Using metrics and cluster analysis for analyzing learner video viewing behaviours in educational videos

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***Abstract*— On line video is a powerful tool for e-learning and this is evident from a number of reports, research papers and university initiatives, which portray that online video is becoming an important medium for delivering educational content. Therefore, research that focuses on how students view educational videos becomes of particular interest and in previous work we argued that in order to efficiently analyze learner viewing behavior we should deploy tools that log the learner activity and assist usage analysis and data mining. Working towards this direction, a framework for recording and analyzing learner behavior was presented together with findings of applying the framework into educational settings. In this paper, we continue this work by presenting a set of metrics that can be derived from the framework and be used to measure learner engagement and video popularity. These metrics in conjunction with the data mining method of clustering are then used to gain insights into learner viewing behavior.**

Keywords*— *video in education; viewing behavior; video usage analysis; cluster analysis; metrics

I. Introduction

Video has been used for educational purposes for many years now. In the beginning, educational videos were delivered to learners through scheduled television programs broadcast by mainstream media. Later, the VCR was a technological advancement introduced to every home mainly for recreational purposes. However, VCRs also entered classrooms and libraries. An article published in 1985 by W. Reider [1] highlighted the significant increase in the use of VCRs in schools in the mid 80's. With the advent of VCR players learners could watch a video in their own time and at their own pace at home or in libraries. Although educational videos are still broadcast by mainstream channels and libraries continue to hold significant video repositories, either in analogue VHS format or in digital DVDs, nowadays, educational videos are also widely distributed through the Internet.

Today, a significant number of educational institutions deliver their educational resources to the public through Open Courseware initiatives, via the Internet. World leading Universities such as Harvard (via EdX that is a consortium of universities, https://www.edx.org), MIT (via EdX and OpenCourseWare, http://ocw.mit.edu) and Stanford (via Coursera, http://www.coursera.org and Stanford online, http://online.stanford.edu) are taking part in these initiatives. The educational resources delivered to the public for free through these initiatives are in various digital forms (i.e., pdf documents, PowerPoint presentations) but video is the prevalent medium used for distributing educational content.

Besides online lectures that are made publicly available by University initiatives, there is a considerable amount of educational videos offered by non-profit and private organizations such as Khan Academy (http://www.khanacademy.org/) and Udacity (https://www.udacity.com/). Furthermore, a vast amount of educational videos is offered by institutions and independent educators in video-sharing sites like You-Tube and Vimeo.

The delivery of online educational videos in Higher education is a growing trend and is most likely to continue over the coming years. This is depicted in a number of scientific articles and reports. Such an example is a report entitled "Video Use in Higher Education" [2] that was published in 2009. Amongst its key findings were that the educational use of video on campus is accelerating rapidly in departments across all disciplines, and although the majority of video usage today is still confined to audiovisual viewing equipment in classrooms or at the library, the faculty staff and administrators expect the sources of their video to shift from offline analog storage to online delivery. Faculty staff also expected their use of video in education to grow significantly over the coming years.

Online educational videos are also important in K-12 education and this is reflected in the findings of the 8th annual survey carried out by the Public Broadcasting Service (PBS) in USA [3]. The survey reveals the increasing extent to which teachers value online video as a teaching resource..

The importance of video usage in education is also depicted by the considerable amount of publications that focus on the topic. Kay [4] provides a literature review on the use of video podcasts in education from 2002 to 2011. Kay notes that research in the particular area before 2005 was limited but this has changed since then. As Kay observes, the increase in the adoption of high speed internet access in homes and schools between 2006 and 2010 and the appearance of the popular video sharing site You-Tube (which hosts a large number of educational videos) was followed by an an increase in video usage in education and an increase in research focusing on this field.

There is an obvious ongoing expansion of online video use in education and, as a consequence, research that focuses on how students view educational videos and how their viewing behavior affects their academic performance becomes of particular interest. Several publications in the literature deal with learner viewing patterns that emerge from watching educational videos. These studies (e.g., [5][6][7]) use mostly surveys, but also interviews and focus groups, to obtain information on learner viewing patterns and understand the factors that lead to specific viewing styles. A very small number of papers in the literature adopt a different approach and use data analysis (or log file analysis) and data mining techniques to analyze viewing patterns (e.g [8][9][18]).

