From Learners to Earners

Enabling MOOC Learners to Apply Their Skills and Earn Money in an Online Market Place

Chen, Guanliang; Davis, Daniel; Krause, Markus; Aivaloglou, Efthimia; Hauff, Claudia; Houben, Geert-Jan

DOI
10.1109/TLT.2016.2614302

Publication date
2018

Document Version
Accepted author manuscript

Published in
IEEE Transactions on Learning Technologies

From Learners to Earners: Enabling MOOC Learners to Apply Their Skills and Earn Money in an Online Market Place

Guanliang Chen†, Dan Davis†, Markus Krause‡, Efthimia Aivaloglou†, Claudia Hauff†, Geert-Jan Houben†
†Delft University of Technology
Delft, the Netherlands
{guanliang.chen, d.j.davis, e.aivaloglou, c.hauff, g.j.p.m.houben}@tudelft.nl
‡UC Berkeley ICSI
Berkeley, California USA
markus@icsi.berkeley.edu

Abstract—Massive Open Online Courses (MOOCs) aim to *educate the world*. More often than not, however, MOOCs fall short of this goal — a majority of learners are already highly educated (with a Bachelor degree or more) and come from specific parts of the (developed) world. Learners from developing countries without a higher degree are underrepresented, though desired, in MOOCs. One reason for those learners to drop out of a course can be found in their financial realities and the subsequent limited amount of time they can dedicate to a course besides earning a living. If we could *pay* learners to take a MOOC, this hurdle would largely disappear. With MOOCS, this leads to the following fundamental challenge: How can learners be *paid at scale*? Ultimately, we envision a recommendation engine that recommends tasks from online market places such as `Upwork` or `witmart` to learners, that are relevant to the course content of the MOOC. In this manner, the learners learn *and* earn money. To investigate the feasibility of this vision, in this paper we explored to what extent (1) online market places contain tasks relevant to a specific MOOC, and (2) learners are able to solve real-world tasks correctly and with sufficient quality. Finally, based on our experimental design, we were also able to investigate the impact of real-world *bonus* tasks in a MOOC on the general learner population.

Index Terms—Learning Analytics, Educational Data Mining, Learning Design, MOOC

1 Introduction

In 2011, the first MOOCs started out with the promise of educating the world. To this day, this promise remains largely unfulfilled, as MOOCs struggle with student engagement and retention rates — on average, only 6.5% of MOOC learners complete a course and those who do often already have a higher degree [1]. At the same time though, the potential reach of MOOCs was visible from the very beginning: learners from 162 different countries engaged with the very first MOOC (*Circuits and Electronics*) offered on the edX platform [2].

Among the many reasons for learners' disengagement from a course are also financial ones: learning is superseded by the need to work and earn a living. Our ultimate vision is to *pay* learners to take a MOOC, thus enabling learners from all financial backgrounds to educate themselves. But how can we achieve this *at scale*? We believe that online work platforms such as `Upwork` and `witmart` can be an important part of the solution; if we were able to automatically recommend paid online work tasks to MOOC learners which are related and relevant to the MOOC content, the financial incentive would enable more learners to remain engaged in the MOOC and continue learning.

Figure 1 shows a high-level overview of our vision: online work task platforms are continuously monitored for newly published work tasks; a recommender system maintains an up-to-date course model of every ongoing MOOC and determines how suitable each work task is for every ongoing course and course week. At any given moment, the suitable open work tasks are shown alongside the course material on the MOOC platform, together with the possible financial gain and their level of difficulty.

While we do not claim this vision as *the* solution for MOOCs to single-handedly "lift ... people out of poverty," [3], we strongly believe this to be a step in the right direction and something to build upon.

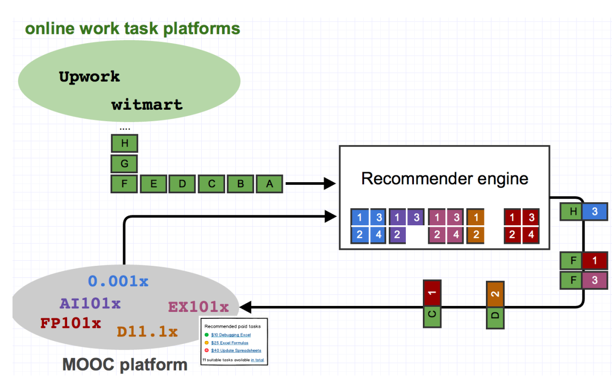

Fig. 1. Paying MOOC learners — a vision.

To lay the groundwork, we investigate the *feasibility* of letting MOOC students solve real world tasks from an online work market place. In a pilot study presented here, we manually selected a number of paid tasks from `Upwork` and offered them to learners of the `EX101x` MOOC (*Data Analysis: Take It to the MAX()*, offered on edX) as bonus exercises. We illustrate that it is indeed feasible to expect students to be able to earn money while taking a MOOC.

Based on these encouraging initial results we then expand our investigation and analyse the realm of online work platforms and their suitability for our vision along a number of dimensions including payments, topical coverage and task time.

Lastly, it is worth nothing that our experimental setup not only allows us to investigate **learning enabling** methods (i.e. paying learners), but also **learner motivations**: we expect that real-world tasks (as shown in the bonus exercises) engage learners more than artificially created course tasks.

The work we present in this paper is guided by the following four **R**esearch **Q**uestions:

RQ1 Are MOOC learners able to solve real-world (paid) tasks from an online work platform with sufficient accuracy and quality?

RQ2 How applicable is the knowledge gained in `EX101x` to paid tasks offered by online freelance work platforms such as `Upwork`?

RQ3 To what extent can a platform such as `Upwork` support MOOC learners in `EX101x` (i.e. are there enough tasks available for everyone)?

RQ4 What role do real-world (paid) tasks play in the engagement of MOOC learners?

The remainder of this paper is organized as follows: we first discuss related work, considering several different views of the problem. We then outline the approach we took to answer our research questions before describing in detail our results. We conclude with an outlook to future work.

2 Background

This study represents a movement towards MOOCs truly living up to their name with respect to their openness. The current demographic of MOOC participants is predominantly educated males from developed countries [4], [5], [6], [7], [8]. Simply putting the content out there on the Web may not be enough to justify calling it “open”. Although it is available, it is not readily accessible to everyone. Based on both survey and student activity data, Kizilcec and Halawa found that “the primary obstacle for most [MOOC] learners was finding time for the course” [8]. By conducting post-course surveys, [8] found that 66% of students struggled to keep up with course deadlines and 46% reported that the course required too much time.

Self-regulated learning

Providing income to students in exchange for real-world tasks can serve as a support mechanism in encouraging students to better self-regulate their study and engagement habits. The study of Self-Regulated Learning (SRL) has a rich history in the traditional classroom setting [9], [10], but now the new challenge arises of how to support and enable non-traditional and disadvantaged students to practice effective SRL habits in online/distance learning endeavors. SRL is defined as a student’s proactive engagement with his or her learning process by which various personal organization and management strategies are used in order to control and monitor one’s cognitive and behavioral process towards a learning outcome [11], [12]. Many SRL tactics hinge on effective time management skills [13], [14]. Although, with proper coaching, many students can be taught to find and make time for studies [14], [15], this is simply not plausible for others who do not have enough time in a day to introduce a new challenge–no matter how well they manage their time. These learners are the primary target of our vision. By introducing these opportunities to earn money while completing a course, we hope that they can essentially “buy time.”

