Animated Narrative Visualization for Video Clickstream Data

Yun Wang*, Zhutian Chen, Quan Li, Xiaojuan Ma, Qiong Luo, Huamin Qu
The Hong Kong University of Science and Technology

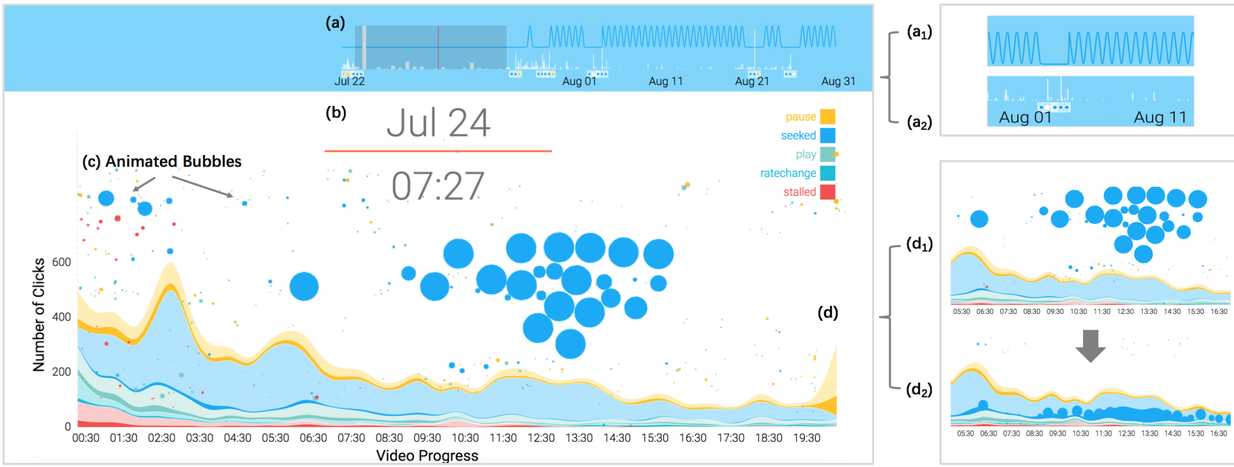

Figure 1: *The system comprises four main components: (a) A focus+context timeline shows a specific time frame in detail while keeping the context part of the timeline covering the entire range of all the click actions; (b) The clock displays the current timestamp explicitly; (c) Animated bubbles in different sizes demonstrate different numbers of clicks, while different colors represent different types of click actions; (d) An animated stack graph represents the accumulation of video clickstream data.*

Abstract

Video clickstream data are important for understanding user behaviors and improving online video services. Various visual analytics techniques have been proposed to explore patterns in these data. However, those techniques are mainly developed for analysis and do not sufficiently support presentations. It is still difficult for data analysts to convey their findings to an audience without prior knowledge. In this paper, we propose to use animated narrative visualization to present video clickstream data. Compared with traditional methods which directly turn click events into animations, our animated narrative visualization focuses on conveying the patterns in the data to a general audience and adopts two novel designs, non-linear time mapping and foreshadowing, to make the presentation more engaging and interesting. Our non-linear time mapping method keeps the interesting parts as the focus of the animation while compressing the uninteresting parts as the context. The foreshadowing techniques can engage the audience and alert them to the events in the animation. Our user study indicates the effectiveness of our system and provides guidelines for the design of similar systems.

Keywords: animated visualization, narrative visualization, data storytelling, clickstream data

Concepts: •**Human-centered computing** → *Information visualization;*

*e-mail:ywangch@connect.ust.hk

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1 Introduction

Video clickstream data depict a large number of users' interaction events with online videos, such as play, pause, and seek actions. Through the exploration of video clickstream data, data analysts discover users' reactions to both video content and real world events. As a typical kind of temporal data, video clickstream data are usually analysed by adopting time series data visualization [Aigner et al. 2007]. Most of them show these data with exploratory visualization systems [Shi et al. 2015]. Data analysts find temporal patterns and trace the causes of the patterns through exploring the elaborate analytical visualization.

