# Merging learner performance with browsing behavior in video lectures

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#### Abstract

Video lectures are nowadays widely used by growing numbers of learners all over the world. Nevertheless, learners' interactions with the videos are not readily available, because online video platforms do not share them. In this paper, we present an open-source video learning analytics system. The system captures learners' interactions with the video player (e.g, pause, replay, forward) and at the same time it collects information about their performance (e.g., cognitive tests) and/or attitudes (e.g., surveys). We have already validated the system and we are working on learner modeling and personalization through large scale data analysis. The tool is a freely available open source project for anyone to try and to improve.

#### **Author Keywords**

User Interactions, Video Based Learning, Education, Learning Analytics

#### ACM Classification Keywords

H.5.2 [Information Interfaces and Presentation]: User Interfaces, user-centered design; K.3.1 [Computers and Education]: Computer Uses in Education - Computer-managed instruction (CMI).

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#### Introduction

The use of videos for learning has become widely employed in the past years [3]. Most of the universities and digital libraries have incorporated video into their instructional materials. Currently, Massive Online Open Courses (MOOCs) are becoming an increasingly important part of education. In order to support video learning, various technological tools have been developed. For example, Matterhorn and Centra are just few of them. However, information from the videobased learners' behavior and navigation is not yet freely available to the educational technology community.



Figure 1 Matterhorn provides an annotated seek-bar in order to improve navigation within a video lecture, but there is no support for collecting and analyzing learners navigation

Capturing and sharing analytics in emerged learning technologies can clearly provide scholars and educators with valuable information. Specifically for the case of video based learning, information obtained from learner (hereinafter Learning Analytics-LA) have recently started to be used in order to provide educators with valuable information about students (Figure 2). However, the usage of LA on video based learning it is still on embryotic research stage.



A heat map of an entire class's snapshot of current proficiency levels across all topics

Figure 2. Khan academy provides the teacher with a dashboard that depicts the performance of students across topics, but it does not link the performance within the respective video sections.

The purpose of this paper is to present an open-source video learning analytics system. The system facilitates the analysis of video learning behavior by capturing learners' interactions with the video player (e.g, seek/scrub, play, pause) and collecting information for their performance (e.g., cognitive tests) and attitudes (e.g., surveys).

## **Open-Source Video Learning Analytics System**

Learners' interactions with the videos are not readily available, because online video platforms do not share or they are not interest on them. In order to be able to capture and store these interactions, we developed an open-source video learning analytics system. Our system facilitates the analysis of video learning

# Video Analytics System

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Figure 3. Video analytics system architecture is modular and cloudbased. Web-based video systems might employ the open-source application logic, in order to dynamically identify rich information segments

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behavior by capturing learners' interactions with the video player (e.g, play, pause).

For developing the Open-Source Video Learning Analytics<sup>1</sup> System (Figure 3), we used the Google App Engine (GAE) cloud platform and the YouTube Player API [4]. There are several benefits of the selected tools (GAE, YouTube, Google accounts). GAE enables the development of web-based applications, as well as maintenance and administration of the traffic and the data storage. YouTube allows developers to use its infrastructures (e.g., YouTube videos) and provides chrome-less user interface, which is a YouTube video player without any controls. This facilitates customization within Flash or HTML 5. As such, we used JavaScript to create custom buttons and to implement their functions. Additionally, learners' used Google account in order to sign in and watch the uploaded videos. In this way, we accomplished user authentication and we avoid the effort of implementing a user account system just for the application. Thus, users' interactions are recorded and stored in Google's database alongside with their Gmail addresses. The Google App Engine database (Data store) is used to store the interactions. Each time someone signs in the web video player application, a new log is created. Whenever a button is pressed, an abbreviation of the button's name and the time it occurred are stored.