For the group of students who complete the paid tasks in order to make “extra” money, the compensation can be viewed as a reward mechanism and an incentive to prioritize the MOOC over other less important tasks [8], [16]. For the other group, the money earned from the extra tasks is a required means for them to commit time. Whereas reward-seeking students would no longer have a reason to complete the extra tasks if the monetary prize was removed, the other group of students would no longer have the time or the ability.

Using rewards to motivate learning

One of the leading critiques of reward programs in traditional education settings is that their prize pool is finite, and once that is exhausted, student motivation will dwindle [17]. In our setup, however, this is not an issue, as online work platforms are consistently replenished with new tasks to recommend to our MOOC learners. This model thus shows the potential for sustainability at scale.

The existing literature on paying or rewarding students with material goods is concerned with young students in traditional classroom settings [17], [18], [19], [20], however the people who stand to benefit the most from the inclusion of freelance projects and tasks into the MOOC environment are predominantly non-traditional students.

[19] approaches the dilemma of incentivising student performance with money through an economic lens. In order to test how financial incentives impact student performance in historically-disadvantaged and under-performing school districts in the United States, this study compared the effectiveness of input-driven versus output-driven reward systems. It was found that incentives based on student input, such as completing assignments or reading books, are more effective than those based on output, such as test scores and grades [18], [19], [21]. In line with the concept of instructional scaffolding, this finding suggests that incentivising and rewarding intermediate tasks along the path to a larger learning goal or objective is more effective than rewarding only the goal itself. Likewise, one of these intermediate tasks especially challenging to open learning is that of allocating and committing time, and we hope the potential to get paid for this time will support learners in

doing so.

Incentives for underprivileged learners

We also see the introduction of opportunities for learners to contribute to online work market places while taking a MOOC as a potential manner by which we can mitigate belonging uncertainty for under-privileged learners [22], [23]. This is characterized by stigmatized or minority group members feeling uncertain and discouraged by their social bonds in a given environment [23]. If a student sees his or her participation in the course with an immediately clear and relevant purpose—learning the necessary skills to complete this real-world task—then it should thus mitigate any uncertainty or doubt about the students belonging. Walton and Cohen found that interventions designed to reduce/remove feelings of belonging uncertainty can have great effects on students' subjective experiences in academic settings which can therefore boost academic performance. Learners of low socio-economic status are not the only ones who stand to benefit from this. Other major demographics, such as women (particularly in STEM courses), are currently outnumbered, and often outperformed [6], by their male student counterparts [5], [7], [8].

Using extra credit to motivate learning

Many studies have examined the effect that offering extra credit assignments to students can have on overall class performance. [24] found that extra credit assignments can be used to motivate students to read journal articles; [25] found extra credit, in the form of an in-class token economy, to increase course participation; [26] saw increases in course attendance stemming form the offering of extra credit assignments; and [27] found that extra credit assignments can facilitate mastery of course material and strongly predict final exam performance.

Similarly, in a study that specifically targeted students on the verge of failing a college course, researchers found that an intervention in the form of a skills-based extra credit assignment increased these students' final exam grades, increased and diversified their engagement, and decreased their dropout/incompletion rate [28].

In December 2015, edX, one of the most popular MOOC platforms announced a new policy which rescinds the free honor code course completion certificates previously made available to any student who earned a passing grade in the course. Instead, according to the announcement on the edX blog [29], "all of edX's high-quality educational content, assessments and forums will continue to be offered for free, but those learners who want to earn a certificate upon successful completion of the course will pay a modest fee for a verified certificate." While both edX and its partner institutions will offer various levels of financial aid to students who apply, the design introduced in this work has the potential to reduce the burden of supporting students. Simply by completing one task from an online marketplace (of high enough value), a student can offset the cost of the verified course certificate.

To the best of our knowledge, this effort to pay students in an open learning environment in order to encourage and enable student engagement is the first of its kind. Research findings in this area promise to help narrow the established achievement gap we currently observe among MOOC learners.

3 EX101X

To investigate our research questions, we inserted bonus exercises, drawn from paid tasks posted on `Upwork`, into the MOOC *Data Analysis: Take It to the `MAX()`*, or in short: `EX101x`. `EX101x` is a MOOC offered on the edX platform; its first edition (the one we deployed this study in) ran between March 31, 2015 and June 18, 2015. The core objective of `EX101x` is to learn to conduct data analysis using spreadsheets. Throughout the first six course weeks, the following set of skills are taught (using Excel as specific spreadsheet instance): string manipulation and conditional statements (Week 1), lookup and search functions (Week 2), pivot tables (Week 3), named ranges (Week 4), array formulas (Week 5) and testing in spreadsheets (Week 6). Week 7 is dedicated to the programming language Python and its use within spreadsheets, while the final week (Week 8) introduces the graph database `Neo4j`.

As is common in MOOCs today, learners were invited to participate in a pre-course and a post-course survey containing questions on the motivation of the learners, the perceived quality of the course, etc. In September 2015 we approached a selected subset of all learners for an additional post-course survey.

The course was set up as an xMOOC [30]: lecture videos were distributed throughout the 8 teaching weeks. Apart from lectures, each week exercises were distributed in the form of multiple choice and numerical input questions. Each of the 136 questions was worth 1 point and could be attempted twice. Answers were due 3 weeks after the release of the respective assignment. To pass the course, $\geq 60\%$ of the questions had to be answered correctly. Each week, alongside the usual assignments, we posted one additional bonus exercise.

Overall, 33,515 users registered for the course. Less than half of all learners (45%) engaged with the course, watching at least one lecture video. The completion rate was 6.53% in line with similar MOOC offerings [31]. Over 65% of the learners were male and more than 76% had at least a Bachelor degree.

4 APPROACH

The design of our experiments was guided by our research questions. As we aim to determine whether learners can solve real-world tasks that are related to the course material with high accuracy and high quality (**RQ1**), for the six weeks of `EX101x` that cover data analysis topics in spreadsheets, we *manually* selected appropriate paid tasks from the `Upwork` platform — one task per course week. No bonus exercises were posted in weeks 6 and 8 due to the topics covered that week: testing in spreadsheets and the graph database Neo4J. We chose `Upwork` (which at that time was still called `oDesk`) as it is one of the largest online work platforms in the English speaking world (cf. Table 4); for each course week, we chose an `Upwork` task that was strongly related to that week's course content by extensively scanning the currently active `Upwork` tasks worth up to $50. We chose this price limit to provide tasks that can be solved in a reasonable amount of time. We kept the task description intact, and added a short introduction to provide the necessary context to our learners (i.e. a clear disclaimer that this is a real-world task). A concrete example of a bonus exercise derived in this manner is shown in Figure 2; it was posted in week 4 of `EX101x`.

To answer **RQ2** and **RQ3**, we explored the suitability of `Upwork` as a source of paid tasks along several dimensions including the covered topics, the task longevity, and the financial gain. In order to investigate **RQ1** and **RQ4** we require exact definitions of a number of metrics (i.e. accuracy, coverage, quality and engagement). In the following section, we describe them in detail.

4.1 Measurements

4.1.1 Accuracy

For each bonus exercise, we developed a gold standard solution in collaboration with the course instructor and verified whether the submitted learner solutions matched the gold standard solution, thus measuring their *accuracy*. We considered a submitted spreadsheet a match to our gold standard if it contained the required solution columns with the correct cell content; additional columns were ignored; slight deviations from the gold standard (e.g. an empty string or "N/A" instead of an empty cell in the gold standard) were allowed. We iteratively refined our automated grading script by randomly sampling 20 submission in each iteration (and manually verifying the correctness of the grading script) until all samples were classified correctly.