To communicate insights, data analysts need to demonstrate the visualization to an audience. However, a general audience who have no knowledge of the visualization designs may find it difficult to understand data stories through exploratory visualization. To support temporal pattern analysis, analytical visualization usually encodes "time dimension" into 2D visual displays. When data become increasingly complex, the design of data visualization systems tends to become too complicated. Novel visual forms, multiple linked views, hierarchical zooming, and interactions are usually used to help data analysts recognize temporal features from different perspectives. To present findings, data analysts need to either demonstrate the visual analytics system in person or display screenshots with further explanations. However, static figures or visual data stories can rarely be created straight out of interactive exploratory tools [Gratzl et al. 2016]. Analysts need to collect artifacts, such as screenshots, to compose a well-structured data story so that users can understand the evolution and composition of temporal data, which is time consuming.

In contrast, animation is a simpler and more attractive visual form to show temporal development and stories behind data. In 2010, Hans Rosling presented an animated bubble chart to illustrate how 200 countries developed in 200 years in 4 minutes. This revealed the story of the world's past, present, and future development, and attracted more than 7 million views [Rosling 2009]. In this example, animated visualization is edited, guided, and explained by the presenter, making the data come to life, while emphasizing critical results from the analysis [Robertson et al. 2008].

Although animated visualization has clear advantages, there are two drawbacks when the animation is directly generated from real-world temporal data without any editing: (1) When the animation contains rich information in a long time span, it may become too long for the audience to stay focused. Viewers can lose patience if they fail to extract meaningful information from it [Tversky et al. 2002]; (2) Real-world data can be irregular and unpredictable. When watching the animation, users may be disappointed when no patterns occur in a long period and can eventually give up.

In cinematography, there are clever tactics to catch viewers' attention. We try to enable data analysts to present more engaging data stories by adapting two representative tactics, namely, time remapping, and foreshadowing, to generate better animated narrative visualization. To reduce the temporal duration of the animation, we introduce dynamic compression in the time dimension of the animated visualization. In particular, we remap physical real-time to animation time based on the existing experience of cinematography. However, varying temporal compression may cause confusion of how to interpret the pace of the animation. Hence, we design an animated timeline to show the time compression rate and provide visual foreshadowing cues to indicate the elapse of time and highlight key events. Moreover, we design a foreshadowing stacked graph to show past and future events to keep users' attention. The major contributions of this paper can be summarized as follows:

- We explore time remapping and foreshadowing techniques and apply them to the compression of animated visualization to make it more compact and engaging;
- We design a focus+context animated timeline to help users understand the context of the evolution and aggregation of temporal data;
- We conduct user studies to validate the design and measure the users' level of engagement with a real world dataset.

2 Related Work

Clickstream Visualization Clickstream data generated from various online activities exist in various forms, such as web browsing behavior [Lee et al. 2001][Montgomery et al. 2004], online shopping navigation [Wei et al. 2012], interaction with videos [Beal and Cohen 2008], and so on. Among different kinds of clickstream data, video clickstream data has long been explored to analyze users' interaction with online videos. Some video interaction analysis focuses on users' play and pause activities [Chorianopoulos 2013] and others on video content [Hou and Zhang 2007]. Video interaction is also visualized [Aguiar et al. 2015] to understand the audience and to predict their engagement. However, existing studies mostly focus on the analysis of clickstream data to reveal user behavioral patterns. There lacks an engaging form to communicate findings to a general audience. Moreover, existing visualization forms cannot clearly demonstrate how the clickstream patterns appear, develop, and disappear over time in a dynamic way.

Animated Transition Abundant research has been conducted on animated transition. This technique is often used to show changes with graphics, such as statistical data charts and the evolution of graphs [Heer and Robertson 2007][Bach et al. 2014]. Traditionally, animated transitions have been frequently used to show spatial change. When the changes are complex and disordered, animation can help users find the differences between consecutive frames of visualization. For example, many researchers have focused on designing animated transitions to provide a smooth transition between the before and after states of dynamic graphs [Bach et al. 2014]. The design goal of animated transitions is to provide a smooth transition and explain how data changes between two separate states. By contrast, we accelerate less important frames in *animated visualization* and introduce traditional narrative tactics to create complete and engaging data narration.

Animation and Data Storytelling Animation is among the seven genres of narrative visualization summarized by Segel and Heer [Segel and Heer 2010]. Film, video, and animation form a genre of narrative visualization with which designers can show the changes in data through motion change. Readers or viewers usually need to follow the order of the film, video or animation set by the designers. When presented in animation, data changes become attractive to users [Thomas et al. 1995]. Amini et al. studied more than fifty professionally designed data videos to understand the structure designers commonly use to construct narrative visualization [Amini et al. 2015]. Recently, more and more researchers have tried to use animation to convey information and ideas. Visual sedimentation is a design metaphor that uses falling object animations, inspired by the physical process of sedimentation, to show data streams [Huron et al. 2013]. Sigovan et al. [Sigovan et al. 2013] uses animation to illustrate dynamic communication patterns and analyse large datasets in parallel application execution to make them easy to understand. Animation can also be used to highlight critical information. For example, Wander et al. studies how to guide users' attention through a flicker in dynamic visualization[Waldner et al. 2014]. In this paper, we utilize the advantages of animation and adapt traditional narrative tactics to create more engaging animated data stories.