In order to conduct behavior analysis on a large scale, we argued in a previous paper [10] that we have to deploy tools that assist usage analysis and data mining. In an attempt to work towards this particular direction and in order to provide the means and tools for video usage analysis and mining, we introduced a framework for capturing and analyzing learner viewing behavior while watching and interacting with online educational videos. This framework was then used in educational settings to obtain a dataset of viewing behaviors and this dataset was analyzed in [11] to obtain some early findings with respect to viewing behaviours.

The aim of the current paper is to present a set of metrics that can be derived from the framework in order to measure learner engagement and video popularity, and to use these metrics with cluster analysis to get comprehensive insights into learner behavior. Cluster analysis is a data mining method often used in the literature to analyze user behaviors while navigating in the open web or in web based environments. Some examples are mentioned in section V. In this paper cluster analysis is used to reveal clusters of: (a) learners with similar engagement metrics, (b) videos with similar popularity indicators, and, (c) viewing patterns with similar characteristics. A short discussion follows the presentation of each result. An attempt is also made to see if there are any correlations between the obtained clusters of learners and the learner performance (i.e., final marks). Finally, association rule mining is used to reveal another aspect of viewing behavior, which is videos that are frequently viewed together in the same session.

More specifically, in Section II, the framework for recording and analyzing learner viewing activity is presented in brief. In Section III, we present the educational settings where the framework is adopted, and, in Section IV, we define a set of useful metrics for measuring learner engagement and video popularity. In Section V, we use these metrics and clustering to gain insights into the learner viewing behaviors. We conclude the paper in Section VI.

II. A FRAMEWORK FOR RECORDING AND ANALYZING LEARNER VIEWING ACTIVITY

Educational videos are typically either a recorded lecture, which takes place in a classroom, or a video lesson, which is designed by an educator or a professional (or a group of professionals) using appropriate software tools such as editing tools or e-learning tools and relevant hardware equipment (e.g., camera, microphone, draw pad, etc). E-learning tools are widely used for the creation of interactive educational content and videos and there are a number of commercial packages developed by lead players in the field such as Adobe and Articulate.

Videos are either linear or interactive. Linear videos are the classic videos with no scope for interactivity besides the typical VCR control buttons that can start, pause, resume, rewind and forward the video. On the other hand, interactive videos prompt the user to interact with the video at various points during video execution. Examples of interactive elements are a button or a hotspot area that must be clicked or a text box that must be filled in for the video to advance. Branching is also a feature that may exist in interactive videos, where the learner can follow more than one viewing routes according to his/her actions. Videos created by e-learning software can also contain a range of other features such as: (a) quiz questions, which may appear at various points in the video timeline to test the acquired knowledge, (b) Powerpoint presentations, which are synchronized to the video timeline, (c) various multimedia elements such as captions, background music and animation, (d) a table of contents, which gives the user the power to access directly specific segments of the video, (e) screencasting, etc.

In the methodology proposed in [10], we use a particular e-learning software (i.e., Adobe Captivate) to produce video tutorials and we follow a certain procedure during the production and distribution phase in order to capture learner viewing activity. We also propose a suitable data model for storing this activity data. Although the methodology relies on the use of specific software, we have to note that for linear videos other methods can also be used to achieve the same results, such as using open source Javascript and Flash video players and their specific APIs.

The proposed methodology provides the means to log activity data from any linear or interactive video as well as from videos containing quiz questions. According to the methodology, videos are divided into sections and the viewed sections are logged, providing in this way the educator with information not only about the videos that were started by learners but also about the segments that were viewed from each video. We note here that the sections in our framework are not defined by equal time intervals but are set by the educator and reflect knowledge topics contained in the video. In other words, there are marker points that determine the start of a “sub-topic”. Care has also been taken to avoid substantial duration differences between sections. For interactive videos and for videos containing quiz questions, the interactive elements and quiz questions attempted are also recorded, together with the outcome of the attempt (i.e., successful or unsuccessful). Media actions performed by learners (i.e., pausing and resuming from the same or from a different point in the timeline) are also recorded.

