Open System for Video Learning Analytics

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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, which is also available as a free service to researchers. Our system facilitates the analysis of video learning behavior by capturing learners' interactions with the video player (e.g, seek/scrub, play, pause). In an empirical user study, we captured hundreds of user interactions with the video player by analyzing the interactions as a learner activity time series. We found that learners employed the replaying activity to retrieve the video segments that contained the answers to the survey questions. The above findings indicate the potential of video analytics to represent learner behavior. Further research, should be able to elaborate on learner behavior by collecting large-scale data. In this way, the producers of online video pedagogy will be able to understand the use of this emerging medium and proceed with the appropriate amendments to the current video-based learning systems and practices.

Author Keywords
User Interactions, Learning Analytics, Video, Education.

ACM Classification Keywords
K.3.1 [**Computer Uses in Education**] Computer-assisted instruction (CAI), Distance learning; H.5.3 [**Group and Organization Interfaces**]: Evaluation/methodology

INTRODUCTION
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. However, the usage of LA on video-based learning it is still on embryotic research stage.

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Many instructors in higher and secondary education are implementing video lectures in a variety of ways, such as broadcasting lectures in distance education, delivering recordings of in-class lectures with face-to-face meetings for review purposes. However, several aspects on the area of video-based learning remain unexplored, such as whether students are viewing the entire video lecture, what segments of the video lecture they select to view, how many times they view the video lecture, and what part of the video are more attractive to them [1]. Based on these concerns, our system design is taking advantage of a LA approach and investigates students' video behavior using an analysis of their interactions with video lectures.

OPEN-SOURCE VIDEO LEARNING ANALYTICS SYSTEM
In this section, we present the video analytics system we used in our study (Figure 1). We used the Google App Engine (GAE) cloud platform and the YouTube Player API. The system has several advantages in comparison to stand-alone applications [2]. Users do not need to go through an installation process (http://goo.gl/SJng6O), they just have to visit the link and if there is an updated version they just have to refresh the page, in addition, system's architecture is modular and it allows re-use of the components.

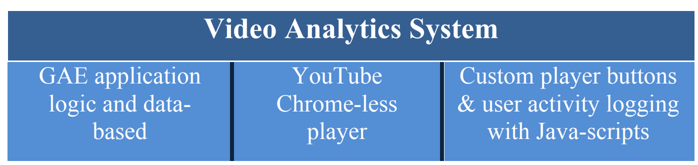

Figure 1. Video analytics system architecture

Web-video systems might employ the open-source application logic (http://goo.gl/vHmk5Y), in order to dynamically identify rich information segments. 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 (Datastore) 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 2) 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).

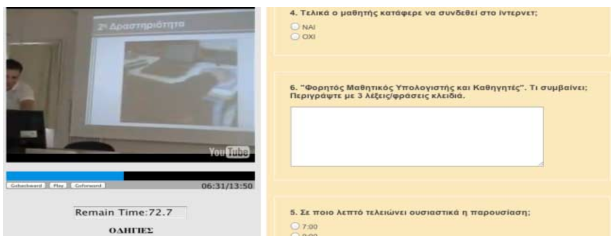

Figure 2. The interface of the system has familiar buttons, as well as questionnaire functionality

USER EXPERIMENT

Methodology

The goal of the user experiment is to collect activity data from the learners, as well as to establish a flexible experimental procedure that can be replicated and validated by other researchers at large scale level. In our small case study, twenty-three university students (18-35 years old, 13 F and 10 M) spent approximately ten minutes to watch a series of videos (buttons were muted). All students had been attending the HCI courses at a post- or under-graduate level. Next, there was a time restriction of five minutes, in order to motivate the users to actively browse through the video and answer the respective questions. We enabled the Replay30 and Skip30 buttons and we informed the students that the purpose of the study was to measure their performance in finding the answers to the questions within time constraints. In order to experimentally replicate learner activity we developed a questionnaire that corresponds to several segments of each video. The survey employed very simple questions that could not be answered by previous knowledge of the students.

Early Results

In order to analyze the results, we created time-series graphs that facilitated the visual comparison between the original Learner Activity Segments (LAS), the Rich Information Segments [segments with the responses of the questions] (RIS) and smooth versions of the LAS [we smooth learners' activity using common technics] (Figure 3). Next, we visually compared the smooth versions of the component and composite times series to the RIS. We observed that in most cases the Replay30 time series closely matched the RIS. Neither the Skip30, nor the composite time series seem to match the RIS (Figure 3).

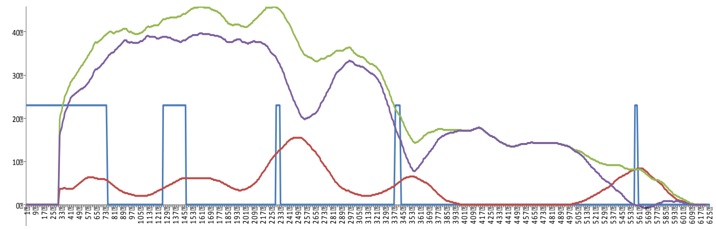

Figure 3. An exemplar graph of learner-video interaction

Therefore, it is possible to compute local maximums of the Replay30 time series for each one of the videos and identify the segments of the video, where students seek the answers or consider more important. The experimental system also can keep logs of the answers to the questions alongside the video interaction logs; as such it is possible to triangulate learners' interaction with their knowledge acquisition and their attitudes.

DISCUSSION AND CONCLUSION

In that paper, we presented a video learning analytics system and the first results of the captured LA. As millions of learners enjoy video streaming from different platforms (Coursera, Khan Academy, EdX, Udacity, Iversity, Futurelearn) on a diverse number of terminals (TV, desktop, smart phone, tablet), they create billions of simple interactions. This amount of LA might be converted into useful information for the benefit of all video learners. As long as learners' watching videos on Web-based systems, more and more interactions are going to be gathered and therefore, dynamic analysis would allow us to better understand learner experience. 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.

Future work is focused on collecting diverse LA (i.e., success rate, emotional states), which should allow the community to understand the use of this learning medium and proceed with the appropriate amendments to the current video-based learning systems and practices.

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REFERENCES

1. Giannakos, M. N. et al. Analytics on video-based learning. In *Proc. LAK '13*, ACM Press (2013), 283-284
2. Chorianopoulos, K., Leftheriotis, I. and Gkonela.C. SocialSkip: pragmatic understanding within web video. In *Proc. EuroITV '11*. ACM Press (2011), 25-28.