Computers in Human Behavior 47 (2015) 108–118

Contents lists available at ScienceDirect

Computers in Human Behavior

journal homepage: www.elsevier.com/locate/comphumbeh

Precise Effectiveness Strategy for analyzing the effectiveness of students with educational resources and activities in MOOCs

Pedro J. Muñoz-Merino [a,*], José A. Ruipérez-Valiente [a,b], Carlos Alario-Hoyos [a], Mar Pérez-Sanagustín [c], Carlos Delgado Kloos [a]

[a] Universidad Carlos III de Madrid, Av. Universidad 30, 28911 Leganés, Madrid, Spain
[b] IMDEA Networks Institute, Av. del Mar Mediterráneo 22, 28918 Leganés, Madrid, Spain
[c] Pontificia Universidad Católica de Chile, Av. Vicuña Mackenna 4860, Santiago de Chile, Chile

ARTICLE INFO

Article history:
Available online 6 November 2014

Keywords:
Learning analytics
MOOCs
SPOCs
Precise Effective Strategy
Metrics

ABSTRACT

Present MOOC and SPOC platforms do not provide teachers with precise metrics that represent the effectiveness of students with educational resources and activities. This work proposes and illustrates the application of the Precise Effectiveness Strategy (PES). PES is a generic methodology for defining precise metrics that enable calculation of the effectiveness of students when interacting with educational resources and activities in MOOCs and SPOCs, taking into account the particular aspects of the learning context. PES has been applied in a case study, calculating the effectiveness of students when watching video lectures and solving parametric exercises in four SPOCs deployed in the Khan Academy platform. Different visualizations within and between courses are presented combining the metrics defined following PES. We show how these visualizations can help teachers make quick and informed decisions in our case study, enabling the whole comparison of a large number of students at a glance, and a quick comparison of the four SPOCs divided by videos and exercises. Also, the metrics can help teachers know the relationship of effectiveness with different behavioral patterns. Results from using PES in the case study revealed that the effectiveness metrics proposed had a moderate negative correlation with some behavioral patterns like recommendation listener or video avoider.

1. Introduction

Massive Open Online Courses (MOOCs) have brought about a revolution in education (Pappano, 2012). During the last year many teachers and higher education institutions joined the MOOC wave, launching courses in different areas. Platforms like Coursera, edX, MiríadaX, or FutureLearn are providing the support teachers need to deploy open courses that may scale up to thousands of participants.

Most of the MOOCs deployed in the aforementioned platforms follow a common structure in which educational resources are offered as short video lectures, accompanied by activities (e.g., automatic correction exercises) that cover both formative and summative assessment activities (Belenger & Thornton, 2013). These types of MOOCs, also known as xMOOCs, are the most widespread, and follow the so-called broadcast model (Kolowich, 2013).

The impact of MOOCs goes beyond providing free and open education to students worldwide, and is now leading to new blended learning scenarios at schools and universities. In these contexts, MOOCs are exploited to enhance teaching and learning in the form of e.g., successful "flipped classrooms" (i.e. students watch videos with the theoretical concepts from home and practice these concepts with automatic correction exercises, and later attend to the classroom to solve problems with teachers) (Tucker, 2012). Such use of the affordances that emerge from MOOCs to improve the quality of teaching and learning in traditional educational settings leads to what has been called SPOCs (Small Private Online Courses) in the media (Coughlan, 2013). For example, Harvard University (through its edX brand HarvardX) has already taken a step forward, launching SPOCs for their Design school and Law school students (Price, 2013).

In both, MOOCs and SPOCs, there can be a very large number of students, so teachers need precise strategies to know what is going on with each individual student and with the whole class. Current learning analytics techniques (Siemens & Long, 2011) enable the collection of huge amounts of low-level data regarding for instance students' interaction among themselves or with educational resources and activities, both in MOOCs and SPOCs (Siemens, 2012). From these low-level data it is possible to infer higher level

* Corresponding author. Tel.: +34 916246233.
E-mail address: pedmume@it.uc3m.es (P.J. Muñoz-Merino).

http://dx.doi.org/10.1016/j.chb.2014.10.003
0747-5632/

behaviors and metrics that can be presented to the teacher as simple and understandable visualizations (Clow, 2012).

Assuming that the objective pursued by teachers in both MOOCs and SPOCs is that students complete all the proposed contents in a correct way (both educational resources such as video lectures, and activities such as automatic correction exercises), then it is necessary to propose metrics to determine how effective students were with respect to this objective. In other words, there is a need of metrics to determine *the effectiveness of students with educational resources and activities*. These metrics can facilitate the classification of students according to their degree of effectiveness in a course, and the comparison of the overall effectiveness of different MOOCs and SPOCs using quantitative measures.

