VisMOOC: Visualizing Video Clickstream Data from Massive Open Online Courses

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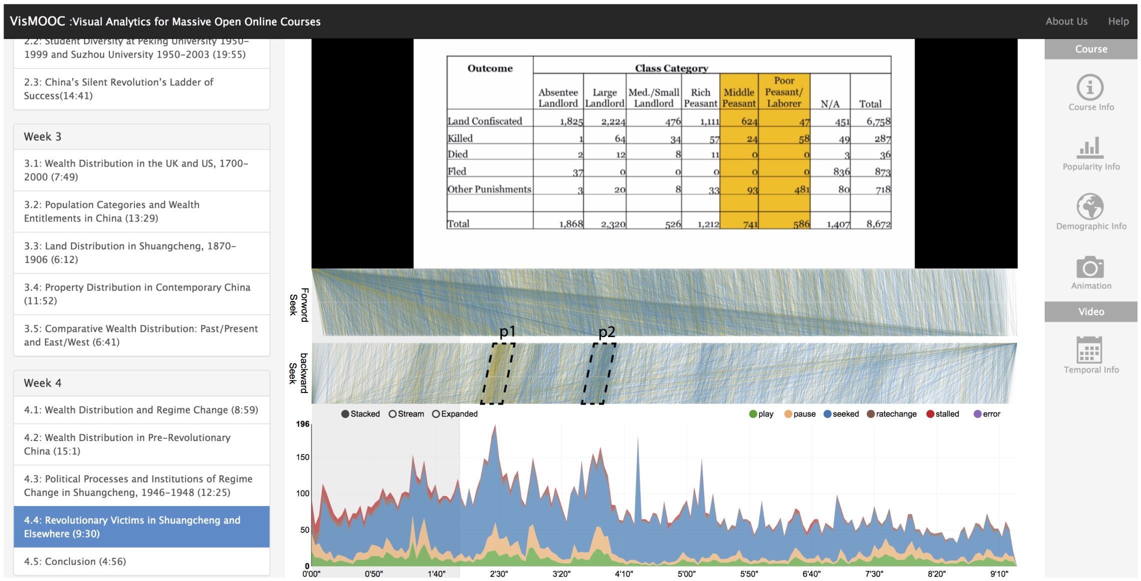

Figure 1: A screenshot of VisMOOC. It consists of three views: the List View on the left, the Content-based View (including the video player, the seek graph and the event graph) in the middle, and the Dashboard View on the right. The Dashboard View includes the course information, the geographic distribution, the video temporal information, the video popularity, and the animation.

ABSTRACT

Massive Open Online Courses (MOOCs) platforms are becoming increasingly popular in recent years. With thousands of students watching course videos, enormous amounts of clickstream data are produced and recorded by the MOOCs platforms for each course. Such large-scale data provide a great opportunity for instructors and educational analysts to gain insight into online learning behaviors on an unprecedented scale. Nevertheless, the growing scale and unique characteristics of the data also pose a special challenge for effective data analysis. In this paper, we introduce VisMOOC, a visual analytic system to help analyze user learning behaviors by using video clickstream data from MOOC platforms. We work closely with the instructors of two Coursera courses to understand the data and collect task analysis requirements. A complete user-centered design process is further employed to design and develop VisMOOC. It includes three main linked views: the List View to show an overview of the clickstream differences among course videos, the Content-based View to show temporal variations in the total number of each type of click action along the video timeline, the Dashboard View to show various statistical information such as demographic information and temporal information. We conduct two case studies with the instructors to demonstrate the usefulness of VisMOOC and discuss new findings on learning behaviors.

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IEEE Pacific Visualization Symposium 2015
14–17 April, Hangzhou, China
978-1-4673-6878-0/15/$31.00 ©2015 IEEE

1 INTRODUCTION

Massive Open Online Courses (MOOCs), which aims at unlimited participation and open access to education, have attracted considerable public attention in the last few years [18, 21]. More than 1000 online courses have been released from three major MOOCs platforms (edX, Coursera and Udacity) and the total number of registrants has reached 10 millions [21]. Many educators believe that MOOCs will even reshape the higher education forever.

Although MOOCs provide a large number of uses with open access to education via the Internet, MOOC platforms usually do not allow face-to-face interactions between teachers and students. Therefore, teachers are not able to directly observe the reactions of the participating students. This issue poses a big challenge for teachers to understand students' learning behaviors and improve their teaching accordingly. Fortunately, the advanced technologies adopted by MOOCs make it possible to acquire huge amounts of data, such as student profiles, video viewing histories, click streams within the lecture videos (e.g., playing, seeking, and pausing), posts in the course forum, surveys, and even the video content. The gathered data provide a good opportunity for educational researchers to detect and analyze students' learning behaviors [4].

