics of University of Pennsylvania's Open Learning Initiative [1] also categorised MOOC students based on their country of origin and educational background as [2] did. However, [1] added a few more categories based on gender, age and employment status of the MOOC students.

One common feature about these categorisation schemes is that they all consider only one of the dimensions of student behaviour, for example, engagement with the course content or forums or demographics or motivation. In this contribution, we present a novel categorisation scheme that considers both the engagement and the achievement of MOOC students. We further report on the different patterns shown by the students from different categories. Moreover, the categories like Completing [6] and Active [4] are more than just engagement patterns; they also represent a mixed population of students with some achievement "flag". Therefore, we propose to further divide this category into subcategories based on the students' achievement.

2. RESEARCH QUESTIONS

In this study, we ask two main research questions:
Question 1: How can we categorise the MOOC students into categories that reflect both their achievement and engagement?
Question 2: What are the basic differences in the online behaviour of the students representing populations from different categories? More specifically, we are interested in finding the different ways to succeed in a MOOC which leads us to the following research questions. **Question 2.1** How does the engagement with the course content relate to the achievement? **Question 2.2** How does the timing of engagement i.e., the engagement with the course structure relate to the achievement? **Question 2.3** How does the effort during graded assignments relate with the achievement?

3. COURSE DETAILS

For this analysis we chose four courses from Coursera. The courses were basic JAVA and C++ both at the fundamental levels and as an introduction to object oriented programming. The courses were in French and were developed at École Polytechnique Fédérale de Lausanne, Switzerland. All the courses were basic level programming courses. All the courses had 7 weeks of lecture material. All the courses had programming assignments to grade the students. Also they had additional non-graded quizzes for practice. All the courses had the last deadline in the 11^{th} week from the beginning of the course. They also had soft deadline for the programming assignments after which the effective submission score reduced to 50 % of the actual score. All the courses were open after the final deadline as well.

4. CATEGORIES

We propose a hierarchical categorisation scheme. The first reason for having a few second levels in the scheme is to be able to include the achievement of MOOC students in the analysis of online behavioural patterns. The existing categorisation schemes lack on this front. They put the completion of the course as the only criterion for having a category, which oversimplifies the different levels of achievement. Having more levels for the students' achievement enables us to identify the different trends to succeed in a MOOC.

We have two first level categories: active students and viewers (based on whether the student participated in the grades assignments or not). Active students are subcategorised based on their achievement levels and viewers are subcategorised based on their further engagement with the course content. The motivation for subcategorising viewers was to have equally distributed categories so that none of the categories have a vast majority of the student population. This improves the generalisation of the categorisation schemes beyond the courses we chose to establish the categories.

We divide the whole student population in two major categories. First, those students who actively participate in the course, i.e., they take part in the assessment processes. We simply call these students "Active students". The active students get an achievement label at the end of the course. Second, those students who just watch the videos from the course (irrespective of the number of videos they watch). We call these students "Viewers". The viewers do not get any achievement label at the end of the course.

We further divide the active students based on their achievement labels that they get at the end of the course. Active students can either be "failed", "normal", or "distinction". The levels of "normal and distinction students may vary from on course to another, but for the courses we chose the criteria is the same for differentiation of these two subcategories of active students. Moreover, all the data for the active students is collected between the start week of the course and the last week of the assignment submission deadline.

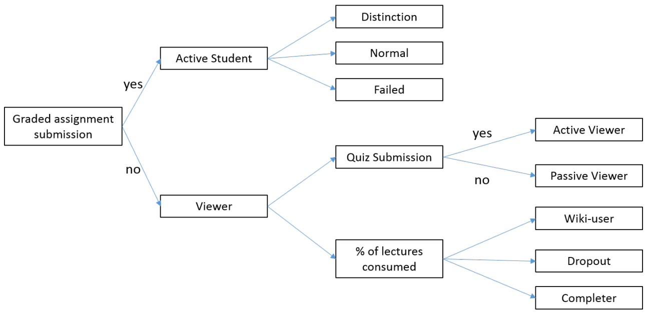

Figure 1: Hierarchy used in the present categorisation scheme.

The viewers, are further divided based on two factors. First, the amount of videos they watch; and second, whether they assess their learning by the means of the non-mandatory quizzes (in-video quizzes or regular non-graded quizzes) or not. Using the first factor, we divide the students into: 1. "wiki viewers" (if a student watches less than 10% of the videos). 2. "dropouts" (if a student watches between 10% and 70% of the videos). 3. "completers" (if a student watches more than 70% of the videos).