Timeline Visualization Timeline is an effective and widely used tool to present temporal events. A well-designed timeline provides useful context and insights into temporal patterns. For example, Google News Timeline [1] aggregates and organizes news stories chronologically. TimeZoom is an interactive timeline widget providing different time levels [Dachselt and Weiland 2006]. TimeSlice supports comparison and exploration of multi-dimensional event data by presenting structured event data in multi-faceted timelines [Zhao et al. 2012]. SchemaLine allows analysts to group notes along compact timeline visualization and helps users to examine chronological events [Nguyen et al. 2014]. TimeLineCurator is an authoring tool for journalists to identify the extent of time referred by a document and combine timelines with multiple documents [Fulda et al. 2016]. Based on previous studies, which tend to use a static timeline, we design an animated timeline to replay how the data comes into being and reflects user behaviors within the time span. Making use of the visual saliency of animation, the temporal changes in data become more noticeable for the viewers.

3 Requirement Analysis

Compared to exploratory interactive visualization, animated visualization provides a more engaging way of data storytelling. Based on the characteristics of video clickstream data, we first analyse the requirements of the design :

- **R1:** *The animated visualization should be simple enough for a general audience.* The goal for the animated visualization is

[1] http://news.google.com/

to tell the data story and convey it to a broader audience. Thus, the visual form to encode the aggregation of clickstream data should avoid possible clutter and be easy to read.

- **R2:** *The system should provide a temporal background of the data.* To understand the animation and the data, viewers need the overall temporal information about the data, which can help both the data analysts and viewers understand when and why a temporal event happens.
- **R3:** *The animated visualization should be able to emphasize the critical events.* There might be several important moments that key events happen within the time span. The animated visualization should be able to guide users' attention to the upcoming key events.
- **R4:** *The animated visualization should be able to engage users.* The encoding of the animated visualization should be able to keep users attention throughout the time. As users may easily lose patience for a long animation, the animation should be informative but not too long. Meanwhile, it should not place too much cognitive burden and tire users out. The design of animated visualization should support both long and short time ranges.

4 Time Remapping and Foreshadowing

One straightforward way to present the temporal clickstream data is to record, compress and replay the click actions to the users. However, when temporal events are too sparse, users may be tired and lose patience; when temporal events are too frequent, users cannot see the events clearly. To address this problem, we adopt and extend two successful storytelling tactics in traditional narratives: (1) we introduce time remapping which is widely used in the traditional filming and narrative field; (2) we use foreshadowing to make the animation more engaging and coherent.

4.1 Pacing and Time Remapping

Pacing is a commonly used tactic in fiction, cartoon, and film when composing traditional narratives. The pace of a narrative relies on plot, setting, genre of the story, and so on. A fast action forwards plot moments one right after the other, making the pace of the story faster. A slower pace contains more details, helping the audience to understand the story more easily. A well-designed story often includes narratives that move at varying speeds to keep the audience's attention [McKee 1997].

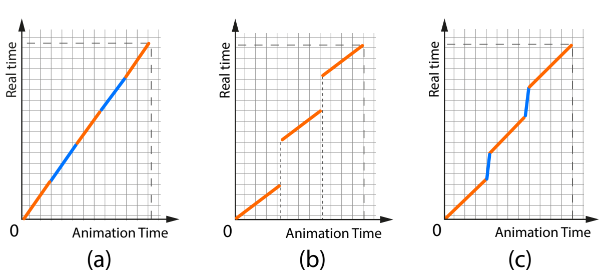

Figure 2: *The mapping from physical time to the time in an animation. (a) Time Lapse, (b) Time Editing, and (c) Time Remapping. We choose to use time remapping to compress the temporal length of our animation.*

In filmmaking, many styles of editing and compression are used to transform videos into more compact and engaging ones [Riedl and Young 2010]. Figure 2 shows three common techniques, which can be adapted to the editing and compression of long animated visualization [Mediacollege 2016].