Numerous statistical studies have been conducted to analyze the MOOCs data from different aspects and provide valuable insight into the learner behaviors in MOOCs [4, 11, 24, 29]. Recent research reveals that the students of MOOCs spend the majority of their time on watching lecture videos [4, 24], whereas other interactive course components, such as the online forum [14], are usually ignored. Therefore, it is important for instructors to understand how the learners behave on watching videos so that they can revise course materials to better fit for student interest and to attract more students. Another recent empirical study of MOOC videos has been conducted to examine which factors of the video production affect students' engagement, which leads to a set of general recommendations [9]. Large-scale analysis of click streams for the lecture videos has also been reported in a recent study [13]. This study provides interesting insight into dropouts and interaction peaks in the videos.

Nevertheless, it is still difficult for instructors to adopt the general guidelines (e.g., making the video as short as 6 minutes long) suggested by previous studies [9] to their lecture videos especially if they have already made the videos. When we interviewed with some instructors of MOOCs, they commented that it was hard to revise their existing videos according to the guidelines, because it costs too much time on reviewing all the videos without any guidance on which parts are good and which parts should be revised. An interactive visualization system that enables quick detection and analysis of students' learning behaviors is greatly demanded by the instructors.

Designing such a visualization system is non-trivial. The major challenge is that the end users, instructors and educational analysts, are not familiar with the collected log data. Also, most of them do not have strong background on data analysis. Thus, although they need a tool to help them understand user learning behavior, they hardly know what they can observe from the data and the specific design goal for the system.

In this design study, we collaborate with five experts, four of whom are instructors offering courses on Coursera and one educational analyst, to iteratively design VisMOOC, a visual analytic system to help them understand online learning behaviors and improve the quality of their MOOC videos in the future.

Guided by the collaborative nine-stage design study methodology framework [25], we began with a literature review of the state-of-art research on MOOC analysis to understand current practices and challenges. After that, we helped our collaborators explore the video clickstream data so that they can have a better understanding about how the data can help analyze learning behavior. The analysis tasks then have been abstracted. We followed a user-centered process to develop the system, which lasted for 7 months. Finally, we released an online version of VisMOOC and two case studies were conducted, which further proved the effectiveness and usefulness of the system.

To the best of our knowledge, our study is the first to propose such a visual analytic system for domain experts to combine content-based analysis with video clickstream data of massive online open courses, and we summarize our contributions as:

- We characterized the analytic tasks of MOOC clickstream data based on thorough literature review and the discussion domain experts. After that, we proposed the corresponding design requirement accordingly.
- We designed and developed VisMOOC[1], an interactive visual analytic system that helps analysts understand learning behaviors of MOOC learners.
- We conducted case studies that provide new insight into learning behaviors of e-learners.

2 Related Work

In this section, we first review current behavior analysis on online education. After that, we specifically discuss some existing research on video watching behavior analysis. Finally, we present several existing clickstream visualizations.

2.1 Online Education Analysis

There have been a lot of work targeting on analyzing online learning behavior. Both statistics and basic visualizations have been widely used to help educational analysts and course instructors analyze students e-learning behaviors [23]. The main goals of these studies can be classified into several categories:

- Student access and activity patterns: the number of visits and the duration per visit, patterns of active periods over time [19, 20]; student access locations (demographic information)[20] and its relations with learning styles [10, 33];
- Forum interaction: statistical analysis on student interactions in forum [22]; social network visualization in online learning groups [2, 20]; community relationship in peer-to-peer systems [23]; patterns of time-varied forum activeness [5];
- Student performance: including grades on assignments and exams [27]; peer evaluation.

Also, some visualization tools and systems have been developed [3]. These systems not only provide multiple innovative visual representations along with basic charts, such as directional and non-directional node graphs and timeline spiral graphs, but also allow users to interact with the graphs based on their specific goals.

CourseVis [16] is a course management system which aims to help instructors become aware of social, behavioral and cognitive aspects of e-learners. Visualizations such as a three dimensional scatter plot are used to present student web log data. Also, they have evaluated the tool in terms of efficiency, effectiveness, and usefulness based on user performance and feedback from interviews. However, it could neither allow changes to student data to be made from the graphics nor handle the scale of MOOCs.

E-learning tracking [10] demonstrates a set of (loosely coupled) visualization tools that help display and analyze students interaction with online courseware. They mainly focus on student access of the course material, and the navigation path that a student follows throughout the course. All the separate graphs can be filtered by either individual students or selected groups. SST [1] presents an interactive visual tool to visualize student temporal activity pattern. A timeline spiral graph with other two inter-linked supporting panels provides better chances of understanding. There are also other visualization tools such as GISMO [17, 7] for dotLRN and PDinamet, WebCT [8] with tabular student views and course narrative analyzer [33]. While prior studies provide specific information about online education from various aspects, most of them only use separate basic visual representations, and hardly any have focused on videos. However, all these works provide us the motivation for this work.

2.2 User behavior analysis in videos

Apart from basic pageview and forum information, MOOC platforms such as edX and Coursera also keep track of student interaction data at a higher level. For example, the various "click" actions (e.g. "play", "pause", "seek") used while watching course videos. Researchers have been studying user behavior in video streaming for decades before MOOCs. However, very little work has been done to visualize the video interaction data of massive open online courses and combine it with content-based analysis [9].