The database schema (described in detail in [10]) consists of tables for storing the video initial information and the learner session activity. Initial information contains descriptive information about a video (length, name, etc.), the video segments that a video is divided into, the elements that exist in an interactive simulation video, and the quiz questions that may exist in a video. On the other hand, session information is obtained from learners viewing the videos. It contains information about the videos started by learners, the segments viewed in each video viewing, the media actions performed, the interactive items and the quiz questions attempted.

Using the information stored in the database, we can derive metrics that portray in detail the viewing behavior of the learners. One can get information on the videos visited and the extent that each video is viewed by each learner. The database maintains information about the sections visited but also the actions performed. It also stores information about the date, time and the exact frame in the timeline of the action performed or the section visited. Having this information and with more elaborate data processing, we can also calculate the exact frame intervals that are covered by each learner (for every video viewed).

Furthermore, two modules were introduced to aid the educator in monitoring individual learner activity. The first is a PHP application that allows the educator to navigate through the database tables and entries, starting either from the users table or the sessions table. The second is an application that provides graphical sequence representations allowing the educator to view individual learner viewing (or activity) patterns in a comprehensive way.

In the next section we describe the educational settings where the framework is adopted.

III. EDUCATIONAL SETTINGS

The framework has so far been adopted for a series of educational videos. These video lessons were created for supporting the course “Introduction to Computers”, taught in the 1st semester and the course “Communication Technologies” taught in the 6th semester at the Department of Digital Media and Communication at the Technological Education Institute of Western Macedonia. In the course “Introduction to Computers” and in the laboratory hours, students are taught principles of word processors and spreadsheets using Microsoft Office Word and Excel. In the lab hours of the course “Communication Technologies”, students are taught web page design with the DreamWeaver software package. Screen capturing was used to produce videos that demonstrated various topics specific to the software packages. The videos were enhanced with sound, captions and text animations.

Two web pages were created for accommodating the educational videos. One column in both web pages contains the links to the linear videos and another column contains the links to the interactive videos. The webpage for the course “Communication Technologies” contains also a third column with links to document files (Fig. 1). The document files consist of detailed instructions and images and cover the same topics as the corresponding videos. These files are intended for those who wish to read rather than watch online videos. The students have to follow a login procedure in order to access these web pages.

Figure 1 - Video lessons for the course “Communication Technologies”

The videos can only be accessed through a live internet connection and a connection to the database. A learner session is defined as the period starting from user login and until the user closes the browser window, exiting in this way the video platform.

The lectures that are supported by the video lessons have obligatory attendance and students are taught the same topics in class as well. Thus, in our setting, videos are not the only source of acquiring the necessary knowledge and this has to be kept in mind when interpreting results from the data analysis. The order in which the topics are covered in class is more or less the same with the order of the videos in the webpage.

The first series consists of 26 linear demonstration videos plus 20 interactive videos and 2 videos consisting mostly of quizzes for learning Microsoft Office Word and Excel concepts. The second series consists of 28 linear demonstration videos and 14 interactive video lessons for learning the Dreamweaver web page design software. The duration of the videos that are designed to support the two courses ranges from 1 to 10 minutes, approximately. However, most of the videos are below 3.5 minutes. It was a design decision to keep these video lessons short in order to keep engagement at high levels and downloading time shorter.

Linear videos cover all topics that the learner needs to know and interactive videos are videos where the learner is asked to perform a series of actions and is guided through the completion of certain tasks (e.g., embedding a video in a website, creating frames and links, etc). In interactive videos, the learner is gaining and consolidating his/her knowledge through interaction, as well as trial and error.

The first series of video lessons were available in the fall semesters of 2012-2013 and 2013-2014 and the second series throughout the spring semester of 2012-2013. During these semesters 350 learners accessed the video platform and viewed at least one video. 147 of these learners were attending the course “Introduction to Computers” (fall semesters 2012-2013 & 2013-2014) and 203 learners attended the course “Communication Technologies” (spring semester 2012-2013). These learners performed over 11,000 viewings for both linear and interactive videos.

