Learning transfer: does it take place?

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ABSTRACT

The rising number of MOOCs enable people to advance their knowledge and competencies in a wide range of fields. *Learning* though is only the first step, the *transfer* of the taught concepts into practice is equally important and often neglected in the investigation of MOOCs. In this paper, we consider the specific case of `FP101x` (a functional programming MOOC on EdX) and the extent to which learners alter their programming behaviour after having taken the course. We find the practical uptake six months after the course to be small: only $\sim 3\%$ of learners that were not applying functional concepts in their programming practice before the start of `FP101x`, begin using them.

1. INTRODUCTION

Existing investigations into student learning within MOOC environments are commonly based on pre- & post-course surveys and log traces generated within those environments by the individual learners. While student learning is indeed an important measure of success, we argue that equally important for MOOCs is the amount of *learning transfer* that is taking place: do learners actually utilize the newly gained knowledge in practice? Are learners expanding their knowledge in the area over time or do they eventually move back to their pre-course knowledge levels and behaviours? These are important questions to address in the learning sciences and their answers will enable us to shape the MOOCs of the future based on empiricial evidence.

The main challenge researchers face in answering these questions is the lack of *accessible*, *large-scale*, *relevant* and *longitudinal* data traces outside the MOOC environments. While learners can be uniquely identified within a MOOC platform, we have no general manner of capturing their behavioural traces outside of these boundaries.

Not all is lost though. Social Web platforms (Twitter being the prime example) have become a mainstay of the Web - they are used by (hundreds of) millions of users around the world and often provide open access to their data (within limits). Importantly, social Web platforms have also entered our professional lives. One such example is GitHub[1]: it is one of the most popular social coding platforms world-wide with more than 10 million registered users. Programmers use GitHub to collaborate on programming projects, host their source code, and organize their programming activities. As GitHub was founded in 2007, we have access to log traces reaching several years into the past; moreover, its continuously increasing popularity will enable us to observe our learners over years to come.

We consider for MOOCs with a strong focus on programming concepts, GitHub to be one of the most detailed, openly accessible and longitudinal sources of relevant behavioral traces. For our specific case of `FP101x`[2], we found 33.1% of all registered learners to also have a GitHub account.

In this work, we aim to provide first answers to questions surrounding the amount of *learning transfer* taking place. To this end, we analysed the GitHub traces of more than $12,000$ `FP101x` learners over a period of six months after the end of the course.

2. LEARNING TRANSFER

In short, the two key characteristics of learning transfer are *generalization* and *maintenance* [1]. Generalization is marked by a learner's ability to apply the learned knowledge & skills to settings different from the learning setting, while maintenance is indicated by the learned knowledge & skills lasting over time. Due to their popularity as a professional development tool and their roots as a (higher) educational resource, MOOCs in combination with external data sources serve as an ideal ground to gain large-scale insights on the current state of learning transfer (in contrast to the existing qualitative insights). To our knowledge, no previous studies have investigated how transfer learning manifests itself in MOOCs. Previous findings in learning transfer (in the non-MOOC setting) include (i) a negative influence of the lag time between training (i.e. learning) and testing on self-efficacy and post-training knowledge [1], and (ii) a lower transfer rate in closed skills (concrete, technical skills) compared to open skills (interpersonal and open to interpretation) [4, 1]. Given that the present study on `FP101x` analyzes the transfer of closed skills with a time lag through tasks the students were never directly instructed to complete (i.e. their own programming activities), one could expect the observed learning transfer to be very low.

3. PRELIMINARY RESULTS

`FP101x` is an xMOOC [3] with 41 lecture videos (10-15 minutes each) and a total of 288 multiple choice summative questions. It ran between October 15, 2014 and December 31, 2014. The overall completion rate of 5.25% is in line

[1] `https://github.com/`

[2] `https://www.edx.org/course/introduction-functional-programming-delftx-fp101x`

with similar MOOC offerings [2].

Of the 37,485 enrolled learners, 12,415 (33%) could be linked to a GitHub account based on their email addresses. Significant differences between the two cohorts of learners (GitHub vs. Non-GitHub Learners) are observed along two dimensions (cf. Tab. 1): (i) GitHub learners are on average **more engaged** with the course material. They spend significantly more time watching lecture videos and attempt significantly more questions. (ii) GitHub learners exhibit **higher levels of knowledge**. They answer significantly more questions correctly.