4.1.2 Coverage

Besides accuracy, we also measured the coverage of learner solutions. We operationalize *coverage* as the percentage of cells that the learner solution *shares* with the gold standard. As for *accuracy*, we ignored additional columns and allowed minor deviations in the cells such as additional white spaces or minimal numeric differences to account for floating point inaccuracy on different computers. Coverage can be seen as an indicator of how close the solution is to the gold standard solution.

4.1.3 Quality

To investigate the *quality* of the submissions, we turned to the concept of *code smells* [32], an established measure of quality in the field of Software Engineering: code smells are specific to particular programming languages; spreadsheets code smells include standard errors (e.g., `#N/A!`, `#NAME?`), high conditional complexity (e.g. involving too many nested `IF` operations), hidden rows/columns/worksheets, etc. We adopted the code smells for spreadsheets proposed in [33] and rank the solutions by the number of smells they exhibit - the fewer smells a solution has, the higher its quality.

4.1.4 Engagement

Finally, based on our experimental setup, we are also able to investigate the effect of real-world tasks on student engagement (**RQ4**). We hypothesize that learners who *view* the bonus exercises and realize that those are real-world tasks that could earn them money, will become more engaged with the course material than learners who did not *view* the bonus material. To this end, we only consider the subset of active learners $L_{noBonus}$ that did *not* submit any solutions to the bonus exercises.

We group learners together that are similarly engaged in the course up to the point of either viewing a bonus exercise or not. If our hypothesis holds, then after that point in time, those learners that viewed the bonus exercise should, on average, exhibit higher engagement than those that did not.

We operationalize this experiment as follows: we measure a learner's engagement through his or her amount of video watching. In week 1, we partition the learners in $L_{noBonus}$ in two groups: we sort the learners in video watching time order and then split them in two equally sized groups - the lower half is the *low* engagement, and the upper half is the *high* engagement group. We then compute for each learner the amount of video watching in all following weeks and determine for the low and high engagement groups separately whether there is a statistically significant difference between those learners that did view and those that did not view the bonus exercise. In week 2, we repeat this analysis by taking as starting point only the subset of learners in $L_{noBonus}$ that viewed the bonus exercise in 1. We repeat those steps until week 7 (in each week resorting the remaining learners into the low and high engagement groups). While we expect significant differences based on bonus exercise viewing in the early weeks of the course, we should not observe significant differences towards the end of the course — in week n we only include learners that up to that point in time have viewed all $n-1$ bonus exercises. At some point, bonus exercises should not provide additional engagement anymore.

5 Results

Before we discuss our results for each of the four research questions in turn, we provide a first global view of our learner population in `EX101x`.

We classified our set of *engaged* learners, i.e., those who watched at least one video[1] (a definition also employed for instance in [34]), according to two dimensions: (i) whether learners attempted to solve at least one bonus exercise (**BE**) or not (**Non-BE**) and (ii) the number of bonus exercises learners attempted to solve. In the latter case, we consider only the **BE** learners. We mark learners as dedicated bonus exercise solvers (**DBE**) if they attempted to solve more than two bonus exercises, the remaining learners are non-dedicated (**Non-DBE**). The basic statistics of both learner cohorts are presented in Tables 1 and 2. It is evident that learners who solved at least one bonus exercise are more engaged than learners who did not - across all important characteristics (average time spent watching videos, average number of questions answered, accuracy of answers)

1. We note, that we also evaluated two alternative definitions of engagement: (1) learners that watched at least 15 minutes of video material (i.e. at least two videos), and (2) learners that submitted at least five quiz questions. While the absolute values reported in Tables 1 & 2 change depending on the definition employed, we did observe the same trends and the same significant differences for all three engagement definitions and thus only report one.

Have you ever sold anything on Amazon.com? For this real-world task (again derived from an actual oDesk task), we put you in the shoes of an Amazon seller who is selling accessories for pets. The seller himself buys these accessories from a supplier. The seller currently has a five star feedback rating on Amazon. To keep it this way, only items that the seller can immediately ship should appear in the sellers Amazon storefront (i.e. those items that the supplier has in stock).

The seller has this Excel sheet which stores the ID of all products to be posted on his Amazon.com storefront and the number of units available, as illustrated in the example below.

ID	Stock
08357EDA-DF5C-392E-F7CC-A27E3AB768DF	?
08357EDA-DF5C-392E-F7CC-DD445453DDEF	?

File 1: Excel sheet of the seller

It is your job to update the **Stock** column based on the information the seller receives from the supplier.

Every day, the seller receives an Excel sheet from his supplier, which contains the suppliers inventory. An example is provided below. Note that the suppliers column **Product** corresponds to the sellers column **ID**.

Product	Inventory
08357EDA-DF5C-392E-F7CC-A27E3AB768DF	7
08357EDA-DF5C-392E-F7CC-DD445453DDEF	188

File 2: Excel sheet of the supplier

To keep his customers satisfied, the seller uses the following two rules to set the Stock column:

- If the suppliers inventory of a product is less than 30, Stock should be set to 0;
- If the suppliers inventory of a product is more than or equal to 30, Stock should be set to 20.

Applying these two rules to our example files above, yields the following result:

ID	Stock
08357EDA-DF5C-392E-F7CC-A27E3AB768DF	0
08357EDA-DF5C-392E-F7CC-DD445453DDEF	20

File 3: Result sheet of the seller

Please send your solutions to ...

Fig. 2. Bonus exercise posted in week 4 of `EX101x`. The original task was posted with a price of $35 to `Upwork` (note that at the time of posting this exercise, `Upwork` was still called oDesk).

the BE learners perform significantly better than the Non-BE learners. Among the cohort of BE learners, this trend continues with the dedicated learner group being significantly more engaged and successful than the non-dedicated learner group.

We note that these results are not surprising — they are dictated by common sense and our manner of classifying learners. Importantly, we do not claim a causal relationship between bonus exercise presence and learner engagement based on *these* results (in Section 5.3 we explore the relationship between engagement and bonus exercises in greater detail).

As our goal is to improve the ability of learners from the developing world to engage and successfully complete the course, we also investigate to what extent they are already capable of doing so now. For each country, we computed the percentage of learners that completed the course (based on all registered learners). Shown in Figure 3 is the completion rate of `EX101x` across countries, split into developed countries according to the OECD (in blue) and developing countries (in red). We observe, that in general, the completion rate of learners from developed countries is higher than those of developing countries (with the exception of Russia and Malaysia). This confirms one of our assumptions that learners from developing countries are facing issues that learners in developed countries do not face. This result is in line with previous findings in [4].

5.1 RQ1: Can learners solve real-world tasks well?

Across all weeks, we received a total of $3,812$ bonus exercise solutions from $2,418$ learners. Since the edX platform has very limited solution uploading capabilities, we asked learners to email us their solutions and then matched the email addresses of the learners to their edX accounts. 352 of the learners could not be matched to an edX account (i.e. these learners used a different email when signing up for edX) and had to be excluded from the subsequent analyses of edX log traces (they are included though in all results analyzing the accuracy/quality of the solutions).