IV. Metrics.

In this section we provide a set of metrics to measure learner engagement and video popularity. The metrics can be derived from the data captured by the framework. As already mentioned, the framework stores information about the videos visited by learners, the sections visited in each video viewing, and the actions performed (pause, resume forward and backward jumps). It also stores the interactive elements attempted by learners who view interactive videos and the quiz questions attempted by learners who view videos containing quiz questions.

The frame intervals watched in each video viewing can also be estimated with sufficient accuracy since we have information about the sections visited but also about any actions performed. For example, for an action such as a forward jump, amongst the stored information we have the frame where the video was paused plus the frame where the video was resumed. Thus, we can calculate the frames that are skipped. All the metrics presented below were calculated either by straightforward SQL queries or by more elaborate data processing.

A. Learner engagement metrics

1) ***Number of videos started by the learner.*** The number of videos started by a specific learner. Multiple viewings of the same video are counted to the total.

2) ***Percent of distinct videos started by a learner.*** To calculate this metric we first find the distinct videos that have been accessed by the learner and divide this number by the number of all available videos

3) ***Percent of videos watched by the learner =*** *overall frames watched in videos / number of overall frames in videos.* Different segments of the same video can also be viewed in different viewing sessions. As already mentioned, from the framework we can derive not only which videos were started but also the frame intervals that were viewed from each video. This metric can be derived for both linear and interactive videos.

4) ***Number of days that the viewings took place.*** This is a useful metric when used in conjunction with the previous metrics. A learner might access a large number of videos in a long or small time interval (e.g., before an assignment or before the exams). However, accessing a lot of videos in a small time interval is bound to have implications in the learning process as the learner might not be able to absorb the required information.

5) ***Percent of interactive elements attempted by the learner =*** *distinct elements attempted in all interactive videos / number of elements in all videos*. This metric can be derived only for interactive videos in order to measure learner engagement. The metric can be more indicative than the metric “Percent of videos watched by the learner” especially for videos with a large number of interactive elements.

6) ***Number of actions performed.*** The number of pause-resume, backward and forward jumps performed by a learner.

B. Video Popularity metrics

1) ***Number of times the video is started***. The number of times the video was started by learners.

2) ***Number of learners that accessed the video.*** The number of distinct learners that have accessed the video.

3) ***Percentage of learners that accessed the video =*** *number of distinct learners that visited the video at least once / total number of learners.*

4) ***Number of times the video was abandoned.*** A video is considered as inadequately viewed (abandoned), if less than 60% of its sections were visited. The threshold number of 60% is of course a general parameter in the database that can be modified.

5) ***Percent abandoned =*** *number of times the video was abandoned / number of times the video was started.*

6) ***Number of Actions***. Number of pause-resume, backward and forward jumps learners performed for the particular video.

V. Data Mining using Cluster Analysis

Several studies have used cluster analysis to analyze user behaviour while browsing web pages or navigating online environments. Krol, Scigajlo and Trawinski [13] deployed clustering to investigate user activity patterns while visiting webpages of a cadastral system. Morisson et al. [14] used clustering to analyze temporal user behavior in online communities. We also have several examples of cluster analysis in educational environments. Beal, Qu, & Lee [15] deployed cluster analysis to group students that used an intelligent tutoring system (ITS). Clustering was based on self reports of motivation and the obtained groupings were used to predict how learners interact with the ITS. Bowers [16] used hierarchical cluster analysis and pattern visualizations on grading histories and student cohorts to aid data driven decision making by teachers and administrators.

Cluster analysis or clustering is the task of grouping a set of objects in such a way that objects in the same group (called a cluster) are more similar (having similar attribute values) to each other than to those in other groups (clusters). The objective of clustering is to track common patterns, group similar objects or to organize them in hierarchies. It is a main task of data mining and a common technique for statistical data analysis used in many fields (machine learning, pattern recognition, etc.).

