Encouraging Metacognition & Self-Regulation in MOOCs through Increased Learner Feedback

Demonstration

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ABSTRACT

Learning analytics for learners has the ability to greatly improve learners' self-regulation. Current learner dashboards are mostly providing learners with an isolated view of their learning behavior, while we believe learners will gain more from a comparison of their own behavior with that of successful peer learners. In this work-in-progress demonstration we describe our design of a `Learning Tracker` widget that provides MOOC learners with timely and goal-oriented (i.e. towards passing the course) feedback in a manner that encourages reflection and self-regulation. We also present some preliminary findings which show how exposure to feedback can significantly increase student success and engagement.

Keywords

Learner Feedback, Learning Analytics, Self-Regulated Learning, Study Planning

1. INTRODUCTION

The asynchronous, open nature of MOOCs presents students with a profound sense of flexibility and freedom in their learning experience compared to the traditional classroom setting. They may study what they want, where they want, and whenever they want. However, along with these ostensibly-positive affordances come major challenges. In order to be successful in such a learning environment—with no pressure from teachers/parents, no financial obligations, and no academic credit on the line—students must stay incredibly disciplined in both the planning and following of their study habits. Dropout rates of around 95% in the average MOOC [8] are a testimony to the challenge learners face in this environment.

The discipline for planning and following a self-imposed schedule does not come naturally to many learners; rather it is a learned skill. And while merely releasing open educational resources to the world for consumption is a great start, the next step in the Open Learning movement ought to equip learners with the cognitive toolset they need to effectively *self-regulate* their learning experience.

Currently, universities, instructors, and researchers are the chief handlers of educational data generated from MOOCs. Learners do not yet form an important part of this data flow ecosystem. We believe that MOOC learners can significantly benefit from a *timely* and *goal-oriented* feedback of their study habits in MOOCs. Currently, major MOOC platforms provide rather generic learner feedback as seen in Figure 1 and Figure 2, which – while being timely – does not enable learners to judge their learning behavior in absolute terms: are they on track to succeed in (i.e. pass) this course? Are they nearly on track? Are they missing a key ingredient to being successful?

We believe that instead of providing a general overview of learner behavior, learners will be able to self-regulate better if we provide them with a comparison of their own learning behavior against that of previous *successful* (in the sense that they passed the course) students. We have developed a first learner widget that reflects this vision, enabling learners to compare themselves to successful learners and thus empowering them to reflect on and adapt their study behavior in a goal-oriented fashion.

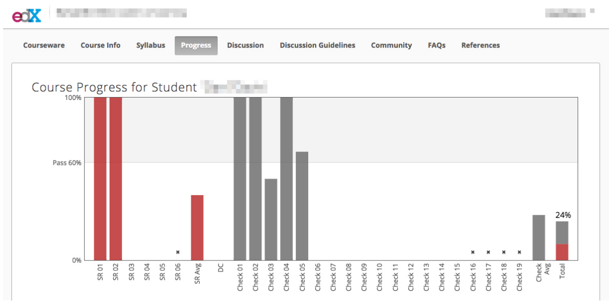

Figure 1: Sample edX dashboard: shows individual students' weekly & total assessment scores

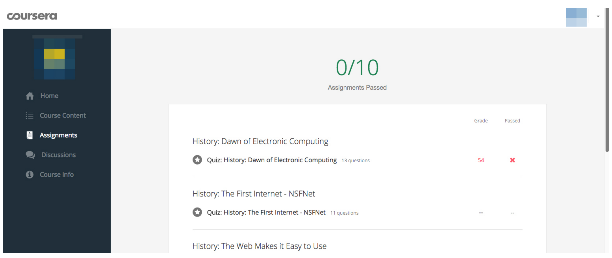

Figure 2: Sample Coursera dashboard: shows individual students' grade for each quiz, whether or not they passed, and the total number of quizzes passed

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Not only does this ease the burden of instructors (the learners decide how to react to and interpret the information shown to them), it also creates a heightened awareness in learners that they can keep with them beyond just this one course and apply in future professional or academic contexts.