Using the second factor, we divide the the student into "Active Viewers" and "Passive Viewers". Since the courses were open even after the last assignment deadline, we consider the data till date of data export from Coursera (20^{th} week) for analysing the behaviour of the viewers.

5. VARIABLES

We used the following variables to analyse the behaviour of the students in different categories:

5.1 Active students

For analysing the differences in the activities among different achievement levels of Active students we defined the **First submission score:** the average score of the first attempt of all the programming assignments, as a proportion of maximum attainable score for each assignment. **First action week:** the first week of any kind of activity after registering for the course, once the course had started. **Activity span:** the difference in weeks between the first activity (as described in the previous item) and the last activity.

Progress within programming assignments: the difference between the two consecutive submissions for the same assignment, as a proportion of maximum attainable score for each assignment. Average number of attempts for each programming assignment. Proportion of videos watched **Delay in watching the lectures:** the time difference in weeks, between the time when the video was released online and the time the students watched it for the first time. Number of forum Views. **Procrastination index:** the ratio of the time difference between the submission time and the hard deadline and time difference between assignment being posted online and the hard deadline.

5.2 Viewers
For analysing the differences across the viewers' subcategories, we use only four of the above mentioned variables: first action week, delay in watching the lectures, activity span and the number of forum views.

6. RESULTS
In this section, we describe the differences between the different levels of active subcategories and viewer subcategories.

6.1 Active students
Concerning the lecture activities, the number of lectures watched by the failed students is significantly lower than the students having normal passing grades or the students with distinction $F[(2, 9914) = 741.95, p < .001]$. The lecture delay (overall and across the 7 weeks of lectures) decreases significantly as we move from distinction to normal to failed students $[F(2, 9914) = 91.43, p < .001]$.

Concerning assignment submissions, we see many differences across the three achievement levels. The first submission score decreases significantly as we move from distinction to normal to failed students $[F(2, 9914) = 210.65, p < .001]$. Number of attempts decreases significantly as we move from failed to distinction to normal students [F(2,2,9914)=222.86, $p < .001$]. The average improvement in two consecutive submissions for the same assignment is significantly higher for the students with distinction than the students with normal and failed levels $[F(2, 9914) = 101.58, p < .001]$. Moreover, the average procrastination index for the students with distinction level is significantly lower than the students from other two subcategories $[F(2, 2, 9914) = 343.83, p < .001]$.

The probability of achieving a higher grade decreases as the first action week approaches the 11^{th} week $[\chi^2(N = 9917) = 201.73, p < .001]$. The activity span for failed students is significantly smaller than passed students (normal and distinction) the course $[F(2, 2, 9914) = 972.68, p < .001]$. If we look at the forum views, the average number of forum views decreases significantly as we move from distinction to normal to failed students $[F(2, 2, 9914) = 135.42, p < .001]$.

6.2 Viewers
The viewer subcategories are based on two factors; first, how much video content they watch and second, whether they participate in non-mandatory quizzes or not. Here we present the results of the different activities for the viewer subcategories. The wiki-users tend to be passive viewers and completers tend to be active users $[\chi^2(N = 35, 193) = 4322.85, p < .001]$.

We observed an interaction effect of the two viewer subcategories on the first action week $[F(2, 35187) = 95.60, p < .001]$. For passive wiki-users and completers the first action week is significantly higher than the active wiki-users and completers. However, we see the opposite trend for the active and passive dropout viewers.

There were two single effects for the two viewer sub-categories on the activity spans. The activity span is more for the active viewers than the passive viewers $[F(1, 35191) = 1484.3, p < .001]$. Also, the activity span increases significantly as we more from wiki-users to dropouts to completers $[F(2, 35190) = 1919.63, p < .001]$.

There was an interaction effect of the two viewer sub-categories on the lecture delays $[F(2, 35187) = 67.50, p < .001]$. For passive wiki-users and completers the first action week is significantly higher than the active wiki-users and completers. However, we see the opposite trend for the active and passive dropout viewers.

7. DISCUSSION
We show that there are clear differences across the subcategories of active students and viewers. Active students are further subdivided into failed, normal and distinction categories. In section 3.1, we can see that the three categories are very different in terms of lecture, assignment, forum activities as well as their timing of these activities. What emerges from the results that the final achievement label that the active students get depends on a number of factors: 1) initial score, 2) engagement with the course content and forums, 3) efforts in assignment submissions and 4) timing of the activities. The variables we chose to differentiate among the achievement subcategories cover all these factors.