There are various clustering algorithms but we have used simple K-means together with some of the metrics presented in the previous section to obtain insights on learner viewing behaviors. K-means is probably the most popular cluster analysis method. It is a centroid based method that aims to partition n observations into k clusters in which each observation belongs to the cluster with the nearest mean. K-means produces k non-overlapping clusters. The only problem with k-means is that k (the number of clusters) has to be determined in advance. One way to determine the optimum number of clusters is by using the "within sum of squared error SSE" a useful measure for assessing clustering results. For each observation, the error is the distance to the nearest cluster. To get SSE, we square these errors and sum them up. More specifically to obtain the optimum k, we start from one cluster and continue adding clusters until diminishing returns are achieved, meaning no significant reduction in within SSE. Another important parameter in accepting the resulting clusters is that we should be able to interpret them.

The software used for the data mining tasks in this paper is WEKA [17], a known open source data mining software that provides a broad collection of machine learning algorithms for data mining tasks.

A. Learner Engagement

The dataset used for obtaining the metrics and performing the cluster analysis was gathered (as mentioned in section III) in the winter semesters of 2012-2013 and 2013-2014 for the course "Introduction to Computers" and the spring semester of 2012-2013 for the course "Communication Technologies".

To gain insight into learner engagement, we decided to perform clustering to the whole dataset gathered in these semesters. The data set consists of 350 learners for which we obtained the metrics mentioned in column "attribute" of Table 1.

TABLE I. LEARNER CLUSTERS

Number of iterations: 22, Within cluster sum of squared errors: 15.92						
Attribute	**Full Data (350)**	**Cluster 0 (26-7%)**	**Cluster 1 (71-20%)**	**Cluster 2 (84-24%)**	**Cluster 3 (29-8%)**	**Cluster 4 (140-40%)**
Percent of linear videos watched by the learner	37.4	22.7	73.9	44.7	79.4	8.5
Percent of Interactive elements performed by the learner	16.5	73.5	7.1	6.3	78.3	3.8
Number of days that the viewings took place	3.6	3.8	6.2	3.1	5.9	2
Number of actions Performed	49.2	16.7	139.2	26.8	115.6	9.3

The "Percent of videos watched by the learner" metric was obtained only for linear videos and we used the "Percent of interactive elements performed by the learner" metric to measure learner engagement for interactive videos. The clusters revealed from the clustering scheme are listed in the table above.

By examining the clustering scheme in Table 1, we see that there are three clusters of increasing percentage of activity for both linear and interactive videos where the activity concerning linear videos is larger (and significantly larger) than the activity concerning the interactive videos (Clusters 4,2,1). In these clusters learners clearly decided to use linear videos and more or less ignored the interactive videos. One possible explanation for this behaviour is that learners did not have time to engage in interactive procedures since most of them decided to make use of the videos only a few days before the exam. The analysis revealed that almost half of the viewings took place only a week before the exam. Another possible explanation for the limited usage of interactive videos, at least by some learners, is their preference to engage with other similar interactive procedures instead. There was a number of students who used the taught software package (e.g., Dreamweaver) in parallel to watching a video in order to replicate the steps in the video, and this was confirmed by a survey the analysis of which is beyond the scope of this paper.

Continuing, we have a small cluster (Cluster 3) where learners gave almost equal emphasis to linear and interactive videos with a high mean value for both. Finally the smallest cluster (Cluster 0) contains learners who gave emphasis mainly to interactive lessons and preferred to follow a more interactive way of learning.

The values for the number of days and number of actions performed do not produce results which can be interpreted with safety.