Video engagement analysis research includes implicit and explicit user data analysis, as well as content analysis [9]. Most video interaction analysis (e.g. "play" and "pause" activities [6]) and content-based video analysis (e.g. saliency detection [12]) are not specially designed for e-learning lecture videos. CLAS [22] is a collaborative video annotation tool based on explicit user data by recording user clicks around points they are interested in.

Lately, a series of MOOC analysis systems have been proposed to analyze in-video dropouts and interaction peaks in lecture videos [9], video production styles with student engagement [13], and student demographic differences in navigation behavior[9]. However, they have not conducted an expert review or implemented multiple interactions, therefore instructors and educators are unable to do further analysis based on their domain knowledge and experience.

[1] http://vis.cse.ust.hk/vismooc

Table 1: Overview of the courses information

Course	#Events	#Videos	#Watchers	#Forum Users	$\frac{\#Watchers}{\#ForumUsers}$	Video Avg. Len.	Video Max. Len.	Video Min. Len.
CH	1204947	17	11061	1152	10.41%	11:33	20:27	3:37
GT	5881090	103	37134	3761	10.13%	7:39	17:41	1:08

2.3 Clickstream Visualization

Existing research on clickstream visualization covers many areas. Some tools target user browsing behavior [15, 28] and online shopping click sequence [32], while others concentrate more on interaction of users with videos [3, 26].

Some of the research on webpage viewing behavior has already been presented in the sections above. Nevertheless, the tools discussed in this session give more information on the transition of page browsing and click sequence. [28] used horizontal stacked bar to visualize a sorted list of web sessions after aggregation. [32] explored visual clusters of web clickstream data through an intuitive user interface. Analysts are able to extract user behavior patterns based on the original overview of clickstream clusters and intuitive grouping. Among all those visual analysis systems for clickstream, very few can be implemented for large-scale interaction data from MOOCs [9]. At the same time, our clickstream data such as "seek" actions contain specific time sequence information which can reveal more information on student learning behavior. We also build and evaluate our system based on the feedback from the domain experts.

3 Problem Characterization

In this section, we first describe the characteristics of clickstream data and preprocessing methods. After that, we discuss about the abstraction of analytics tasks together with five experts, four instructors from two Coursera courses offered by our university and one educational analyst. Accordingly, design principles are proposed.

3.1 Data Description and Task Analysis

We obtained the user log data of the two courses (denoted by *CH* and *GT*) offered by our university from Coursera. The log data consist of three parts: the video clickstream data recording user interactions with course video; the forum data containing user posting information in course forums; and the user grading data. Table 1 shows some basic statistics of the two courses. We can see that only about 10% learners used the forums offered by the courses, which confirms that usually learners spend majority of their time on watching videos [4, 24]. Due to the limited amount of forum data, we finally decided to focus on the analysis of clickstream data. The clickstream data contain all the events triggered by users or systems in each course video. Each data entry comprises *[user ID]*, *[timestamp]*, *[in-video position]*, *[event type]*. There are six event types: "*play*", "*pause*", "*seek*", "*stalled*", "*error*", and "*ratechange*". For "*seek*" events, there is another field *[original in-video position]*. Table 2 shows the definition of different events as well as the percentage of the events in each course.

Our task analysis is based on a survey of existing work about analyzing learner behavior on MOOCs platforms and also feedback from the experts. From the survey, we collected a list of potential tasks the experts might be interested in. As the five experts were not familiar with the clickstream data, during the interview, we first gave a short introduction about the clickstream data and used simple visualizations (e.g., bar charts and stacked graphs) to show the sample data, which helped them understand different aspects of the data. This initial stage can help our collaborators connect their needs with the data, so that they can better formulate the tasks that can possibly be solved by analyzing the clickstream data.

Table 2: Explanation and statistics of different event in course videos

Type	Meaning	% (CH)	% (GT)
play	Users clicked the play button. When the video is loaded at the first time, it will play automatically and a play event will be recorded.	21.3%	26.6%
pause	Users clicked the pause button. When a video is over, a pause event will be recorded.	16.8%	21.0%
seek	Users dragged the video from one time point to another time point.	42.3%	25.7%
stalled	The video is stalled due to buffering.	11.8%	17.1%
ratechange	Users changed the playback rate.	7.2%	8.9%
error	Errors occurred.	0.6%	0.7%

The details description of all the tasks are as follows:

T.1 **What is the overall statistics of clickstream data?** Unlike traditional face-to-face education, instructors have no idea about the background of students and how they react to the course content. Overall statistics offer them basic knowledge about learners information and their clickstream distribution. Moreover, the overview can also provide guidance on filtering out irrelevant parts. More specifically, they want to know the demographics of the learners and the popularity (i.e., the number of people have watched the video) of the course videos.

T.2 **In each video, which parts are more interesting to research?** Real-time interaction between instructors and students is a big advantage for face-to-face education. In order to exploit similar information and further interpret student actions, the experts want to know how the online learners interact with a particular video. For example, they want to know which types of events happened at some particular position of a video.