The following research question guides our line of inquiry into the topic:

Can a comparison to previously successful learners serve as a helpful form of feedback to increase MOOC learners' engagement and success?

In this paper, we describe our prototype widget, the design decisions behind it, the setup we are currently employing in our experiments, and a preliminary analysis of the results.

We find that indeed, our implemented feedback has a significant positive effect on the success of the learners (in terms of grading) as well as on two out of six evaluated engagement metrics.

2. RELATED WORK

2.1 Search Dashboard

The main inspiration for this research comes from Bateman et al. [1] who, in the context of Web search, created a "Search Dashboard" that provides an interface for search engine users to see and reflect on their search behavior and, furthermore, a comparison of this data against "archetypal expert profiles." Their approach is very similar to ours in that they outline searching as something people have come to depend on in every day life, but rarely do people consider searching as a skill that may be developed and improved. The same can be said about learning. Bateman et al. [1] found that people rarely change their search behavior no matter the situation, but, once exposed to the dashboard, they become more active, aware, and critical of their searching habits—adapting them to be more in line with those of the visualized expert searchers.

2.2 Feedback to Encourage Metacognition

The key processes underpinning our `Learning Tracker` widget are that of (i) feedback prompting and (ii) metacognition, which then results in (iii) more effective self-regulated (or self-directed) [7] learning. Durall and Gros [3] and Verbert et al. [16] also outline this process of providing students with "self-knowledge" as being key to developing the necessary metacognitive skills for self-regulated (or directed) learning. And in order to ease the translation from data to actionable knowledge, Heer and Agrawala [5] found information visualization to be an effective sense-making tool due to its ability to synthesize complex data in a way for viewers to quickly understand and compare.

An early example of instructions designed to empower learners to shape their own learning experience dates back to 1965, where Keller [6] introduces and documents the result of a "go-at-your-own-pace" course. This resulted in an inverted (U-shaped), polarized (highest concentrations for Grades 'A' and 'F') grade distribution at the conclusion of the courses, making clear the difference between students who can and cannot self-regulate effectively. Increased learner feedback and awareness could be the nudge some of these students need to remain engaged and pass the course.

2.3 Increasing Learner Efficiency

Guo and Reinecke [4] studied to what extent students in MOOCs access the full offering of learning materials. Sampling from four edX MOOCs, they found that, on average, certificate-earning students do not access, or "ignore," 22% of course materials [4]. Although instructors and instructional designers may not be too pleased by this finding, it has the potential to make future students more efficient in their learning. If there is certain content that students repeatedly skip without having their grade suffer, future students—maybe low on time or extrinsically motivated—can refine their learning plan based on this information.

2.4 Open Learning Analytics

The `Learning Tracker` realizes much of the personal-level, student-facing dashboard envisioned in [14]. Along with the three other views (educator, researcher, and institutional), [14] proposes a dashboard in which students can see metrics ranging from progress compared to current peers, previous students who took the course, their own past activities, and instructor-defined benchmarks. Siemens et al. [14] here also suggest multiple levels of the dashboard, such as options for "drilling down" into more detailed data visualisations.

Siemens [12] calls for Personal Learner Knowledge Graphs to boost awareness of a student's own current knowledge state in a given topic. This idea then evolved into Personal Learning Graphs [13], which stress the "importance of individuals owning their own learning representation" [13]. While the present `Learning Tracker` widget is not owned by the learner, it empowers MOOC students to assume a more active role in shaping their own learning experience. To our knowledge, these remain undeveloped and only conceptualisations of what dashboards *should* be.

2.5 Dashboards as Explorable Visual Narratives

To see if learner feedback data visualisations can elicit change in student behavior (similar to our research question), Yousuf and Conlan [17] implemented a dashboard (VisEN) that intended to emphasize to the student viewers a sort of "visual narrative" in the form of data visualizations. There is no text-based narrative provided for the students; rather, this dashboard, pictured in Figure 3, consists of heavily-annotated data visualizations from which students were expected to draw their own narrative arc. Findings from their three studies, taking place over three years and including 223 students, yielded a very strong Pearson correlation coefficient between dashboard views and learner engagement [17]. A fundamental difference between this approach and our `Learning Tracker` presented here is that VisEN incorporated tactics to directly encourage engagement such as reminders and "bad or poor engagement notifications". Our `Learning Tracker`, on the other hand, stops short of any direction-giving or motivation and merely presents the learners with a comparative view of their own behavior and that of successful learners. Furthermore, the `Learning Tracker` dashboard operates at scale in MOOCs.