A visual representation of the clusters is given below in Figure 3:

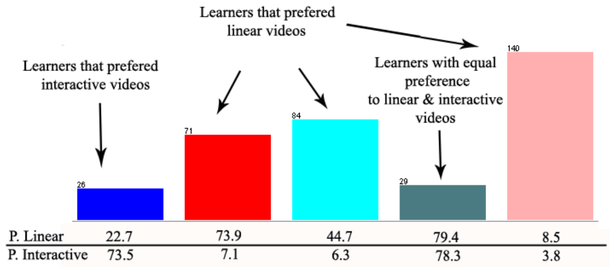

Figure 3. Learner clusters

When projecting these clusters to the 0-10 scale of marks obtained by the learners (Figure 4), we can not associate the level of engagement to the marks obtained. Most clusters seem to be equally or proportionally represented in the continuous scale of marks. However, although no correlation is revealed we have to keep in mind that in our setting the educational videos serve as a supportive material and are not the only source of acquiring the necessary knowledge since the topics are covered in class as well. The case may be different if the experiment was carried out in a setting where video is the main or only source of acquiring the necessary knowledge like it is in a MOOC environment (e.g., Coursera, Edx).

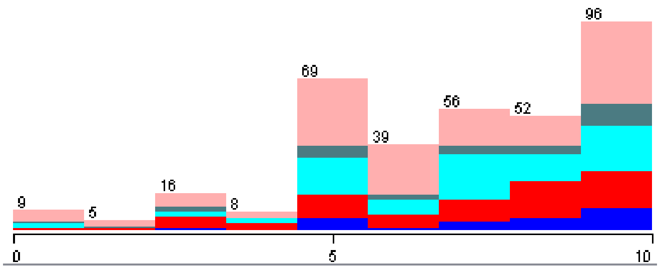

Figure 4. Projecting clusters on the marks (0-10 scale) obtained by learners

B. Video Popularity

The next step was to use clustering to obtain insights into video popularity. The clusters formed for the videos of both courses are presented below:

TABLE II. CLUSTERING VIDEOS

Videos for the course “Communication Technologies” **Number of iterations: 2** **Within cluster sum of squared errors: 4.00**			
Attribute	**Full Data (42)**	**Cluster 0 (20-48%)**	**Cluster 1 (22-52%)**
Times started	144.8333	227.35	69.8182
Times abandoned	23.7857	37.45	11.3636
Number of learners	75.1429	107	46.1818
Actions per video	112.9286	199.5	34.2273

TABLE III. CLUSTERING VIDEOS

Videos for the course “Introduction to Computers” **Number of iterations: 3** **Within cluster sum of squared errors: 4.08**			
Attribute	**Full Data (48)**	**Cluster 0 (28-58%)**	**Cluster 1 (20-42%)**
Times started	111.9167	146.8214	63.05
Times abandoned	40.4375	58.3214	15.4
Number of learners	61.5	79.8571	35.8
Actions per video	303.75	467.8929	73.95

The clustering scheme above differentiates videos of high interest (i.e., Cluster 0, videos that received many visits and actions) from videos of low interest (i.e., Cluster 1, videos that received far less visits and actions). The “Times abandoned”, “Number of learners”, and “Actions per video” metrics increase as the number of video viewings increase and seem to be dependent.

What is not obvious from the tables is that the clustering scheme revealed that interactive videos all fall in the second cluster (Cluster 1) meaning that interactive videos failed to attract learners. The second cluster also contained a few linear videos that covered topics of low difficulty or topics excluded from the examination syllabus.

C. Clustering viewing Sessions

Researchers who focused on the behaviour of learners while watching educational videos or listening to educational audios have distinguished various viewing or listening styles.

De Boer, Kommers, & de Brock [9] noted four distinct styles of viewing behaviour: (a) linear (watching a complete video once), (b) elaborative (watching a complete video twice), (c) maintenance rehearsal (watching part of a video repeatedly), and, (d) zapping (skipping through video and watching brief segments). They also noted that viewing style is not constant and appears to shift based on the cognitive needs of the user.

Moran et al. [12] dealt with listening profiles from students that listened educational audios. They recorded listening profiles that portray different salvaging activity. They noted five profiles: (a) Straight-Through (listening to an audio file sequentially), (b) Stop-Start (performing a number of pauses and resumes from the same point at a number of points in the audio track), (c) Re-listen (stopping and going back at specific points to re-listen portions of the audio), (d) Skip ahead (pausing and moving forward, skipping portions of the audio), and, (e) Non sequential (going back and forth and listening to portions of the audio). One can clearly see that there are similarities between the viewing and listening styles recorded by the researchers.