T.3 **What are the differences of viewing behaviors between different user groups?** Both the previous research [11] and interview with the experts show that it would be interesting to study how different user groups behave when watching course videos. For example, instructors are especially interested in the differences between the learners from different countries. They want to compare and analyze how students from different areas react to the same course materials.

T.4 **How do the learning behaviors change over time?** For a single video, students may have different learning motivations over time. For example, besides spending more time on the most difficult parts when they watch for the first time, students would probably focus on more specific parts related to assignments or exams when they watch the videos again later. Accordingly, instructors also want to know exactly where the differences are so that they can

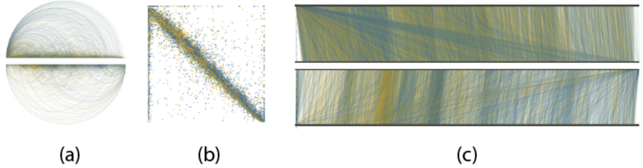

Figure 2: Comparison among three design candidates: (a) arc diagram; (b) scatter plots; (c) parallel coordinates. Blue color encodes the seek event happened when learners watched the video for the first time, while orange color encodes the seek event happened when learners reviewed the video.

adapt course materials and instructions to timely intervene in student learning process. Moreover, as time can be naturally viewed in multiple scales, such as by month, by week, and by day, the experts are also interested in analyzing how the learning behaviors change in different time scales.

T.5 **What other factors can affect the user viewing behaviors?** User viewing behaviors can also be influenced by other factors, such as the content of videos, the length of videos, the release time of videos, and the number of videos released in one week.

3.2 Design Requirement

According to the tasks we want to address, design requirements are then presented as follows:

R.1 **Simple visual design** According to [34], educators prefer simple visualizations, and they can quickly understand the underlying stories and make decisions. This fact is also confirmed by our collaborators.

R.2 **Video-embedded design** The content in the video can help instructors understand the patterns found in the clickstream data. During the first interview, all the experts pointed out that in most cases, they couldn't understand the patterns found in the clickstream data alone without course videos. When they saw some patterns, they had to open the course video files and jump to the corresponding points to understand why such patterns happened. Therefore, for the visualizations that are associated with the position in the video, it should be aligned with video content (task T.2 and task T.5). In addition, for the accuracy issue, they pointed out the events should be aligned with the video by second.

R.3 **Multi-level-scale exploration** It is important to understand the learning behaviors in different scales, including the time scales (task T.4) and the learners scales (task T.3). Therefore, some visualizations and interaction techniques that can help instructors explore the data in different scales are needed.

R.4 **Multi-perspective exploration** Understanding the learning behaviors from different perspectives is also important according to task T.1 and task T.5. Thus our system needs to provide multiple coordinated views with each view encoding information from a unique perspective.

4 VisMOOC Design

Before running VisMOOC, the raw data from Coursera will be first preprocessed, including data cleaning and calculation. After that, VisMOOC can perform interactively. Users can select videos in the *List View* which lists all the video titles ordered by released weeks and the detailed information will be shown in the *Content-based View*. The *Dashboard View* can be used to filter users due to different criteria, such as geographic information and time period.

4.1 Content-based View

In the *Content-based View*, analysts are allowed to analyze the clickstreams aligned with the video. In this view, two visualizations are used to encode different types of information.

4.1.1 Event Graph

The event graph shows the distribution of events on a video as required by task T.2. According to the interview with the experts, they want to see the number of different types of events as well as the total number of events happened at different positions in a video. We construct second-by-second counts for the six types of events. There are six types of events and we want to see the number of individual events as well as the total number of events over time. In this case, a stacked graph is a simple but effective (R.1) visualization that can be used to show the information. Colors are to encode event types, and the height is to encode the number of events.

4.1.2 Seek Graph

When collaborating with the experts, we first help them freely explore the clickstream data from different aspects. Among the six types of events, they found that seek events particularly can be good indicators of learners' interest. For example, when a forward seek event happened (i.e., seeking from an earlier time point to a later time point), some content in the video are skipped, which means learners pay less attention on the contents; when a backward seek event happened (i.e., seeking from a later time point to a earlier time point), some contents in the video will likely be watched again, which means that learners pay more attention to the contents.

A seek event can be denoted as (t_i, t_j), where t_i is the starting position and t_j is the ending position in the videos. We use the arc diagram, which is widely used to show the referenced relation in one-dimensional axis [31], to show the seek events (Figure 2(a)). The horizontal axis represents the length of the video. We draw an arc from t_i to t_j for the seek event (t_i, t_j). Because forward seek events and backward seek events indicate opposite behaviors, we separately draw the forward seeks and backward seeks on different spheres. The upper part shows the forward seeks and the lower part shows the backward seeks.

By exploring the data, we find that most of the seek events are over a short distance. However, in the arc diagram, less ink ratios will be used for the short-distance seeks. To make it worse, it suffers a lot on the visual cluster problem since start points and end points of arcs are mixed together in one axis.