3. WIDGET DESIGN

Based on prior works [11, 10, 9, 15] that have investigated the factors impacting learner success in MOOCs and effective feedback strategies (such as the "simple design principles" outlined in [2]) and some subjective judgement on

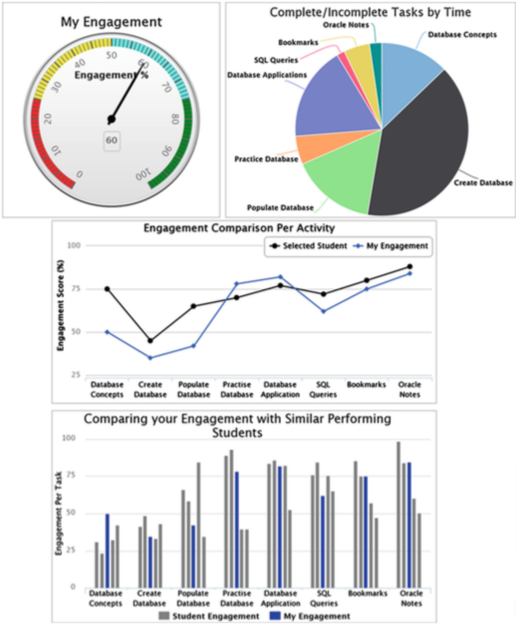

Figure 3: Selected visualisations from a VisEN student's visual narrative

our behalf, we identified six indicators that are related to learner success and at the same time readily understandable to learners:

- Time on the platform in seconds
- Time watching videos in seconds
- Fraction of time spent watching videos while on the platform: whereas the previous two give total time commitment measures, this provides feedback on *how* they allocate their time in the course
- Number of course videos watched
- Number of graded quiz answers submitted
- Timeliness of quiz answer submission: how early students submit answers relative to the deadline, to expose procrastinating behavior

In order to enable learners to directly compare their behavior to successful learners, we require a set of "gold standard" successful learners. In MOOCs that are reruns (our target in this work) we can simply consider all learners that *passed* one or more of the MOOC's previous editions to make up this set. These successful learners do not exhibit a uniform behavior. However, if we consider the average or median across all these learners for each indicator, we have a relatively robust indicator. For each indicator, the values that fall in the bottom 5% and the top 5% of the data range are omitted.

Having prototyped several different visualizations of our indicators (including bar charts, gauges and calendar charts), we settled on the use of a spider chart as shown in Figure 4. Spider charts allow for (i) a concise visualisation of numerous metrics in a small space, (ii) simple legibility—data are shown as single points along straight lines, and (iii) a visual depiction of one's coverage and consistency across all metrics. To allow for a consistent representation in the same graph, all metric values are scaled in a range from 0 to 10, where 0 indicates no activity and 10 the maximum value among the middle 90% of gold standard learners—thus the value of the outer ring increases each week, and the zero point remains constant.

We aim to ensure that any actions learners take in response to the widget are self-conceived. In order to do so, we try to minimize any feelings of external judgment or assessment from the visualisations by making them as "modest" as possible—"simply making things visible that would otherwise remain invisible" [2]. There are no red "danger zones" or green "in-the-clear zones" on the chart as are found in other learning dashboards such as VisEN [17] or Coursera (Figure 2). Rather, we present a chart free of not only zones, but also any numbers, similar to the "degraded information" concept in [2]. All students see is their *relative* position compared to the set of successful learners on the same plane. It is left up to the learners how to interpret it, what to learn from it, and how to convert this information into actionable knowledge.