In a previous paper [11], we observed that traces of the styles presented by these researches are present in our dataset as well. We tracked these traces by observing the video and section sequence graphs generated by our framework and carried out a data processing procedure to reveal dominant viewing patterns. The same patterns are again revealed in this experiment only this time a different method is used, that of cluster analysis.

In [11] and in this paper every viewing is classified in one of the following classes: (a) linear viewing (or straight-through) with no intermediate actions, (b) linear viewing that was abandoned (less than 60% of the sections were visited), (c) non sequential viewing (with one or more intermediate actions), and, (d) non sequential viewing that was abandoned. The type and number of actions were also recorded for non sequential viewings. There are three types of actions all performed by using the pause and resume button on the video player as well as the slide bar. The actions are: (a) pause-resume, i.e., pausing and resuming from the same point in the video time line, (b) backward jump, i.e., pausing and using the slide bar to go back in the time line in order to view a certain part of the video again, and, (c) forward jump (or skipping) i.e., pausing the video and using the slide bar to jump to a point ahead in the time line. We also set a threshold in the number of frames jumped in order to define backward jumps and forward jumps. Very small jumps (<150 frames) were counted as stop-resume actions.

Clustering was then applied on the dataset consisting of all the linear video viewings from both courses. The analysis was confined to linear videos and the results obtained are shown in Table IV:

TABLE IV. CLUSTERING VIEWING PATTERNS

Viewings from courses "Introduction to Computers" & "Communication Technologies" Number of iterations: 16 Within cluster sum of squared errors: 29.69					
Attribute	Full Data (9403)	Cluster 0 414- 4%	Cluster 1 3998- 43%	Cluster 2 88- 1%	Cluster 3 1176- 13%
sequential_view	0.6062	0	1	0	0
forward_jump	0.3615	2.529	0	0.6932	0.108
backward_jump	0.4298	1.0531	0	5.125	1.8206
stop_resume	1.1362	2.6667	0	32	2.4039
drop_out	0.2737	0	0	0	0

Clusters continued….				
Attribute	Cluster 4 872- 9%	Cluster 5 135- 1%	Cluster 6 1018- 11%	Cluster 7 1702- 18%
sequential_view	0	0	0	1
forward_jump	0.9805	6	0.4902	0
backward_jump	0.531	2.4889	0.2102	0
stop_resume	1.2901	4.5778	2.1552	0
drop_out	1	0	0	1

From the clustering scheme, we can see that sequential view is the dominant style of viewing videos. Cluster 1 consists only of sequential viewings and contains 43% of the viewings. The second larger cluster formed (Cluster 7) is a cluster containing 18% of the video viewings and consists of sequential viewings which were abandoned (dropout) at some point. By dropout, we mean that less than 60% of the video was viewed. We used 60 as the default threshold value in our experiment but this can be adjusted as desired. Then, we have Cluster 3 that contains 13% of the viewing sessions consisting of non sequential viewings. Stop-resume actions (stopping and resuming from the same point) are the most frequent actions detected in viewing sessions of this cluster and backward jumps have a significantly larger mean value when compared to forward jumps. Then, we have Cluster 6 containing 11% of the viewings where stop-resume is again the dominant action followed this time by forward jumps (skipping).

In our setting, sequential views formed a cluster that contained almost half of the views. One reason for this may be that videos were easy for the learners to understand and this caused less media actions such as pausing and going back in the timeline to view a part that was not understood. As observed in our previous work [11], in a survey conducted, the majority of learners stated that that they found the quality of videos very good. Moreover, videos were used for revision purposes since almost half of the viewings took place only a week before the exams. It is probable that learners did not have the time to engage in more interactive ways of learning such as pausing the video at various points in the timeline to perform the taught actions in the software (Dreamweaver, Microsoft Word & Excel).

Another reason may be that besides being clear and easy to understand the videos had also short duration. As mentioned in section III, the videos used in this experiment are short demonstration videos but longer videos are frequently used for educational purposes, such as lecture recordings. Longer videos can cause different behaviours such as more frequent forward jumps (skipping) as well as more dropouts as the authors of [18] observed. The authors of [18] provide evidence that shorter videos are more engaging causing less dropouts.