To reduce the visual clutter problem, one natural way is to draw the starting point and ending point on two different axes. Therefore, we proposed two visual designs: a scatter plot design with two orthogonal axises (Figure.2(b)), and a parallel coordinate design with two parallel axis (Figure 2(c)).

In the scatter plot (Figure 2(b)), both the horizontal axis and vertical axis represents the length of the video. The horizontal position shows where the seek event starts while the vertical position shows where the seek event jumps to. The seek event will then be mapped to one point in 2D space. However, it will be hard to trace the start point and the end point. In the parallel coordinate view (Figure 2(c)), we also separately draw the forward seek and backward seek events.

Unlike the scatter plot, we use two parallel axes to encode the starting position and the ending position of seeks (Figure 2(c)). A line is drawn between two axes to connect the starting and ending positions together for each seek event. Compared with the other two designs, the parallel coordinate alike design avoids the disadvantages mentioned above and in practice works well in our case. The interview with the experts also confirmed the choice. They all agree that the parallel coordinate design is easy to understand and shows the information more effectively.

Furthermore, a seek event can happen when learners watch the video for the first time or when they review the video. The experts are interested in if there are differences between the seeking behavior when watching for the first time or when reviewing it (Task T.4). Therefore, we use different colors to encode the learners event happened on first watching (blue) or watching again (orange).

In order to further reduce visual clutter problem, we render the lines using adaptive transparency[1], which is a widely used technique to solve the visual clutter problem in parallel coordinates to make the overlaps more visible.

4.2 Dashboard View

In the *Dashboard View*, analysts can see several statistics in different tabs. As required by task T.1 and T.5, we choose several well known visualizations to show the information. We choose a calender visualization 5 to show the daily popularity of one video, which can be used to better inspect the periodical pattern [30]. We choose a bar chart to show the overall video popularity. Also, we use a simple animation to show the temporal information of all the clickstream data, which could give users a general idea about how the clickstream happened over time shown in Figure 8. Each line represents a video and the length of the line represents the video length. Each circle dot on lines represents a clickstream event. We use the same color encoding as the event graph design. We randomly sampled clickstream from 1000 learners and play back the events at fast speed so that the animation can be watched within manageable time.

4.3 View Coordination

The interaction between the views is carefully designed to support the exploration of the clickstream data from different aspects and at different levels of detail. Selecting&Filtering and Highlighting are the two major operations in VisMOOC.

According to task T.3, analysts are interested in exploring the differences between different user groups. Therefore, in the *Dashboard View*, all the visualizations support the selection of some particular groups. For example, in the demographic chart, we can select learners from particular countries. The union operation and intersection operation are naturally supported to further filter the interested group of users. According to task T.4, analysts are interested in exploring the dynamics of learning behaviors overtime. Thus, in the *Dashboard View*, analysts are allowed to select a particular time range. Learners Selection and Time Range Selection can be done at the same time. Highlight operations allow analysts to connect the same information in different views together to give the analysts a visual hint.

5 Case Studies

To demonstrate the usefulness and effectiveness of our system, We invited the instructors to analyze the clickstream data for their own courses. We use a PC with 2.7GHz Intel Core i7 CPU with 8GB memory as data server and web server, and conduct the experiments in the Chrome Web browser which is common in laptops. After data preprocessing, the system can perform interactively. During the analyzing processing, we encouraged them to explain the underlying reason for the patterns they found and they were freely to refer any course materials they used during teaching. We then summarize the major findings and the insights accordingly.

5.1 Overall Statistics

The overall statistics give the experts a first impression of the data, including the demographic and popularity distributions of course videos. The results for the two courses are shown in Figure 3. From the histogram, we can see that for both courses, the number of viewers stabilized after the first two weeks, which is different from the conclusion in [11]. From the demographic distribution in Figure 4, we can see that the majority of learners are from the U.S, while all the learners originate from more than 150 countries. These two visualizations are also used by the experts to filter or select some particular groups of users.

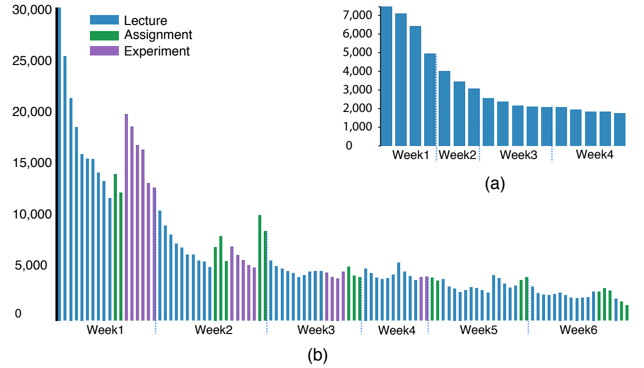

Figure 3: The histogram shows the popularity of videos. The color encodes the video type and height encodes the number of learners. We can see that the popularity becomes stable after two weeks for both courses.