Nevertheless, as far as we know, the existing metrics that capture students' interactions with educational resources and activities in MOOCs and SPOCs are very rough (e.g., the number of videos completed, the number of exercises accessed or the number of exercises correctly solved). Furthermore, these metrics do not take into account how educational resources and activities were structured (e.g., the most important parts in a video lecture), and how they relate to each other (e.g., the suggested order of completion). Visualizations to see the effectiveness of thousands of students at a glance are also missing in current platforms. For instance, the Khan Academy, which offers one of the most detailed learning analytics, only represents with colors four states of an activity (proficiency, struggling, started or not accessed), and does not provide graphical visualizations to represent students' progress in a video.

In this context, the specific research questions addressed in this work are:

- Can we propose a general strategy for calculating the effectiveness of students when interacting with resources and activities in a precise way, giving some general guidelines on how to apply it?
- How can we particularize the general strategy for calculating the effectiveness of students with resources and activities in a case study with an intensive use of videos and exercises (which are some of the most commonly-used contents in MOOCs and SPOCs)?
- How can we use the effectiveness metrics to compare students, contents and courses?
- Are the effectiveness metrics related to other important student's behavioral patterns?

This paper presents Precise Effectiveness Strategy (PES), a generic methodology for supporting the calculation of the effectiveness of students when interacting with educational resources and activities. PES guides the process for defining metrics to calculate this effectiveness, considering the main particularities of the learning context (e.g., the relationships among the different video resources). PES has been applied to a case study to calculate the effectiveness of students when interacting with video lectures and automatic correction exercises in four remedial SPOCs deployed in the Khan Academy platform. The metrics defined in the case study enable: (1) the representation of the effectiveness of students' interactions with videos and exercises in a simple way; (2) the measurement of the relationship of the effectiveness metrics with behavioral patterns; and (3) the comparison of the overall effectiveness of students when interacting with educational resources and activities between the four SPOCs.

The remainder of this paper proceeds with a review of the literature regarding the definition of effectiveness in educational contexts in Section 2. Section 3 presents PES, detailing its four phases. Then, Section 4 describes the case study and the specific metrics proposed for it. Section 5 presents and discusses the results obtained from the case study. Finally, Section 6 draws the conclusions and summarizes the main lines of future work.

2. Related work

Much of the traditional educational literature addresses the concept of effectiveness from the perspective of learning (students' learning effectiveness): "how much did the students learn, how well did they master skills and how well can they apply knowledge" (Hiltz & Arbaugh, 2003). The concept of effectiveness applies to face-to-face, blended and online education, but becomes more important in the latter, where teachers cannot easily track learning gains (Ni, 2013; Swan, 2003). In order to measure learning effectiveness, most authors typically use (if possible) achievement tests or surveys for collecting student perceptions (Moody & Sindre, 2003).

The study by Swan (2003) goes further and proposes measuring students' learning effectiveness in terms of interactivity with peers (social presence), with instructors (teaching presence) and with contents (cognitive presence) (Rourke, Anderson, Garrison, & Archer, 1999). Following this idea, it is possible to split the concept of students' learning effectiveness into three new concepts: *effectiveness of students with peers*, *effectiveness of students with instructors*, and *effectiveness of students with contents*. In online courses, such as MOOCs and SPOCs, the first and the second kinds of effectiveness can be measured by considering the number and type (e.g., question, answer, etc.) of messages submitted by students in discussion forums and addressed to their peers or to the teachers, as well as their quality (e.g., measured through voting systems or Natural Language Processing approaches); the third kind of effectiveness can be measured considering the number and type of educational resources and activities completed by students.

Delving a little deeper into the effectiveness of students with contents, Zhang, Zhou, Briggs, and Nunamaker (2006) collected students' low-level interactions with educational resources offered as videos (annotating interactions such as clicking "*next*" to skip the video, "*prev*" to go back, or movements over the video content) and concluded that videos that provide individual control to content (instead of random access) lead to a higher learning effectiveness. Moreover, Feng, Heffernan, and Koedinger (2006) found that the final students' scores are correlated with specific students' actions, such as asking for hints when solving automatic correction exercises with the support of an Intelligent Tutoring System (ITS). These authors also proposed a model to predict future scores based on students' interactions on an ITS. Therefore, these two works support Swan's thesis about the existing relationship between the effectiveness of students with contents and students' learning effectiveness.

Currently, there are several learning analytics techniques that enable to capture students' low-level interactions with educational resources and activities in online courses (Siemens, 2012) and that can thus be employed to calculate the effectiveness of students with contents in MOOCs and SPOCs. Low-level events collected through these techniques can be transformed into datasets, useful to understand students' higher level behavior (Clow, 2012). For example, Blikstein (2011) collected low-level interactions, such as "key presses", "button clicks" and changes in code in programming activities, categorizing students according to their performance (e.g., "*copy and pasters*", "*self-sufficient*", etc.). Other types of higher level profiles inferred from low-level interactions with educational resources and activities that have been reported in the literature for students who watched videos and solved automatic correction exercises are "*hint abuser*", "*hint avoider*", "*student misuse*", "*video avoider*", "*unreflective user*" or "*procrastinator*" (Aleven, McLaren, Roll, & Koedinger, 2004, 2006; Muñoz-Merino,