The distinction students get higher scores in their first submissions for the graded assignments than the normal and failed students, they improve more than the other two categories within two consecutive submissions for the same assignments and hence they reach the maximum attainable grade in fewer attempts. This reflects the effect of the initial score and efforts on the achievement level (**Question 2.2**). On the other hand, in spite of having similar improvements to the failed students the normal students get a better achievement level because of submitting more number of times. This shows the relationship between efforts and achievement (**Question 2.3**). Moreover, the distinction students have lower procrastination index for all the assignments than the other two categories. This reflects the relation between engagement with the structure (**Question 2.3**) and the achievement level.

The students who pass the course (distinction and normal) watch more videos than the students who fail. This simply reflects the fact that the students who pass the course engage more with the course content than those who fail the course, and establishes a relation between the engagement with the course content and achievement (**Question 2.1**). More interesting fact is that there is almost no difference between the distinction and normal students in terms of engagement with the course content, however, there is a big difference in the delays that the students display in watching the video lectures. The distinction students have a smaller delay, especially in weeks 2 to 6, than the normal students. This shows the that there is a effect of engagement with the course structure (**Question 2.2**) on the achievement level.

Furthermore, the distinction students visit forums more often than the students from other two categories and the passed students (distinction and normal) have longer activity span than the failed students. It also reflects the effect of engagement on the achievement level (**Question 2.1**).

We see some peculiar behavioural patterns for viewers. One clear relation we see is between the engagement level and the activity span of the viewers. The passive users have smaller activity span than the active users. This simply translates to the fact that the people who assess their knowledge in some manner they tend to engage longer with the course content. We observed this fact for all the viewers.

The wiki-users have a very short activity span. This could be explained in two ways: either they started the course very late and realised that they can not pass the course and hence they left; or, they look for very specific content, look at a few videos for the required content and leave the course. The second behaviour is very similar to a Wikipedia user who looks for a very specific piece of information, obtains it and leaves the website. This was the main reason we called this category wiki-users. The passive wiki users start the course very late (only earlier than the passive completers), have an activity span of less than a week, i.e., they visit the course for some very specific content, then leave the course, this behaviour is closer to what we called a wiki-user's behaviour.

The completers display very interesting patterns, viewers in this category watch more than 70% of the video lectures. The difference in the activity spans of passive and active completers is about 4 weeks, this can be explained by the fact that the passive completers are only interested in the content and not in any kind of self assessment, hence they go through the whole content at a very high pace.

There are some overlaps between the categories we propose and the categories proposed by other researchers. For example, the wiki-users are similar to the sampling in [6] and observers in [4, 3]. Similarly, dropouts are a midway (or a mixed population of) category to disengaging in [6] and drop-ins in [4]. The passive viewers are similar to auditing and passive in [6] and [3] respectively. The completing category in similar to active students and completers in viewer population are similar to auditing [6]. However, the main motivation of putting these two in different categories was to capture there different activities which are clearly driven by different motivations, for the active students the main motivation is to get a certificate and for the completers in viewer population just want to watch the videos as a source of knowledge but do not want a completion certificate.

8. CONCLUSIONS

We presented a new MOOC student categorisation scheme. Its basic idea is to have a hierarchy to categorise MOOC students. We used both engagement and achievement to achieve this goal. First, we categorise students into two broad categories active students and viewers. Active students are those who submit graded assignments and viewers do not take part in this process. Further, we divide active students into normal, distinction and failed students, based on their grades; and we divide viewers into active and passive viewers (whether they attempt quizzes or not) and into wiki-users, dropouts and completers (based on how many video lectures they consume).

Throughout our analysis, we highlight the basic activity differences between subcategories of active students and viewers, proposing a few novel variables, like delay in watching lectures and procrastination index. We identify the different paths of success for the active students and different styles for the viewers. One clear difference between the proposed categories and existing categories is that in all the existing categories there is one category that contains a majority of the student population; whereas in the categories we propose, there is no such category.

The present categorisation scheme might have long term implications. First, for initiating a feedback system for those who dropout midway out of a course, we need a benchmark behaviour to compare against. The online behaviour of the students who passed and/or the completers in the viewer categories can be used in such cases. From the differences among different subcategories we report, it is clear that the different behaviour tend to start emerging as early as from the second week. This can be used to proactively help those students who are lagging behind in their engagement with the course content and course structure.

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