Table 3 lists the main results of our accuracy and quality analyses. Between 1% (in week 7) and 15% (in week 1) of active learners participated in the bonus tasks each week. The percentage of *accurate* solutions varies widely between tasks and is not correlated with the amount of pay for a task. In fact, the two tasks with the lowest pay ($20 in weeks 3 & 5) resulted in the lowest percentage of accurate solutions (11% and 17% respectively). The low accuracy for the seemingly simple (as cheaply priced task) is intriguing. We sampled 50 of the incorrect solutions and found most of them to miss a required final step in the task. Both tasks require students to carefully read and understand the assignment to be successful. In week 3, learners needed to

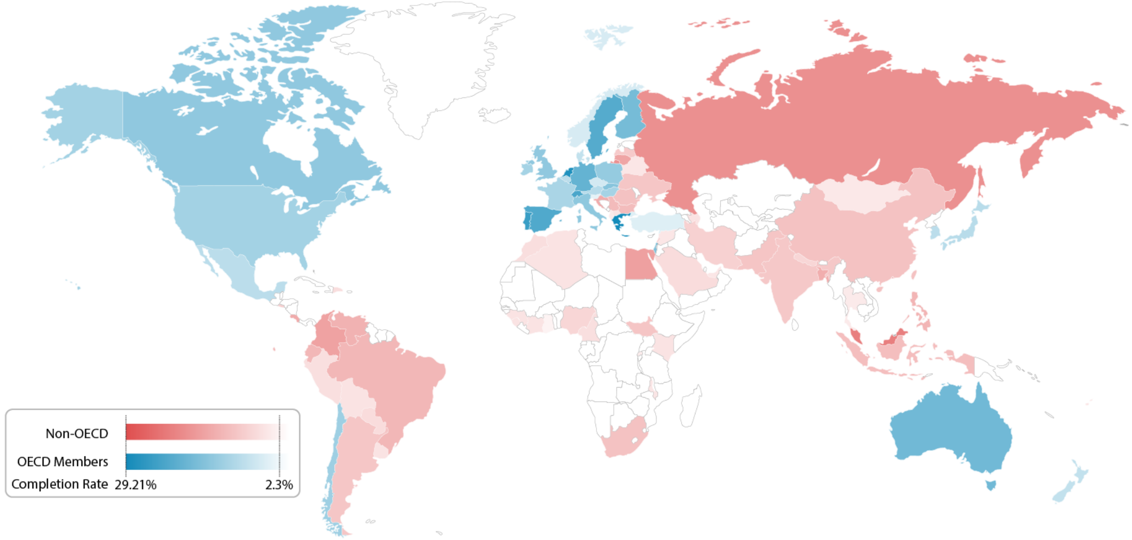

Fig. 3. Developed countries according to the OECD are shown in blue, developing countries are shown in red. The color shade indicates the overall completion rate of learners from that country. A darker shade indicates a higher completion rate.

TABLE 1
Basic characteristics across all learners and their partitioning into those who attempted to solve at least one Bonus Exercise (BE) and those who did not (Non-BE). Where suitable, significance tests between the BE/Non-BE groups were performed according to Mann-Whitney. All performed tests exhibited significant differences - indicated with ♣ (significant difference with $p < 0.001$).

	All Engaged Learners	BE Learners	Non-BE Learners
#Learners	15,074	2,020	13,054
Completion rate	14.02%	44.11%	9.36%
Avg. time watching video material (in min.) ♣	58.78	133.48	47.21
%Learners who tried at least one question	59.89%	98.56%	53.91%
Avg. #questions learners attempted to solve ♣	24.06	67.41	17.36
Avg. #questions answered correctly ♣	19.56	*55.60*	13.98
Avg. accuracy of learners' answers ♣	53.40%	90.09%	47.73%
#Forum posts	10,106	4,341	5,765
%Learners who posted at least once	16.20%	43.61%	11.96%
Avg. #posts per learner ♣	0.67	2.15	0.44

TABLE 2
Basic characteristics of BE learners partitioned into dedicated BE learners (DBE) solving 3+ bonus exercises and non-dedicated BE learners. Where suitable, significance tests between the DBE/Non-DBE groups were performed according to Mann-Whitney. All performed tests exhibited significant differences - indicated with ♣ (significant difference with $p < 0.001$).

	DBE Learners	Non-DBE Learners
#Enrolled learners	314	1,706
Completion rate	86.31%	36.34%
Avg. time watching video material (in min.) ♣	189.45	123.18
%Learners who tried at least one question	100.00%	98.30%
Avg. #questions learners attempted to solve ♣	110.52	59.47
Avg. #questions answered correctly ♣	93.99	48.53
Avg. accuracy of learners' answers ♣	94.83%	89.22%
#Forum posts	1,626	2,715
%Learners who posted at least once	59.87%	40.62%
Avg. #posts per learners ♣	5.18	1.59

implement an equation containing an *absolute* value. As the equation text is fairly long, students tended to miss this vital piece of information; 78% of all wrong answers that week show this misconception. In week 5, the solutions had a similar issue, often missing a final re-ranking step of the result columns as required in the task description.

An alternative view of submission accuracy is presented through the average *coverage* of all submissions, that is the fraction of gold standard result cells, that were also present in the submissions. Coverage is 1.0 for the correct submissions, but usually lower for incorrect ones (note that it is possible for an incorrect solution to reach a coverage of 1.0 if it contains all gold standard result cells as well as additional result cells - this happens rarely though). In Table 3 we observe that the coverage across all submitted solutions is rather high (with the exception of week 3), thus even solutions that are not correct are at least sensible.

Having considered accuracy and coverage, we now turn to the *quality* of the solutions. Among the correct solutions, a large fraction (between 38% and 96%) are of high quality, that is they exhibit zero code smells as shown in Table 3. Again, we do not observe a correlation between the price of a task and the quality of the solutions. The quality of the accurate and inaccurate solutions (as measured in code smells) is comparable. Across all weeks and submitted solutions, the median number of code smells is less than 10, indicating that most learners were able to code high-quality solutions. The vast majority of solutions across all weeks have less than 50 reported code smells.

Overall, we can positively answer **RQ1**: it is indeed possible for MOOC learners to provide correct and high-quality solutions to selected real-world tasks from an online work platform.

5.2 RQ2 & RQ3: An exploratory analysis of `Upwork`

We first note that `Upwork` is only one of multiple large online work platforms in the English speaking world as shown in Table 4. Together those companies facilitated more than 2.5 billion dollars in worker payments. Important for us, some of these platforms (including `Upwork`) provide API access to their content, thus enabling a recommender system as we envision.

For our analysis, we took a snapshot of all available tasks on `Upwork` on September 15, 2015 leading to a total of 56,308 open tasks. Each task is assigned to one or more topical categories, e.g. *Translation* or *IT & Networking*. Additionally, tasks can be tagged with particular required skills such as *excel* or *python*. Tasks either pay per hour or have a fixed budget. We focus on the latter, as the budget is a direct indicator for the amount of work required. A task pays on average $726 (SD: $3,417) and stays 27 days on the platform (SD: 34 days) before being solved or canceled. Among all tasks, we found 574 spreadsheet tasks (potentially relevant for `EX101x`) in the budget range from $1 - $50. A task in this (*budget*) subset stayed 25 days on the platform on average (SD: 40 days).

To estimate the proportion of tasks that may be suitable recommendations for `EX101x` learners, we analysed a random sample of 80 tasks of the *budget* set. An expert classified these tasks into three categories:

1) *lecturable* are tasks that would make them suitable as course material for a specific lecture (e.g. a task that requires knowledge of a spreadsheet's `VLookUp` function);
2) *relevant* are tasks that fit the topic yet do not fit into a specific lecture (e.g. a task that requires the use of spreadsheets but otherwise does not rely on knowledge taught in the course);
3) *unrelated* are all other tasks that do not fit in the courseware in general.