- **Time Lapse** compresses time range proportionally. This technique is usually used to show long processes that are subtle, such as the motion of the sun, stars in the sky, and so on.
- **Time Editing**, a.k.a. Montage, extracts the important segments of the time series and concatenates the segments. Editing cuts involves careful planning to skip from one shot to a later shot, but it may make the video more fragmental.
- **Time Remapping** varies the speed of the animation from time to time, rather than limiting it to a single speed for a video clip.

Among the above three techniques, *Time Lapse* can be used when the data are regular and the scale is small. However, it may not be suitable for real-world data where user behaviors change significantly because there is no single suitable speed throughout the entire time span. With an increase in compression rate, critical information may pass too quickly for an audience to catch, which might even cause substantial loss of valuable details. *Time Editing* can be used to show important parts of the temporal data. But it also has drawbacks: By cutting off insignificant segments, the audience may not understand how the data develops over time. It becomes harder for them to understand the differences between the usual and unusual characteristics of the data without the context of the commonly seen data. Moreover, some viewers may seek particular information they are interested in. Therefore, it is still important for the users to access the entire time series. In the final design, we adopt *time remapping* tactic, which is extensively used in traditional video productions to make duration shorter than in real time [Bordwell et al. 1997], providing more understandable temporal connections of the whole story. Specifically, we adopt an inverse ratio for the data volume and the compression rate. More click actions in a time range correspond to a lower compression rate.

4.2 Foreshadowing

Foreshadowing is a narrative element that hints at what is to come and is thus widely used to engage the readers. By using foreshadowing in storytelling, the authors can add tension to a story by building anticipation about what might happen next.

Existing foreshadowing tactics can be divided into several types (Fig. 3): (a) explicitly show future events with a flash-forward jump; (b) implicitly forecast with some elements used in the later story, such as a gun hidden in a drawer; and (c) signify future events with the characters or symbolizing the events with metaphors, such as a mirror breaking, or a black cat crossing [Foreshadowing.org 2016]. These tactics in the literature or cinematography usually aim at building suspense, so as to leave a deep impression on the audience. However, storytelling for real data and real events needs to consider the facticity. We need to establish anticipation of the users for future events based on real data to keep the audience' attention on our animated visualization. Therefore, we design *visual foreshadowing* as visual cues to facilitate the audience' preparation for the upcoming moments when critical events happen.

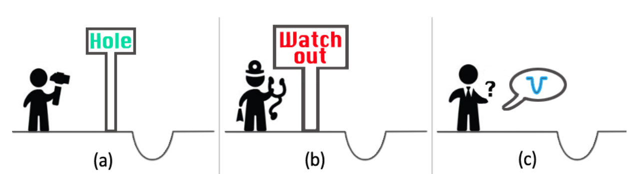

Figure 3: *Three styles of foreshadowing. (a) explicit, (b) implicit, and (c) signified.*

5 Animated Visualization Design

Although there have been applications for animated visualization, there is still a lack of design guidelines for generating animated narrative visualization. Therefore, our system is created in an iterative refinement process. Based on the initial requirements we outline in Section 3, we implement a preliminary design, work closely with data analysts to gain direct feedback, and then refine it in multiple rounds.

We integrate all the components into the interface of the system. The top of the system shows a focus+context timeline, on which we show the accumulation of the video clickstream over time (Fig. 1a). With animated bubbles to symbolize click events (Fig. 1c), a clock is provided to show certain moments when click events happened (Fig. 1b). Below, a stacked graph gradually filled with bubbles indicates the accumulation of past events in dark colors and data events to come in the future in light colors (Fig. 1d).

5.1 Designs for Animations

There are three kinds of information in clickstream data: the timestamp of each click action, the video time of each click action, and the type of click action (e.g., “play” and “seek”).