4. EXPERIMENTAL SETUP

We deployed our widget in the TU Delft MOOC *Introduction to Drinking Water Treatment* running in its second edition on the edX platform between January 12 and March 29, 2016 (11 course weeks in total). The first iteration of the MOOC ran in 2014, with 10,695 registered learners of whom 281 (2.6%) earned a passing grade.

For this year's edition 10,943 users enrolled before the official start of the course and, in turn, participated in our experiment. Using A/B testing, we presented the `Learning Tracker` widget to 49.91% (5,462) of the learners. At the start of every course week, the learners were shown on the course page how they compared (up to that point in the course) to our gold standard learners from last year. Alongside the visualisations (concrete examples of which are shown in Figures 4 and 5) we also provided a short explanatory text that included the following statement:

> *These graphs are not meant to be judgements or assessments of your learning in any way; rather, they are a source of feedback for you, the learner, to make you more aware of your study habits and, hopefully, help you change them for the better!*

This 11-week course consists of one introduction week, five weeks of content delivery, and two design assignments that cover the remaining five weeks. The material published in each content delivery week included an assignment with five quiz questions. The video-lectures were complemented by a total of 63 practice quiz questions that were not graded. In order to graduate, learners had to earn a final grade higher than 60. We observe an increase in the percentage of certificate-earning learners compared to last year's edition of the MOOC: 3.18% (348 out of 10,943 learners).

5. RESULTS

We now provide an overview of our preliminary findings. The results are based on all edX log traces up to and including week 9 of the MOOC[1]. Due to the low number of learners that visited the course material after the course started (3,787 - 34.6% of enrolled) and the high drop-out

[1]The remaining course weeks are not included in the analysis, as the log traces are not yet available.

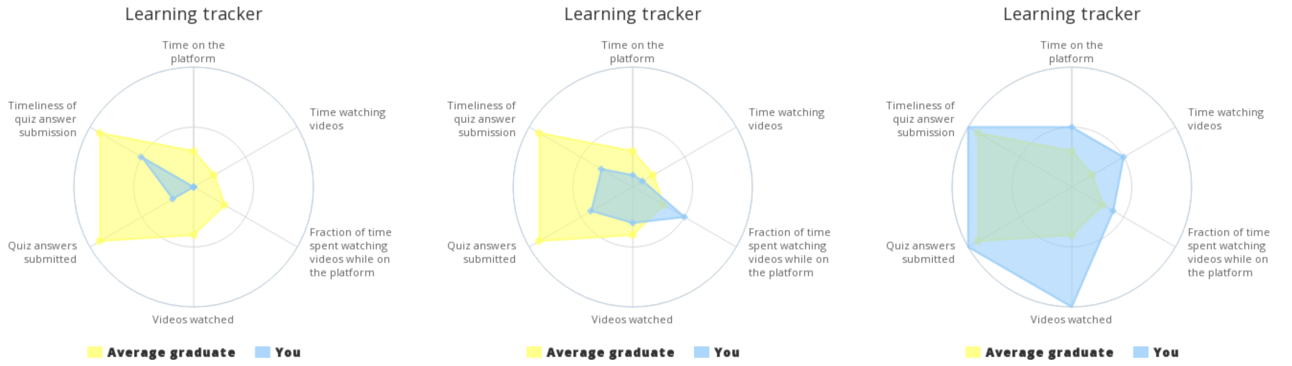

Figure 4: Three versions of our `Learning Tracker` widget with data from week 9, one showing a learner who dropped out early in the course (left), one who dropped out in the middle of the course (middle), and one graduate who is highly engaged with the course (right).