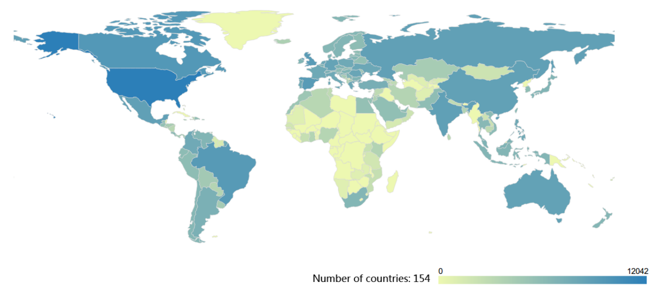

Figure 4: A world map show the distribution of learners around the world for the Course *GT*. We can see that the majority of learners are from the U.S, while all the learners are from more than 150 countries.

5.2 Content-based Analysis

The *Content-based View* is the center component of VisMOOC. It allows the experts to analyze the clickstream data together with the content of the video, so that they can better understand the patterns found from the data.

The experts can freely choose the video they are interested in from the *List View* and the details shown in *Content-based View* can clearly indicate the difference between the videos, including the lengths of videos, and the events distribution within the videos. Course *GT* has three different types of videos: lecture videos, assignment videos, and experiment videos. We can clearly see the differences between different types of videos. In Figure 6(a,b,c), the typical shapes of the event distribution for different types of videos are shown. We also observed another interesting distribution of the events shown in Figure 6(d). In general, in the lecture videos, several peaks can be observed and in most cases the peaks are caused by an increase in play/pause events. By exploring the peak positions within the video content, we can observe that most of the peaks happened when the

Figure 5: The calendar view shows the temporal popularity for the selected video. We can see that there are two weeks with a lot of acitons.

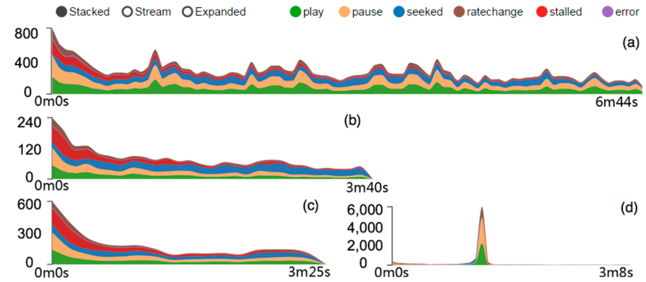

Figure 6: Event graphs show the distribution of different clickstreams in different types of videos in Course *GT*: a) the lecture video; b) the assignment video; c) the experiment video; d) the experiment video with an in-video question.

video content switches to a slide. Furthermore, the height of the peak is highly related to how many words there are in the slide. This pattern indicates that usually learners like pausing a video when they see some slides. This also confirms the findings in [13].

For the experiment and assignment videos, we hardly observe any similar peaks to those in the lecture videos. One instructor commented that "Unlike the lecture videos, there are almost no PPT presentations or other text presentations"

In the fourth stacked graph, the abnormal peak is later confirmed by the instructors as caused by an in-video question. In Coursera, instructors are allowed to plug in some questions at some point in the video. When learners watch the video at that position, a pause action will automatically be triggered.

5.2.1 Seek Graph Analysis

Seek graphs can further help instrutors understand leaners proactive information seeking behavior on watching videos. From the seek graph, we can clearly observe some positions of interest with dense seek lines. According to the video content and the watching time, the experts can explain the insight of seeking patterns.

The forward seek event that happened when learners first watched one video can be used as a metric to evaluate whether the learners are getting bored or not. The instructors for Course *GT* found that for some of the experiment videos, a lot of forward seek events in the latter part of the video can be observed. Before the instructors saw the clickstream data, they had gotten feedback from the forum complaining that the experiment was too long.

By exploring the data, the experts found that for different in-video questions, although they have a similar pattern in the event graph, we can clearly observe the differences in the seek graph. Figure 7 shows the seek graphs for two in-video questions, and we can see that there are obvious differences between them. For the video on the left, there is a considerably large percentage of backward seek events happening around the question, while there are fewer forward seek events. This pattern clearly indicates that the first question is harder for the learners. The instructors for this course also confirmed the findings.

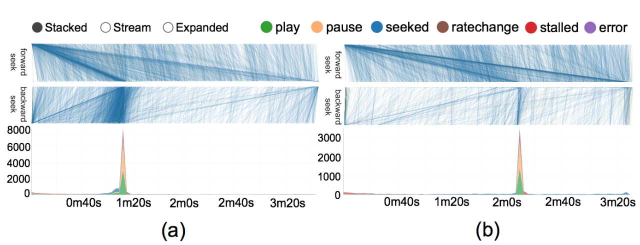

Figure 7: Comparison between the Content-based views of two videos with a in-video question.