	GitHub Learners	Non-GitHub Learners
#Enrolled	12,415	25,070
%Course completions	7.71%	4.03%
%Enrolled learners watching at least 1 video	50.58%	36.02%
Average grade $\in [0, 1]$	0.80	0.81
Average #minutes watching videos	96.78†	76.74
Average #questions answered correctly	84.16†	77.07

Table 1: Characteristics of FP101x's GitHub and Non-GitHub Learners. Significant differences according to Mann-Whitney are marked † ($p < 0.01$).

	Expert Learners	Non-Expert Learners
#Enrolled	1,647	10,768
%Course completions	15.54%†	6.51%
%Enrolled learners watching at least 1 video	64.91%	48.39%
Average grade $\in [0, 1]$	0.82†	0.79
Average #minutes watching videos	116.60†	92.71
Average #questions answered correctly	102.24†	79.57

Table 2: Characteristics of FP101x's Expert and Non-Expert Learner cohorts.

Next, we focused on our GitHub Learners only and split them into two cohorts according to their functional programming expertise as identified from their GitHub traces. We restricted our traces to those generated between March 2013 (2.5 years before `FP101x`) and June 2015 (6 months after the end of `FP101x`). A GitHub trace is generated each time a GitHub user *alters* a file in any way (creating, deleting, inserting, etc.). Each file containing source code is automatically tagged with the corresponding programming language. We consider *Expert Learners* (15% of GitHub Learners) to be those learners who altered at least once a file tagged as either `Haskell`, `Scala` or `Clojure`[3] *before* the start of `FP101x`. *Non-Expert Learners* are those learners whose GitHub traces show no activities in either of those three languages. Comparing the two cohorts (Tab. 2) yields similar trends to Tab. 1, though with a greater magnitude. The Expert Learner cohort exhibits a significantly higher completion rate, watched on average more of the video material and answered more questions correctly. While these results are not that surprising (learners with prior exposure to functional programming outperform novices), they give further evidence to the argument that GitHub traces provide a reflection of learners' expertise.

Lastly, we focus on learning transfer and its extent in `FP101x`: we consider learning transfer to have taken place if (i) Non-Expert Learners pick up functional programming in practice, or, (ii) Expert Learners increase their functional programming activities after the course. In order to investigate this, we split the GitHub traces of all GitHub Learners into three distinct sets according to their timestamps: traces generated *before*, *during* (those are ignored) and *after* the running of `FP101x`.

We find learning transfer to be extremely limited: the number of learners that did not program functionally before `FP101x` and did start coding functionally after the end of `FP101x` is 346. That means only **3.2% of Non-Expert Learners make the transfer** and employ functional languages in their post-`FP101x` programming practice. Encouragingly though, these learners are enthusiastic practitioners: on average, the majority of their programming activities were subsequently performed in functional languages. We also observed positive changes among our Expert Learners (i.e. learners with prior functional experience): the percentage of functional activities among their GitHub traces increased by 15.3%.

[3] `Scala` and `Clojure` are the two most popular functional programming languages; `Haskell` is the functional language used as instruction language in `FP101x`.

4. CONCLUSIONS

In this paper we have argued for the inclusion of external (social Web based) data sources to track learners' progress not just within, but also outside of MOOC platforms. Such tracking enables long-term observations that will allow us to conduct large-scale learning transfer experiments, to test & validate existing qualitative observations made on a smaller scale, usually through surveys and interviews. Exemplary for `FP101x` we have shown that for programming-language oriented MOOCs, a fine-grained and detailed source of external log traces (GitHub) is indeed available.

Our analysis revealed the importance of investigating learning transfer as it is a very precious commodity: very few learners progress beyond the initial learning stage and actually employ the learnt concepts in practice. Many different explanations may account for this observation including learners' motivations and goals, which may not align with learning transfer. However, we believe that these insights will help to shape the discussion on the benefits of MOOCs especially within the professional and adult learning fields.

5. REFERENCES

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