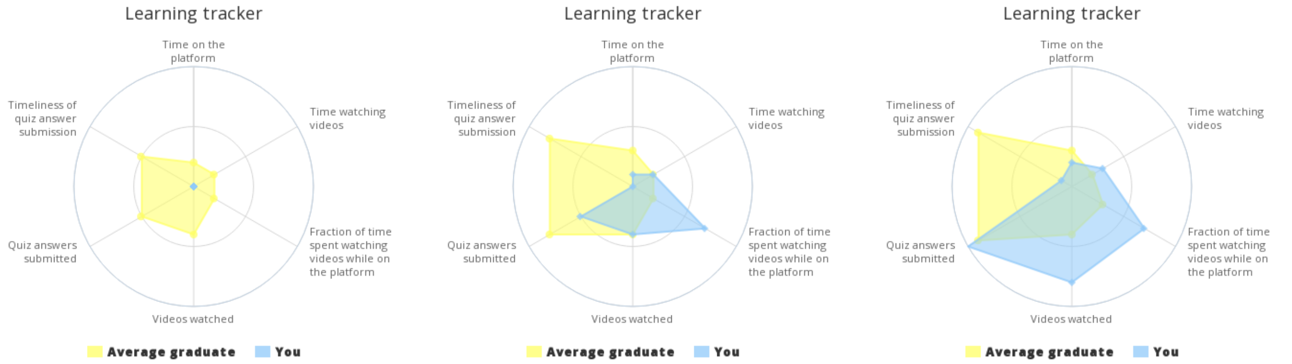

Figure 5: One learner's widget for weeks 3 (left), 6 (middle) and 9 (right). These show that this particular learner was a late starter and began engaging with the course some time between weeks 3 and 6.

rate in the first week of the course (19.26% of enrolled did not return after week one), the data distribution is highly skewed. We analyzed *active* learners only, defined by having spent at least five minutes in the platform.

To explore whether our `Learning Tracker` widget had any effect on our learners, we ran a Mann-Whitney U test (normal distributions not assumed) between the *test* (widget shown) and *control* (widget not shown) groups. In all analyses that follow we set $\alpha = 0.05$.

We perform the following analyses on the six dimensions shown in the `Learning Tracker`. We find **significant differences** between the two groups for the following two dimensions (and no sig. differences for the remaining four):

- *number of graded quiz answers submitted*;
- *the timeliness of the quiz answer submission.*

In Figure 6 we show the progression of both groups through the course with respect to the number of learners that submitted answers to graded quiz questions. Consistently, a larger number of learners in the test group submit their work. By week 9, 34.12% (550/1612) of the active users in the test group submit graded quiz answers compared to 30.77% (485/1576) of learners in the control group. The difference between the groups becomes visible in week 3, a week after the first `Learning Tracker` widget was made available to the test group.

In Figure 7 we present the timeliness of the two groups with respect to the weekly quiz deadlines: the test group is better able to self-regulate their behavior, with many learners submitting their work well before the deadline, in contrast to the learners of the control group.

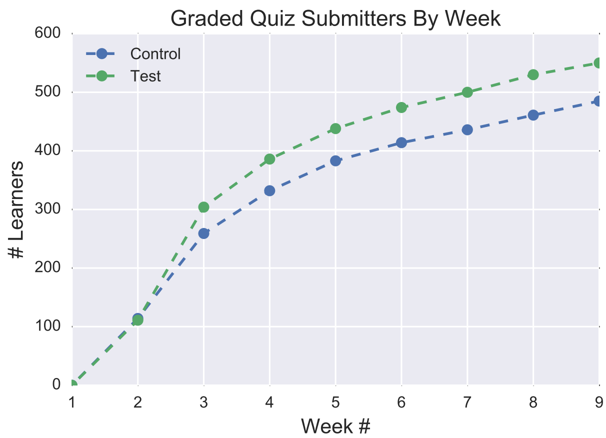

Figure 6: The total number of learners, by course week, whose #quiz answers submitted > 0.