Among the 80 tasks we found 34 *unrelated* tasks, 39 *relevant* tasks and 7 *lecturable* tasks. Based on these numbers and the average time a task stays online we can estimate how many tasks are added every day to `Upwork` that fit our criteria (i.e. have a price between $1 and $50 and require spreadsheet knowledge): 10 *unrelated* tasks, 11 *relevant* tasks, and 2 *lecturable* tasks. These numbers indicate that there are not yet enough budget tasks available to provide individual MOOC learners with weekly opportunities to earn money whilst learning — at least for the `EX101x` MOOC.

One limiting factor in our design is the budget limit we set ourselves ($50). The majority of tasks have a higher budget as shown in Figure 4 and future experiments will investigate the question up to which budget level learners are able to solve tasks in a reasonable amount of time, with high accuracy and high quality.

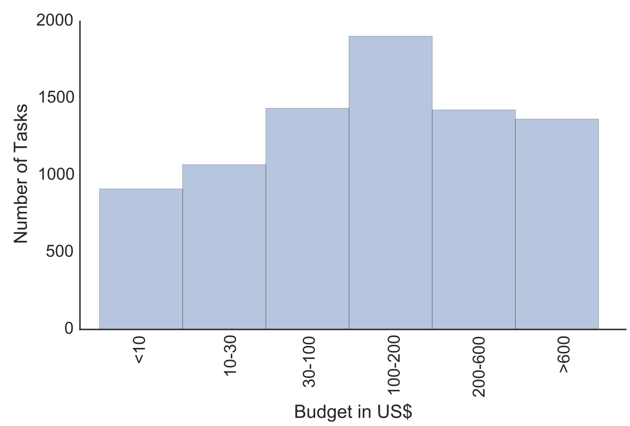

Fig. 4. From the 56,308 `Upwork` tasks available on 15/09/2015 a total of 8,153 have a fixed budget (the remaining tasks are paid by the hour). Budgeted tasks are binned according to the budget they have.

Tasks that have a higher budget (on the topic of spreadsheets) are usually more intricate and instead of solving one specific problem in a spreadsheet (as less pricey tasks, cf. Figure 2) they often require the development of a complete solution as exemplified in the three task examples priced between $100 and $500 at `Upwork`:

$500 *"We are commercial real estate brokers and are looking for an expert in Microsoft Excel to create an interactive Excel worksheet(s) for rental comparison purposes."*

$250 *"I need to have financial calculations for a customer equity/lifetime value model integrated into an excel workbook. (...)"*

$100 *"I currently plot support and resistance zones manually on a chart like the attached image. (...) I need to calculate these support and resistance levels within MS Excel programmatically or using some sort of algorithm. (...)"*

In contrast to the budget, the longevity of tasks on `Upwork` is beneficial for our vision. Figure 5 shows that many tasks remain available for at least 20 days, which is beneficial in the MOOC setting where assignments also commonly have a grace period of 2-3 weeks.

Recall, that additionally to a general category each task is tagged with a set of required skills. Table 5 shows *Excel* (the comon tag for spreadsheet tasks) to be a relatively popular task. More general skills such as proficiency in *HTML* and *CSS* occur more often than specific skills such as proficiency in *R*. Overall, programming tasks only make up a small percentage of all available tasks, as shown in

TABLE 3
Learners' performance on real-world tasks. The second column shows the number of active learners. The third column shows the number of students taking the bonus exercise. The fourth column shows the task payment offered at UpWork. Accurate submissions are those matching our gold standard (with the additional requirement of the correct order for tasks 3 and 5). High-quality submissions are those correct submissions without code smells. The coverage column reports the average (and standard deviation) fraction of cells covered by all of a week's submissions.

Week	# Active learners	# Bonus (% from active)	Task payment	# Accurate (% of active)	# High quality (% of accurate)	Coverage (SD)
1	13,719	2,145 (15.64%)	$ 25	1,731 (80.70%)	1,230 (71.06%)	0.88 (0.32)
2	8,228	594 (7.22%)	$ 50	227 (38.22%)	87 (38.33%)	0.91 (0.27)
3	5,825	390 (6.70%)	$ 20	44 (11.28%)	28 (63.64%)	0.54 (0.32)
4	4,270	414 (9.70%)	$ 35	354 (85.51%)	296 (83.62%)	0.95 (0.22)
5	3,709	231 (6.23%)	$ 20	39 (16.88%)	16 (41.03%)	0.69 (0.24)
7	3,059	38 (1.24%)	$ 35	26 (68.42%)	25 (96.15%)	0.73 (0.68)

TABLE 4
Paid total worker fees by company in Million US Dollar. These numbers are self reported by the companies and are not given for a specific year.

Company	Paid worker fees	API
Upwork	$ 1,000 M	yes
witmart	$ 1,000 M	no
freelance	$ 462 M	no
Guru	$ 200 M	yes
Envato	$ 200 M	yes
Topcoder	$ 72 M	yes

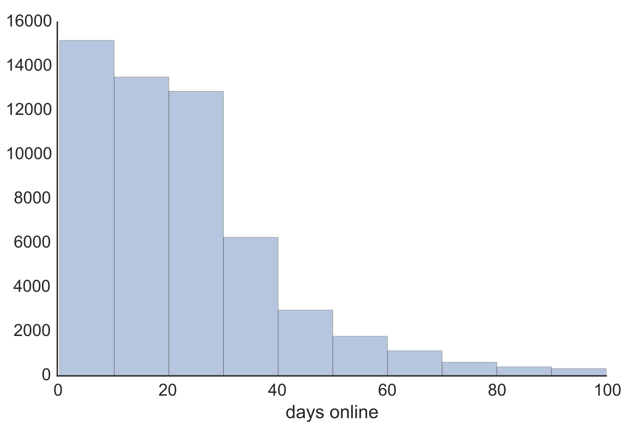

Fig. 5. The 56,308 `Upwork` tasks available on 15/09/2015 are binned according to the number of days they have been "online" (i.e. the task is open).

Table 6. Indeed, the breadth of tasks offered on `Upwork` indicates the tremendous potential of online work platforms for suggesting paid tasks to learners across a range of MOOCs.

To conclude, we observe that, indeed, the knowledge gained during `EX101x` can be used to solve paid tasks (**RQ2**), though the number of tasks posted per day that fit our criteria is rather low: we estimate that, an average, 13 tasks a day are posted in the $1-$50 category, requiring spreadsheet knowledge fitting the course topic of `EX101x`.

This result also provides an answer to **RQ3** in the context

TABLE 5
Overview of programming tasks among our crawl of 56,308 `Upwork` tasks on 15/09/2015.

#Tasks	Skill Tag
5,443	HTML5 & HTML
5,034	PHP
3,928	Javascript
2,731	Excel
616	Python
559	Ruby & Ruby-on-Rails
537	Objective-c
450	Java
26	Perl
34	R

of `EX101x`: as per day, on average, only 13 MOOC students stand to benefit from these paid tasks (i.e. can earn money from them), there are not sufficient tasks available to sustain a standard MOOC population of learners throughout an entire run of `EX101x` — at least at the current rate of online work tasks being posted to `Upwork`.

5.3 RQ4: Learner engagement

We hypothesize that our bonus exercises, in particular the realization that those are real-world tasks with which money could be earned, are beneficial for learner engagement.

In Figure 6 we present the results of our experiment, comparing the amount of video watching between learners who did view and did not view the bonus exercises (computed separately for low and high engagement learners). Let's consider week 1: in the low engagement group, the learners that did not view the bonus exercise spent on average 0.08 hours (5 minutes) in subsequent weeks on video watching, while the learners that did view the bonus exercise spent 1.3 hours in subsequent weeks on videos. This difference is statistically significant ($p < 0.001$, Mann-Whitney test). Similarly, in the high engagement group, learners that did not view the bonus exercise continued to spend 0.4 hours (24 minutes) on video watching, while learners that did view the bonus exercise spent 1.7 hours on the course. Across both engagement groups, the low amount of overall time spent in watching videos can be

TABLE 6
The 56,308 `Upwork` tasks available on 15/09/2015 are partitioned according to their category. Shown are the number of tasks per category, the average number of days online and the average task payment (for the subset of 8,153 tasks with a fixed budget).