The video player (Figure 4) employs custom buttons, in order to be simple to associate user actions with video semantics. We have modified the classic forward and backward buttons to "Skip30" and "Replay30". The first one jumps backwards 30 seconds and its main purpose is to replay the last 30 seconds of the video, while the Skip30 button jumps forward 30 seconds and its main purpose is to skip insignificant video segments. The main reason for developing these functions is to identify the video segments which learners' consider as important (repeated views). We decided to use buttons that are similar to the main controls of VCR remote controls because they are familiar to users. In addition, questionnaires and performance tests can be employed next to the main interface of the player (Figure 4) and the respective data will be integrated in the Data Store.

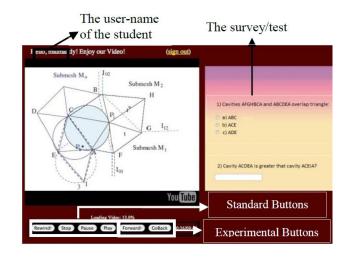


Figure 4. The interface of the system has familiar buttons, as well as questionnaire functionality

<sup>&</sup>lt;sup>1</sup> Open source project: https://code.google.com/p/socialskip/

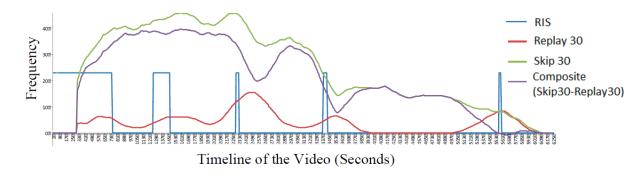


Figure 4. An Example of Learner Activity Visualization

The system is also providing all these interactions in an form which can be easily visualized, using for example times series (Figure 5). To this end, researchers and scholars are being able to extract all the rich information and understand better the learner behavior. In addition, the results from the questionnaires and performance tests can be used to triangulate the results. By taking into account learners' interactions and many other data—such as their demographic characteristics, prior background knowledge, their success rate in each section, their emotional states, the speed at which they submit their answers, which video lectures seemed to help which students best in which sections, etc. - we will be able to understand how this medium is being used by the students and proceed to the appropriate amendments to the current video based learning systems and practices.

#### **Benefits and Perspectives**

Many corporations and academic institutions are making lecture videos and seminars available online, there have been few and scattered research efforts (i.e., [5]) to understand and leverage actual learner experience. In addition, to the best of our knowledge there are no efforts using LA from diverse sources in order to triangulate them and derive valuable information about students.

In that paper we present an open-source video learning analytics system. Although we designed the system as a web-based one, the concept of mapping implicit learner interactions to a time-series for further analysis has a much broader application.

This large amount of LA produced during the interaction of the learner with video-based learning system can be converted into useful information for the benefit of all video learners. As long as learners' watching videos on Web-based systems [1], more and more interactions are going to be gathered and therefore, dynamic analysis would represent in a timely fashion the most important (rich-information) segments of a video according to evolving learner interests. We also expect that the combination of richer user profiles and content metadata provide opportunities for adding value to LA obtained from video based learning.

By taking into account learners' interactions and many other data—such as students' demographic characteristics of gender, ethnicity, English-language skills, prior background knowledge, their success rate in each section, their emotional states, the speed at which they submit their answers, which video lectures seemed to help which students best in which sections, etc.— new avenues for research are opening. As Butin [2] clearly articulated in ACM eLearn, using students' data, we can feed powerful algorithms and create seemingly personalized feedback [6]. Future work will help to collect diverse LA (i.e., success rate, emotional states), which will allow the community to consider the challenges for developing a "recommender system", which we have all encountered on Amazon. Such a system would have allowed video lectures to discover that perhaps certain lecture characteristics and practices, help some students more effectively at different points in a course.

The intellectual merit of this proposal is the development of a novel experimental video analytics system. The presented tool aims to contribute to the area, by providing an open source solution for video analytics capturing (the first of its kind to the best of our knowledge) for further improvement and experimentation.

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