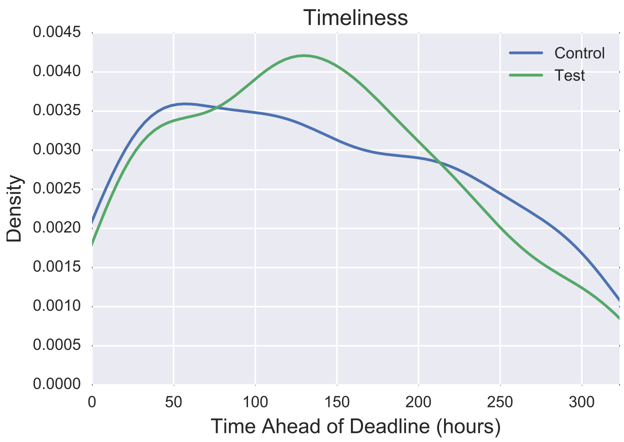

Figure 7: Kernel Density Estimation (Gaussian kernel) plot visualizing how far ahead of the deadline learners in each group typically submitted their weekly quiz answers. The left side of the plot is indicative of procrastinating behavior, whereas the right side indicates proactivity. Differences are significant at the $\alpha = 0.05$ level.

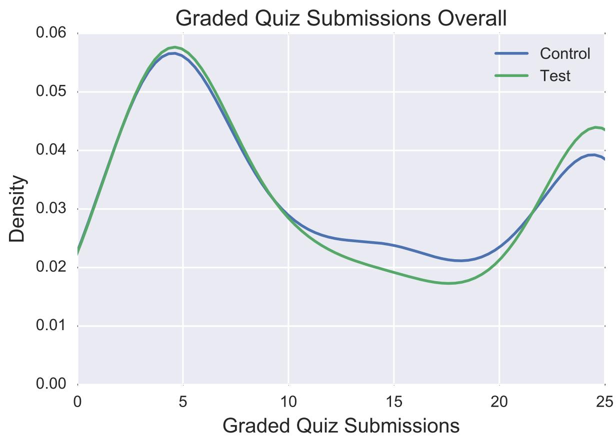

Figure 8: Kernel Density Estimation (Gaussian kernel) plot visualizing the distribution of the number of submitted graded quiz answers for learners in each group. Differences are significant at the $\alpha = 0.05$ level.

Lastly, there are differences in the percentage of passing learners per group as well: 13.17% among active learners in the test group compared to 11.35% in the control group. According to another Mann-Whitney U test, the differences between the final grades attained by the active learners in both groups are **statistically significant** with means of 14.4 for the test group and 12.7 for the control group. In Figure 9 we plot the distributions of the final course grades; the test group exhibits a consistent, positive shift in grade compared to the control group.

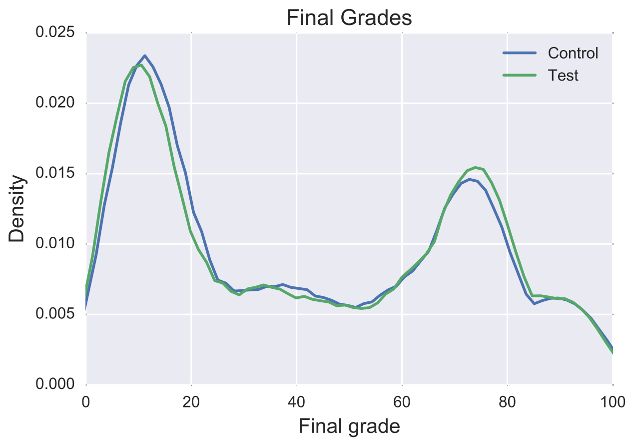

Figure 9: Kernel Density Estimation (Gaussian kernel) plot visualizing the distribution of final course grades between the two groups. Differences are significant at the $\alpha = 0.05$ level.

6. CONCLUSION & FUTURE WORK

We have described in this paper work-in-progress in which we developed and deployed a `Learning Tracker` widget in an edX MOOC with more than 10,000 learners. In an A/B test setup, we found our widget to *significantly increase learner success* (in terms of final grade) *and two of the six specified measures of learner engagement* (specifically, more timely assignment submissions and more assignment submissions overall). We conclude that a dashboard like ours enables learners to better self-regulate their learning behavior based on a concrete anchor point for comparison (the successful learners of the past).

In future work, we plan to expand our experiments across a number of MOOCs and a number of different `Learning Tracker` designs with different levels of granularity and study dimensions to answer the following research questions:

- Can data visualization feedback elicit positive change in MOOC learners' study habits?
- How literate are learners of this type of feedback? Are they able to draw their own insights from simple data visualizations?

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