Another important factor that may affect the viewing behaviours is the number of available methods for accessing video segments provided by the interface. In our setting the only means for performing media actions is the pause, play buttons and the slide bar in the video player. There are however environments that provide a variety of methods for getting to different points in the video timeline, such as a table of contents, which is pretty similar to the table of contents in a book. The variety in the accessing methods provided by an interface can cause more media actions and therefore more viewings which are not sequential.

It has to be noted that what is being examined here is viewing sessions. A general trend is that learners adopt different viewing behaviours from viewing session to viewing session and we observed this after projecting the clusters to individual learners. For example, a learner can view one video linearly without any actions, and, then, view the next one by performing a number of stop and resume actions. More investigation, however, needs to be carried out to identify reasons that cause different viewing behaviours.

D. Association Rules

Besides clustering, association rule mining is a data mining method that can be used to investigate learner behaviors in e-learning environments. The patterns and rules discovered by this method are based on the majority of commonly repeated items in the dataset.

We used WEKA and the Apriori algorithm in an attempt to find out which videos are often viewed together in viewer sessions. The term session here indicates the period starting from learner login. At that point a session id is attached to the learner and all videos viewed from that point onward belong to the same session. When the learner closes the browser window, a new login will be needed in order to get to the webpage containing the links to the educational videos and a new session will be started.

Apriori revealed that there are strong associations between certain videos that tend to be viewed together within sessions. For example, for the course "Communication Technologies", we obtained a set of rules from which the first three are listed in Table V. The results imply that there is a strong association between the occurrences of the listed videos. Videos 13, 14 and 15 occur together within a session very often. In the authors' view these videos besides being consecutive also covered topics that students had most difficulty learning when taught in lab sessions.

TABLE V. ASSOCIATION RULES

Rule	Confidence
video13=1 video14=1 (123) ==> video15=1 (111)	0.9
video14=1 (198) ==> video15=1 (176)	0.89
video17=1 (158) ==> video16=1 (140)	0.89

VI. CONCLUSIONS

This paper briefly reviews a framework for recording and analyzing video viewing behaviors while watching and interacting with online educational videos. The framework was used in educational settings to obtain a dataset of viewing behaviors and this dataset was used in a previous paper [11] to obtain some first insights into learner behaviors.

In this paper, the task of analyzing viewing behaviors went one step further by introducing a set of metrics to measure learner engagement and video popularity and by deploying cluster analysis to get more insights. In particular, cluster analysis was used to find groups of learners with similar indicators regarding their engagement on linear and interactive videos, groups of videos with similar values regarding their usage by learners, and groups of similar viewing patterns. An attempt was also made to give possible explanations for the outomes of the analysis.

More specifically, and with respect to learner engagement, the analysis revealed three clusters of learners with clear preference in linear videos but with different levels of engagement, a smaller cluster of learners which gave equal emphasis to linear and interactive videos and an even smaller cluster of learners who preferred a more interactive way of learning, by attempting mainly interactive videos. The analysis showed no association between the clusters and the learner performance (i.e., final mark obtained from assignments and final exam) but we have to take into account that the videos in our setting are not the only source of acquiring the necessary knowledge since the same topics are also taught in lab hours.

The cluster analysis on the video popularity metrics revealed two clusters of videos (for both taught courses) differentiating videos of high interest from videos of low interest. Interactive videos all fell in the second cluster meaning that interactive videos failed to attract learners. Association rule mining was used to reveal videos that were most frequently viewed together within sessions. These were consecutive videos that covered topics that learners had most difficulty learning when taught in lab sessions.

The analysis also revealed clusters of different viewing patterns. Sequential viewings formed the largest cluster followed by sequential viewings that were dropped out. A cluster containing non sequential viewings with mostly stop resume actions and backward jumps was the third bigger cluster. Some factors that may have caused these behaviours were discussed. More investigation, however, needs to be carried out to identify reasons that cause different viewing behaviours.

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