Category	#Tasks	Days Online (SD)	Payment (SD)
Customer Service	986	74.76 (83.24)	$1,817 ($6,692)
Engineering & Architecture	1,432	53.70 (61.50)	$1,699 ($6,640)
Translation	2,109	53.02 (74.64)	$1,156 ($3,710)
Admin Support	5,961	50.33 (89.14)	$ 982 ($4,855)
Accounting & Consulting	1,095	49.37 (77.77)	$ 997 ($4,642)
IT & Networking	2,182	39.60 (52.38)	$ 854 ($4,356)
Data Science & Analytics	1,156	37.29 (45.94)	$ 777 ($3,308)
Writing	8,448	32.31 (58.54)	$ 418 ($ 832)
Legal	333	27.97 (33.67)	$ 377 ($2,055)
Web, Mobile & Software Dev	16,328	25.39 (46.02)	$ 376 ($2,028)
Design & Creative	9,667	24.60 (45.70)	$ 274 ($ 710)
Sales & Marketing	6,724	21.54 (34.31)	$ 263 ($2,124)

explained by the fact that over time, more and more learners drop out of a course. In week two, we only consider the subset of learners that viewed the bonus exercise in week 1, and again we observe significant differences in engagement between those that viewed the second bonus exercise and those that did not. As the weeks go on, the difference in video watching time between learners viewing and not viewing the bonus exercise of the week tends to decrease—also evident in the fact that in weeks 5 and 7, we find no significant differences in engagement for the high engagement learners. We consider these results as a first confirmation of **RQ4**: our bonus exercises (real-world tasks) are likely to have a positive effect on engagement. We realize that this experiment can only be considered as first evidence: we observed that similarly engaged learners diverge in their behavior after having (not) viewed our real-world bonus tasks. We assume that this divergent behavior is caused by the action of (not) viewing the task, but this assumption cannot be directly verified. We attempt to verify it (among others) through a post-course survey, outlined next.

5.4 Post-course survey

We sent a follow-up survey with 11 questions (about success & engagement in `EX101x`, financial incentives in MOOC learning and the bonus tasks in `EX101x`) to a subset of learners who expressed their willingness to be contacted after the course had completed. An overview of all questions can be found in Table 7.

We partitioned the set of contacted learners into four groups according to their origin (developed vs. developing country) and their engagement with the bonus exercises (submitted vs. not submitted):

- from developed nations & submitted at least one bonus exercise (126 learners contacted, 26 replied);
- from developing nations & submitted at least one bonus exercise (114 learners contacted, 29 replied);
- from developed nations & did not submit a bonus exercise (357 learners contacted, 34 replied);

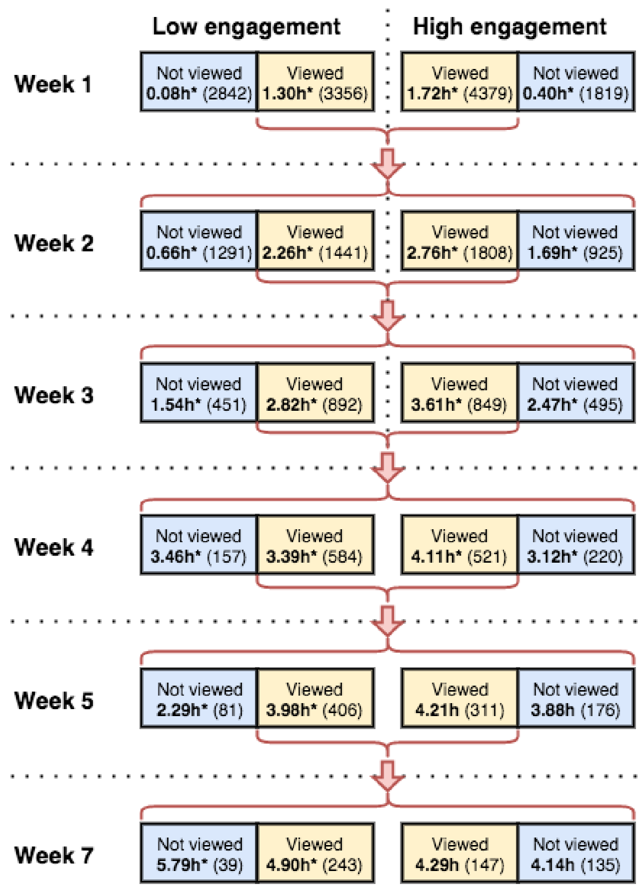

Fig. 6. The average amount of time (in hours) that learners spent in watching video after viewing (but not submitting) the bonus exercises. The numbers of learners within each group are given in brackets. Results marked with * ($p < 0.001$) are significantly different (*Viewed* vs. *Not viewed*) according to the Mann-Whitney U-test.

- from developing nations & did not submit a bonus exercise (271 learners contacted, 22 replied);

Besides the questions and answer options, in Table 7 we also report the distribution of given answers for all closed-form questions and each learner partition. We note that a

TABLE 7
Overview of the 11 questions in our post-course survey. For presentation purposes, some questions and answers appear slighlty condensed. For all closed-form questions, we provide the distribution of answers (in %) across the four learner partitions in the form A | B | C | D%: (A) from developed nations + at least one bonus exercise submitted, (B) from developing nations + at least one bonus exercise submitted, (C) from developed nations + no bonus exercise submitted, and, (D) from developing nations + no bonus exercise submitted.

Success & engagement							
1.	How engaged were you in EX101x?	Completed successfully	Stopped mid-way	Stopped in weeks 1 or 2	Registered, but nthg. else	-	-
		75|87|67|45%	14|10|16|23%	11|0|14|27%	0|3|3|5%	-	-
2.	To what extent did you engage with the bonus exercises?	Submitted 3+ exercises	Submitted 1-2 exercises	Attempted 1+ exercises, but not submitted	Looked at 1+ exercises, but not attempted	Knew about exercises, did not look at any	No knowledge of exercises
		48|52|8|0%	41|38|25|32%	11|3|20|45%	0|7|20|9%	0|0|19|9%	0|0|8|5%
3.	In case you did not complete EX101x successfully, were financial reasons a major factor?	Not applicable	No	Yes, a minor factor	Yes, a major factor	-	-
		74|71|62|35%	26|18|32|50%	0|11|0|10%	0|0|6|5%	-	-
Financial incentives in general							
4.	If you require financial incentives to complete a MOOC, how much (in US dollar) would you need to earn per week via real-world freelance tasks in order to complete a MOOC?	No financial incentive required	\$0-\$9	\$10-\$29	\$30-\$49	\$50-\$99	\$100+
		80|52|77|64%	0|7|0|5%	0|10|6|9%	8|7|11|13%	4|14|3|9%	8|10|3|0%
5.	If earning that much money per week, how many hours per week would you commit to a MOOC?	*Open-answer form*					
6.	Would you consider this income essential to your well-being or more like extra spending money?	Not applicable	1 (Essential)	2	3	4	5 (Extra)
		80|48|66|55%	4|10|3|9%	0|4|9|5%	8|17|6|23%	0|14|8|9%	8|7|8|0%
Bonus exercises in `EX101x`							
7.	How many hours per week did you actually commit to EX101x?	*Open-answer form*					
8.	Did the bonus exercises increase your motivation to engage with the course (beyond the standard course material)?	1 (Not at all)	2	3	4	5 (Very much)	-
		8|7|33|11%	12|0|23|21%	28|24|17|31%	32|41|20|26%	20|28|7|10%	-
9.	How difficult did you find the bonus exercises?	1 (Too easy)	2	3	4	5 (Too difficult)	-
		0|0|7|0%	4|4|7|6%	56|31|61|50%	36|62|21|31%	4|3|4|13%	-
10.	Why did you begin attempting the bonus exercises?	*Open-answer form*					
11.	Why did you stop?	*Open-answer form*					

small number of learners who we classified as not having submitted a bonus solution self-reported having done so. The converse is also true: a small number of learners that we have received bonus exercise submissions from reported not having submitted any. These self-reporting errors could be explained by the amount of time (12 weeks) passed between the end of `EX101x` and the release of the survey. Overall though, the vast majority of learners were remembering their (lack of) submissions for our bonus exercises correctly.