5.3 Temporal Pattern Analysis

The calendar view shows the day by day popularity of a selected video (Figure 5). In this figure, we can see that the popularity decreases at first, but then increases weeks after. By referring to the course syllabus, we found that the increase appeared a week before the exam. The animation is also supported for the experts to see clickstream data by time. By watching the animations, we found some interesting patterns shown in Figure 8. The first burst of click actions appears almost on all course videos followed by another more acute burst on a specific day (August 26th), The first burst corresponds to the findings in the calendar view, while the second one happens precisely on exam day, but it is barely observable in the calendar view. After the exam day, all the clickstream activities cease dramatically. Another interesting observation from the animation is that "pause+play"'s are the dominant events in the release week when learners are watching the videos for the first time, whereas seek becomes the most frequent event when learners are reviewing those videos. Instructors agree it is quite reasonable since when learners watch the videos for the first time, they have no ideas about which parts are important and would pause more often in order to better understand the content. On the contrary, when learners re-watch the videos, most of them might have specific needs and watched videos selectively with more seek actions.

5.4 Coordinated Analysis

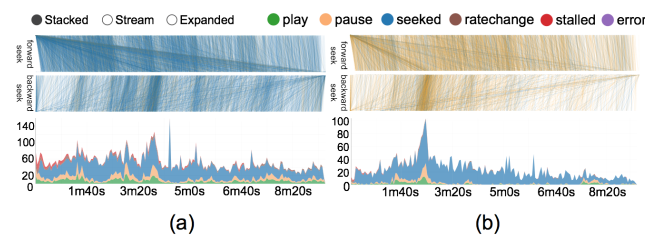

Figure 9: The Content Views for the same video shown in Figure 1 but with different time periods. a) the clickstream data from the first week when the video released; b) the clickstream data from the week when the related assignment released.

The experts also find that coordinated analysis play an important role for analyzing complex patterns. When the experts saw the *Content-based View* in Figure 1, they pointed out a strange pattern in the Seeked Graph. There are two positions with dense backward seek events, however, the earlier position (p_1) is filled by the seek events (orange color) that happened when learners reviewed the video, and the later one p_2 is filled by the seek events (blue color) that happened when learners first watched the video. From the Event Graph, both positions correspond to one peak, which means learners most watched the content at both positions.

By examining the video content at position (p_1), the instructors of this course figured out that the video content appeared in the assignment as well as in the final exam. Thus, when we selected only the clickstream data before the assignment and the exam (Figure 9(a)), the first peak with re-watched seek events disappeared. To further confirm whether the assignment or the exam led to the phenomenon, the instructors selected the assignment release day and the exam day separately, and finally confirmed that this pattern was triggered by the assignment (Figure 9(b)).

5.4.1 Behavior differences between user groups

The overall statistics give an overview of the course and both course instructors and educational analysts are greatly interested in these as they are quite easy to understand. Take the demographic view as an example, all the experts are amazed at the student distribution and

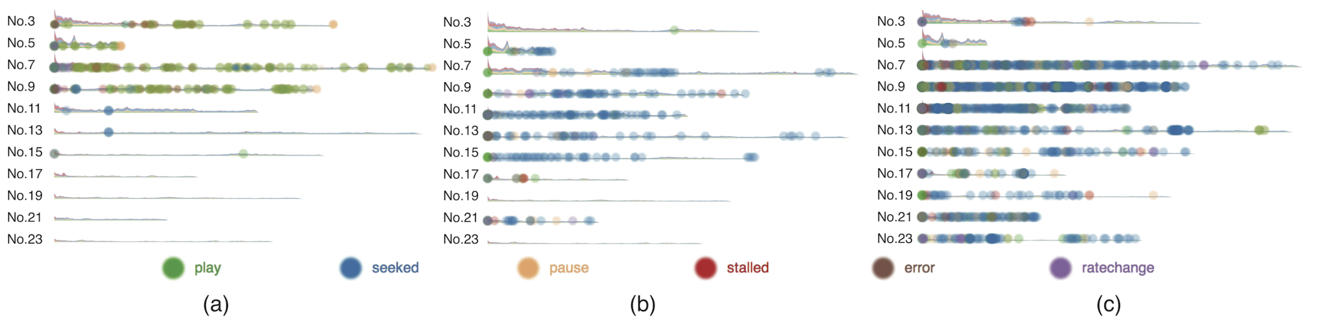

Figure 8: Animations show three patterns: a) pause events and play events are dominant when learners watch the videos for the first time; b) seek events are dominant when learners review the videos; c) there is a burst of events on the exam day.

