How employment constrains participation in MOOCs?

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ABSTRACT

Massive Open Online Courses (MOOCs) changed the way continuous education is perceived. Employees willing to progress their careers can take high quality courses. Students can develop skills outside curriculum. Studies show that most of the MOOC users are pursuing or have received a university degree. Therefore it is beneficial to consider motives and constraints of this class of participants while designing a course. In this study we focus on time constraints experienced by full-time and part-time employees and students. Surprisingly, activities of students and employees are very similar regarding timing. We found that part-time employees spend more time on forum and are more active during the day. Employees are more active in the evening hours from Monday till Thursday. Based on our findings we suggest course design insights for practitioners.

1. INTRODUCTION

Time management in Massive Open Online Courses (MOOCs) is indispensable for success [2]. Recent studies show that difficulty with keeping up to deadlines is the main obstacle for engaging in a course [1]. Motivated by previous research, we assume that problems with time management are due to either professional constraints or issues with self-regulation [1] as illustrated in Figure 1. In this study we plan to provide a basis for understanding motives and limitations of MOOC participant depending on their employment status. Our general objective is to investigate: **How occupation (student, employee or part-time activity) influences participants time management in MOOC? How is it reflected by their engagement?**

2. DATASET

Our analysis is based on three successive offerings of an undergraduate engineering MOOC offered in Coursera entitled "*Functional Programming Principles in Scala*". The initial dataset contains 133,129 users. However information about the employment status is provided only by 8.7% of the participants. Based on this information, we extracted three categories of users: *full-time employed* (702 users), *full-time student* (110 users), *part-time activity* (66 users). 84% of full-employed participants hold a master or bachelor (45% and 39% respectively) and this ratio for the part-time group is 64% (32% and 32% respectively). Interestingly there is a noticeable percentage (22%) of participants with part-time activity who do not possess an academic degree.

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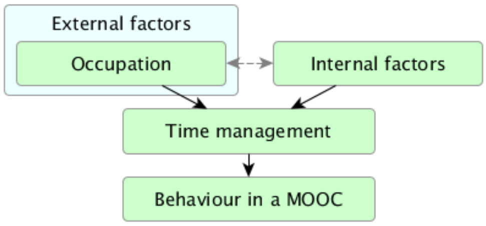

Figure 1: Time management is crucial for success in MOOC. We investigate the influence of occupation on time management.

For the analysis of users' performance we consider two types of events: watching videos and forum activities including viewing the forum (passive events) and writing or voting messages (active events). We extracted a set of features for each user, including final grade, count of forum events (total, active and passive), count of forum messages, average length of messages, count of submitted assignments and average number of attempts per assignment. In addition, we also extracted number of videos watched on different times of the day (Midnight, Morning, Midday, Afternoon, Evening, Night), different days of the week (Monday to Sunday) and different times of each week day. The final set includes 63 feature which were used in the analysis and building a predictive model in the following section.

3. FINDINGS

Q1. Are employed participants more likely to engage in the course? Based on χ^2 test, there is a significant relation between employment status and dropping out ($\chi^2 = 29.06, df = 2, p < 0.01$). According to the test residuals, among the three categories, employed participants are more likely to engage in the course, whereas students are most likely to drop out.

Q2. Do employed participants have higher achievement level? ANOVA on linear model of final grades reveals marginal significant difference between grades for students and employed participants (F[1, 810]=3.8, p=0.05): employed participants on average achieved a higher grade compared to the students (70 vs. 63 out of 100).

Q3. Are employed participants more engaged in forum? Total forum activity (active and passive events) by students and employed participants is similar, whereas part-time participants are significantly more active in forum compared to the other two groups (87 vs. 51, Mann-Whitney-Wilcoxon test, W=20516, p<0.01). Similarly number of posts by students and employed participants are not significantly different, while part-time participants have significantly more posts (M=4.6 vs. 1.7 posts, Mann-Whitney-Wilcoxon test, W=21282, p<0.01). Posts by part-time participants are the longest (M=83 words, t=-2.21, df=441.78, p= 0.02) and post by students are the shortest (M=53 words, t=3.14, df=239.35, p<0.01).

Q4. Do employed participant have different weekly pattern of activity? Distribution of videos watched on each week day shows that part-time participants watch more videos during the weekdays, whereas employed users and students are more active during weekends. Sundays and Mondays are the most active days for all groups and the activity level decreases from Monday to Saturday, mainly for employees and student. This trend could be related to the fact that video lectures were released on Sundays.

Q5. Do employed participants have different time distribution of activities? Number of videos watched in different parts of the day shows to be related to the employment status of participants ($\chi^2 = 109, df = 10, p < 2.2e-16$). As shown to Figure 2, employed participants are the most active group during evening hours (F[1, 876]=4.92, p=0.02), students are the most active group during night hours and part-time participants are the most active group during mid-day. Furthermore unlike part-time participants, the activity level of the other two groups is higher during the afternoon and evening compared to the mid-day hours.

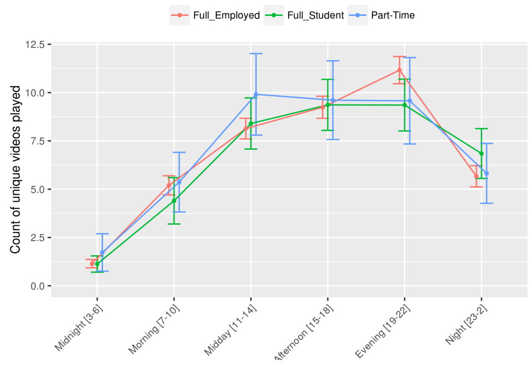

Figure 2: Distribution of number of videos watched at different times of the day.

Further investigations of participants' activity patterns in different days of the week reveals that the observed evening activity peak for the employed participants is related to the working days (Monday to Thursday). On Friday their overall activity level is low and on weekends their activity peak time is shifted to the afternoon hours. Remarkably, all groups are active in the mornings and during the midday. In particular, this could suggest that full-time employees engage in MOOCs during the morning commutes and also during the work day. Nevertheless this finding should be further confirmed in interviews with MOOC participants.

Q6. To what extent can we predict user's employment status based on derived features? In order to predict employment status of participants based on the features described in Section 2, we trained several classifiers including Neural Network, Penalized Multinomial Regression, Random Fores and Support Vector Machine with linear kernel. Using 10-fold cross validation, the highest Cohen's κ (0.45) was achieved by Random Forest classifier.

4. CONCLUSION

Our analysis revealed that employment is reflected by different activity patterns. This confirms our hypothesis that time constraints influence user's participation in MOOCs. Our findings partially confirm previous theories. In particular, higher drop-out rate from MOOCs among students versus employees can be attributed to lower academic and social commitment [3]. This phenomenon can also be linked to better time management of employees (participation in MOOC during the evening just after work) [2]. Further controlled studies should be conducted to discover true causality.

Based on the insight from our analysis, we suggest following design considerations while designing MOOCs courses: **(1) Choose the lecture release day depending on the target audience.** We found that activity of employed participants drops during the weekdays. On the other hand, video release on Sunday make participants work on Monday despite the general lower activity during workdays. Therefore, releasing lectures on Saturday might increase overall activity. **(2) Choose activities convenient for commute time and short sessions.** Our analysis showed activities during potential commuting hours, therefore designing short and mobile-friendly videos and activities could facilitate users engagement during this time. **(3) Choose accurate timing for communication with users,** such as the time when they are most likely to visit the MOOC **(4) Include temporal activity indicators in predictive models,** as time-related features showed to be correlated not only with employment status but also with the success in a MOOC.

5. REFERENCES

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