Students from developing nations who did not attempt any of the bonus exercises report that if they could earn somewhere between \$10 and \$100 per week through such online work platform tasks, they would commit up to six more hours to the course per week. In this same group, 45% of respondents attempted one or more bonus exercises but did not submit it to the course instructor. In contrast, of the survey respondents from developed nations who did not submit a bonus exercise to the instructor, only 20% reported having attempted to solve any. This difference suggests that learners from developing nations are more motivated and eager to engage with course material, but there seems to be a barrier stopping them from fully engaging as much as they would like. Providing an opportunity for them to gain income in the process could be a key factor in enabling them to fully commit to a MOOC.

In question 9 we asked students how difficult they found the bonus exercises to be on a five-point Likert scale—"1" being too easy and "5" being too difficult. Of the entire group of learners (across all partitions) that responded, the average score was 3.48. As bonus exercises, they are expected to be slightly more difficult than the rest of the course material, and the students seem to generally view them as such—slightly more difficult, yet accessible. This sentiment is also echoed in the students' comments in the survey when asked why they chose to engage with the bonus exercises in the first place; the three most common words to appear in the responses, in order, are "challenge," "real," and "test." To synthesize, students generally see these activities as an added challenge in which they test their ability to apply what they learned in the course to a real-world problem.

Also interesting is that learners from developing countries perceived the bonus exercises as being more difficult than learners in developed countries (Mann-Whitney U-test with $U = 781$, $Z = -2.13$ and $p < 0.05$). This discrepancy underlines the importance for learners in developing countries to be able to commit the necessary time for these types of tasks, as a higher perceived difficulty would require more time from the learner to understand and/or master the content.

Finally, we also explored the effect of the bonus exercises on learners' motivation to engage with the course (survey question 8). These responses, also on a five-point Likert scale, ranged from "Not at all" (1) to "Very much" (5). A difference emerged in the way learners from different backgrounds are affected by the presence of the bonus exercises. Learners from developing nations report that bonus exercises increased their motivation to engage with the course significantly more than learners from developing countries (Mann-Whitney U-test with $U = 617.5$, $Z = 2.61$ and $p < 0.05$).

6 Freelance Recommender System Design

Based on our analyses presented in the previous sections, we have to take the following two requirements into account when designing our freelance task recommender:

- The recommender should support multiple task platforms, as we have found `Upwork` (at this point in time) to only offer a very limited number of tasks in our specified price range and on our specific MOOC's topic each day.
- Once we recommend learners tasks on `Upwork` and other similar platforms, we need to continuously track the tasks' status (are they still available?) as well as the number of times we have recommended them to different learners (to avoid hundreds of learners trying to "bid" for the same task — only one of them can get the job and be paid).

Figure 7 shows our designed recommender system, which — for any given MOOC — will automatically retrieve real-world tasks relevant to the topics covered in the MOOC and recommend them to our learners. We briefly discuss the different layers in turn:

- **MOOC**. The MOOC layer serves as the playground for learners to interact with course components and our freelance task recommender system.
- **Data layer**. This layer is responsible for collecting learners' activity data and gathering real-world tasks from freelance platforms. To be specific, the component *MOOC data collector* collects data of learners' interactions with course components (e.g., watching lecture videos, viewing forum posts, submitting quiz answers) and the recommender system (e.g., viewing recommended freelance tasks, dwell time). On the other side, the component *Freelance task collector* retrieves course-relevant tasks from multiple freelance platforms including `Upwork`, `witmart`, `Guru` and `Envato`. As some of the discovered freelance tasks may not be suitable for our setting of "earning whilst learning" (high budget tasks often require deep knowledge of several fields), the *Task filtering* component filters out unsuitable tasks by applying rule-based strategies (e.g., by setting the maximun budget). In addition, the *Task availability tracker* component regularly checks whether the recommended freelance tasks are still open & available before generating the recommendations for our learners.
- **Analysis layer**. In this layer, the *Learner profiling* component analyzes learners' interaction patterns with the recommender system and how/whether learners' course engagement can be influenced by freelance task recommendations. The *Task relevance estimation* component computes the relevance of the discovered tasks with respect to the specific MOOC as well as (potentially) the learner profile.
- **Intervention layer**. At last, the intervention layer makes task recommendations to our learners. The *Recommendation diversification* component is responsible for presenting a diverse selection of recommendations (to avoid hundreds or thousands of learners competing for the same freelance tasks).

In future work we will implement this design and test its influence in various MOOCs by exploring its effect on MOOC learners.

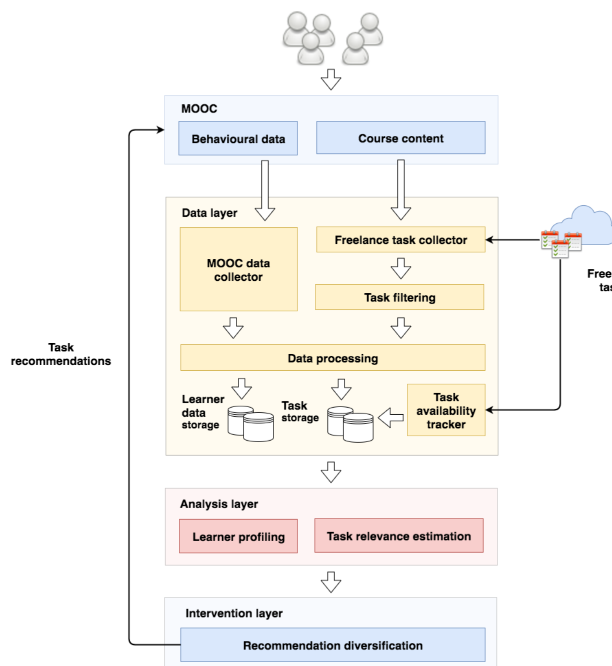

Fig. 7. Overview of the freelance work task recommender system's design.

7 Conclusions

Can MOOC learners be paid to learn? We set out to provide a first answer to this question in the context of the `EX101x` MOOC. We found that indeed, work tasks of up to \$50 can be solved accurately and in high quality by a considerable percentage of learners that attempt it. We also explored the suitability of the online work platform `Upwork` in providing tasks to MOOC learners - while there are many budget tasks available (between \$1 and \$50), those specific to `EX101x` are rather low in number; at the moment we expect no more than 13 suitable tasks (i.e. specific to taught course material) to be posted per day. Finally, we investigated the matter of engagement: does knowing that real-world tasks may be solved with course knowledge increase learners' engagement? Our evidence suggests that this is may indeed be the case. We note that while we did observe correlational relationships between learners' bonus exercise engagement and in-course behavior, the present research cannot yet claim any causality.