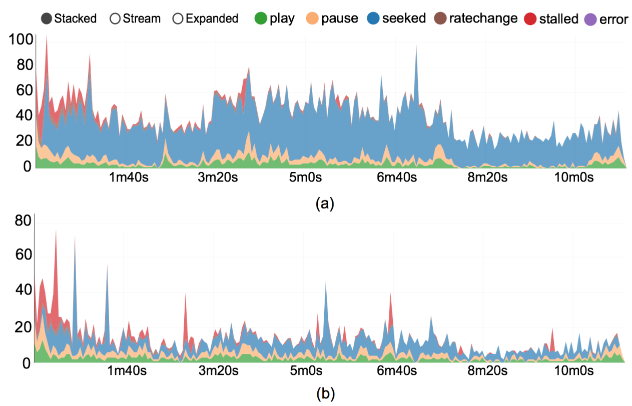

Figure 10: The Event Graphs showing the clickstream data of the same course during the same time period but for learners from different countries. a) Learners from the U.S; b) Learners from China. We can clearly see that the percentage of seek events happened in the U.S is much larger than the one in China.

number of countries they come from, one instructor immediately points out that he wants to see how learners from different countries react to the same topics. Thus, they selected one video in the Course *CH* and filtered the clickstream data by the demographic information (Figure 10). From the Event Graph, we can clearly see that the percentage of seek events for the U.S is much larger than the one for China and this was not a single case: they explored more videos and found that the clickstream data of all the videos followed the same pattern. In order to further validate if there is a significant difference between individuals from this two countries, we offered the experts statistical information about the clickstream distribution on U.S and China and the result also confirmed this finding. The experts tried to explain the phenomenon. One possible reason is that, from their own experience in face-to-face education, more Chinese students prefer taking notes. Thus, when watching MOOC videos, Chinese learners may prefer to pause the video, take notes, and then play it again. This explained the lower percentage of seek events for Chinese learners.

6 Expert Feedback and Discussion

We have presented VisMOOC in different occasions, including six presentations and trials of the system in six different E-Learning seminars. The participants are mainly instructors who have opened their own MOOCs, education analysts who are specifically researching on online education, and people in charge of MOOCs platforms. In general, VisMOOC is highly rated by them. They commented that our system is easy to use and the findings are insightful: *"Comparing to the traditional education, in which the course materials are prepared according to the instructors interest, this data driven analysis will greatly help instructors understand the learners interest and prepare the course materials according it to improve the learning engagement."* They appreciated that VisMOOC can indeed help them understand online learning behavior from clickstream data. They particularly mentioned that from the Content-based View, they can immediately find the content learners are interested in, which would greatly help instructor understanding the preference of the learners so that they can prepare the course more specifically in the future.

We also illustrated VisMOOC in *Coursera Regional Workshop* hosted by Coursera and we further get positive feedback from them. For example, a chairman of MOOCs Working Group in one university said :"*this work is simply amazing, we hope our university in the future can collaborate with you to take the project to a new level*". An expert of education said that "*The findings from your research result will surely bring new practice of MOOCs research*." They also suggested several potential problems that are worth to being researched. For example, they were interested in if students with high grades and students with lower grades have different watching behavior. This poses an interesting research topic on co-joint analysis of log data from MOOC platforms.

However, there are also some limitations of our system. Still, the clutter reducing method used in seek graphs suffers several problems. First, the transparency values for seek lines in different seek graphs varies, which would affect the effectiveness of comparison task between two seek graphs. Second, in some extreme cases, the method may not be effective. For example, a position with extremely dense seek lines would undermine interesting patterns in other places. Another limitation is that log data only record what the learners did, but the reason why they did is unknown. Extra data are needed to confirm the internal motivation of users. Other drawbacks are referred in the future work.

7 Conclusion and Future Work

In this paper, we have presented VisMOOC, a visual analytical system to help instructors and educational analysts understand online learning behaviors related to course videos using clickstream data from Coursera. We have collaborated with five experts (i.e. four instructors of two Coursera courses and one educational analyst) to abstract the analysis tasks and work on the design rationale accordingly. The case studies and the feedback from the experts have confirmed the usefulness and effectiveness of the system. To the best of our knowledge, this is the first visual analytical system to specifically help the experts conduct content-based analysis with clickstream data for MOOCs. Though the system is designed for analyzing the course videos, it can be extended and applied to the general analysis of other video watching behaviors.

In the future, we will try more advanced clutter reducing methods used in parallel coordinates which also can achieve a real-time-rendering speed. Further more, we will work on enhancing current event graph design with statistical information embedded so that it can better support comparison tasks to verify the significant difference between individuals from two learning groups. Our work can be extended in two directions. The first direction is to improve VisMOOC by integrating the analysis modules for forum data and grading information. Before analyzing the clickstream data, the experts can only get feedback from the forum where learners can post questions and communicate with other learners and instructors. Combining the two datesets together could further help the experts understand the learning behaviors. Furthermore, the grading information can provide the ground truth about how well the learners perform, which would offer a new opportunity to identify the different learning patterns between learners who get higher grades and those who get lower grades. The other direction is to generalize the tool for analyzing the general online videos, which would help for online advertising and video making.

ACKNOWLEDGEMENTS

The authors would like to thank Prof. James Lee, Prof. Ting-Chuen Pong, and Prof. King-Lau Chow in HKUST for participating this project as domain experts, Dr. Yingcai Wu, for his help on constructive suggestion of revising the paper and the anonymous reviewers for their valuable comments. This work is supported by grant RGC GRF 16208514, HKUST grant F0547, and HKUST CSE department grant for showcase projects.

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