Based on the work presented here, we will explore several promising directions (beyond the development and deployment of the presented recommender design). We will investigate (i) experimental setups that allow us to further investigate the causal relationship between real-world tasks and learner engagement, (ii) the suitability of more complex tasks (i.e. tasks with a budget greater than $50) for MOOC learners, (iii) the acceptance of the "learners can be earners" paradigm in different populations, and (iv) setups that aid MOOC learners to take the first steps in the paid freelance task world, inspired by [35].

References

[1] K. Jordan, "Initial trends in enrolment and completion of massive open online courses," *The International Review Of Research In Open And Distributed Learning*, vol. 15, no. 1, 2014.

[2] L. Breslow, D. E. Pritchard, J. DeBoer, G. S. Stump, A. D. Ho, and D. T. Seaton, "Studying learning in the worldwide classroom: Research into edXs first MOOC," *Research & Practice in Assessment*, vol. 8, no. 1, pp. 13–25, 2013.

[3] T. Friedman, "Revolution hits the universities," *The New York Times*, January 26, 2013.

[4] G. Christensen, A. Steinmetz, B. Alcorn, A. Bennett, D. Woods, and E. J. Emanuel, "The MOOC phenomenon: who takes massive open online courses and why?" *Available at SSRN 2350964*, 2013.

[5] P. de Vries and T. Hennis, "TU Delft Online Learning Research Working Paper #6," 2014.

[6] A. D. Ho, I. Chuang, J. Reich, C. A. Coleman, J. Whitehill, C. G. Northcutt, J. J. Williams, J. D. Hansen, G. Lopez, and R. Petersen, "HarvardX and MITx: Two Years of Open Online Courses Fall 2012-Summer 2014," *Available at SSRN 2586847*, 2015.

[7] S. Rayyan, D. T. Seaton, J. Belcher, D. E. Pritchard, and I. Chuang, "Participation and performance in 8.02x electricity and magnetism: The first physics MOOC from MITx," *arXiv preprint arXiv:1310.3173*, 2013.

[8] R. F. Kizilcec and S. Halawa, "Attrition and Achievement Gaps in Online Learning," in *Proceedings of the Second ACM Conference on Learning at Scale*, 2015, pp. 57–66.

[9] P. R. Pintrich and E. V. De Groot, "Motivational and self-regulated learning components of classroom academic performance," *Journal of Educational Psychology*, vol. 82, no. 1, pp. 33–40, 1990.

[10] B. J. Zimmerman and M. Martinez-Pons, "Student differences in self-regulated learning: Relating grade, sex, and giftedness to self-efficacy and strategy use," *Journal of Educational Psychology*, vol. 82, no. 1, pp. 51–59, 1990.

[11] S. Vassallo, "Implications of institutionalizing self-regulated learning: An analysis from four sociological perspectives," *Educational Studies*, vol. 47, no. 1, pp. 26–49, 2011.

[12] B. J. Zimmerman, "A social cognitive view of self-regulated academic learning," *Journal of Educational Psychology*, vol. 81, no. 3, pp. 329–339, 1989.

[13] B. K. Britton and A. Tesser, "Effects of time-management practices on college grades," *Journal of Educational Psychology*, vol. 83, no. 3, pp. 405–410, 1991.

[14] V. Pammer, M. Bratic, S. Feyertag, and N. Faltin, "The Value of Self-tracking and the Added Value of Coaching in the Case of Improving Time Management," in *Design for Teaching and Learning in a Networked World*. Springer, 2015, pp. 467–472.

[15] T. H. Macan, C. Shahani, R. L. Dipboye, and A. P. Phillips, "College students' time management: Correlations with academic performance and stress," *Journal of Educational Psychology*, vol. 82, no. 4, pp. 760–768, 1990.

[16] G. Farkas, R. P. Grobe, D. Sheehan, and Y. Shuan, "Cultural resources and school success: Gender, ethnicity, and poverty groups within an urban school district," *American Sociological Review*, pp. 127–142, 1990.

[17] D. T. Willingham, "Should Learning Be Its Own Reward?" *American Educator*, vol. 31, no. 4, pp. 29–35, 2007.

[18] E. L. Deci, R. Koestner, and R. M. Ryan, "A meta-analytic review of experiments examining the effects of extrinsic rewards on intrinsic motivation," *Psychological bulletin*, vol. 125, no. 6, pp. 627–668, 1999.

[19] R. G. Fryer Jr, "Financial incentives and student achievement: Evidence from randomized trials," National Bureau of Economic Research, Tech. Rep. 15898, 2010.

[20] D. Guttenplan, "Motivating students with cash-for-grades incentive," *The New York Times*, November 20, 2011.

[21] B. M. Allan and R. G. Fryer, *The power and pitfalls of education incentives*. Brookings Institution, Hamilton Project, 2011.

[22] J. Kim and W. Lee, "Assistance and possibilities: Analysis of learning-related factors affecting the online learning satisfaction of underprivileged students," *Computers & Education*, vol. 57, no. 4, pp. 2395–2405, 2011.

[23] G. M. Walton and G. L. Cohen, "A question of belonging: race, social fit, and achievement," *Journal of Personality and Social Psychology*, vol. 92, no. 1, pp. 82–96, 2007.

[24] D. M. Carkenord, "Motivating students to read journal articles," *Teaching of Psychology*, vol. 21, no. 3, pp. 162–164, 1994.

[25] K. A. Boniecki and S. Moore, "Breaking the silence: Using a token economy to reinforce classroom participation," *Teaching of Psychology*, vol. 30, no. 3, pp. 224–227, 2003.

[26] D. A. Wilder, W. A. Flood, and W. Stromsnes, "The use of random extra credit quizzes to increase student attendance," *Journal of Instructional Psychology*, vol. 28, no. 2, 2001.

[27] L. M. Padilla-Walker, "The impact of daily extra credit quizzes on exam performance," *Teaching of Psychology*, vol. 33, no. 4, pp. 236–239, 2006.

[28] E. N. Junn, "Empowering the marginal student: A skills-based extra-credit assignment," *Teaching of Psychology*, vol. 22, no. 3, pp. 189–192, 1995.

[29] A. Agarwal, "News About edX Certificates," 2015.

[30] O. Rodriguez, "The concept of openness behind c and x-MOOCs," *Open Praxis*, vol. 5, no. 1, 2013.

[31] D. Koller, A. Ng, C. Do, and Z. Chen, "Retention and intention in massive open online courses: In depth," *Educause Review*, vol. 48, no. 3, pp. 62–63, 2013.

[32] E. Van Emden and L. Moonen, "Java quality assurance by detecting code smells," in *Proceedings of the Ninth Working Conference on Reverse Engineering*. IEEE, 2002, pp. 97–106.

[33] F. Hermans, M. Pinzger, and A. van Deursen, "Detecting code smells in spreadsheet formulas," in *Proceedings of the 28th IEEE Software Maintenance Conference*, 2012, pp. 409–418.

[34] P. J. Guo, J. Kim, and R. Rubin, "How video production affects student engagement: an empirical study of mooc videos," in *Proceedings of the First ACM Conference on Learning at Scale*, 2014, pp. 41–50.

[35] R. Suzuki, N. Salehi, M. S. Lam, J. C. Marroquin, and M. S. Bernstein, "Atelier: Repurposing Expert Crowdsourcing Tasks As Micro-internships, booktitle = Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems," 2016, pp. 2645–2656.