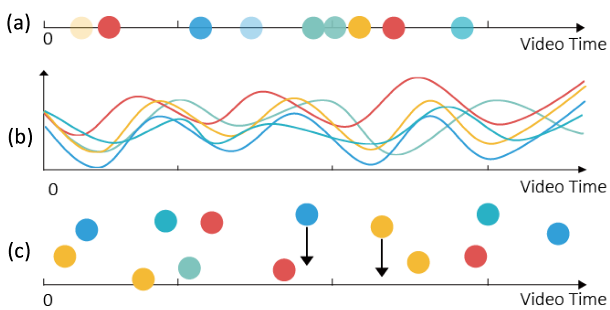

Figure 4: *Design alternatives to show the video clickstream data. (a) Bubbles flicker along the video time bar; (b) Curves move upward in the line chart , showing the accumulation of click events; (c) Bubbles fall towards the time bar.*

Click Event Representation To show click events along the video progress bar, we use small bubbles moving downward as time goes and colors representing different types of click events. The clock starts from the time the video was released. When the clock starts to run, small bubbles in different colors start to fall, representing how people interact with this video throughout a time range (Fig. 4c). Fig. 4 shows three potential designs to represent click events: (a) A simple design is to directly show the video progress bar with bubbles flickering in different colors, indicating the types of the click action. This design gives users a direct impression of the distribution, and the amounts of different types of click events over time. However, when the animation is compressed, quickly flickering small dots causes severe memory problem. Users may forget the pattern immediately after they see the dots. (b) Line charts are commonly applied to show continuous changes over time. Animating line charts by enabling them to move upwards from the baseline is another straightforward design to indicate the accumulation of click actions with time. However, this may raise visual clutter issues and users cannot easily figure out the changes of different types of click events. Therefore, we adopt the third design (c) to keep the design simple and legible. When the bubbles fall on the screen, users can compare and trace patterns around certain timestamps more easily.

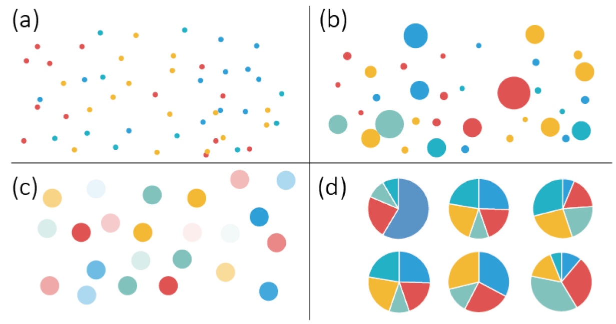

Figure 5: *Design alternatives for the bubbles. (a) Each bubble shows one click; (b) The size of each bubble shows the number of clicks in a small time interval; (c) The opacity of each bubble shows the number of clicks in a small time interval; (d) The video progress bar is equally divided and each pie chart bubble shows the number and percentage of clicks within a certain time range.*

Event Aggregation When the number of bubbles increases, there is a higher cognitive burden on the users. Therefore, we aggregate the number of click actions by small time intervals, and use the size of bubbles to encode the click counts of videos (Fig. 5b). We consider four design options:

- Fig. 5a uses small bubbles of the same size, with each bubble representing a unit number of clicks. Users perceive the number of clicks through the density of tiny bubbles. However, with this design, bubbles at the same time stamp could overlap, causing visual ambiguity.
- Fig. 5b uses bubbles of different sizes, with larger bubbles representing more click counts. Users can easily observe the larger bubbles, with the event time and the position over the video progress bar.
- Fig. 5c depicts bubbles of different opacity: the more opaque the bubbles, the more click counts. Unfortunately, this design does not scale well when a burst of click events happens in a short period of time.
- Fig. 5d involves a combination of bubbles and pie charts (or other glyphs). We equally split the time of the video progress bar into N segments and aggregate the information in each segment. The ‘pie bubbles’ represent the numbers of different types of click actions. The aggregation further reduces the number of bubbles. However, we do not adopt this design because: (1) Using pie charts is not very intuitive and may add a cognitive load to the users. (2) The performance of this design relies heavily on the proper choice of N. The aggregation along the video progress bar risks losing valuable information and missing potential patterns.

5.2 Designs for Time Remapping

As discussed in Sec. 4.1, we edit the animated visualization using *time remapping* to make it more compact and engaging. In traditional films and cartoons, which record motions in the real world, the speed changes do not affect humans’ perception of the story because the internal logic of the plot and human knowledge about the real world motion make it easier for an audience to understand the passage of time. However, for abstract and complex InfoVis, it is much more difficult for humans to identify the play rate changes. For example, when the number of falling bubbles suddenly increases, viewers may consider two potential causes: (1) the play rate of the animation increases, and (2) the number of click events increases. To tackle the problem, we design visual cues to indicate time and speed of our animation.

Rate Changes To reduce the ambiguity problem, we redesign the motion of falling bubbles. We adopt force-based animation by modelling the physical movement of falling bubble in the air. Therefore, there are two main forces for each bubble: Their weights (the force of gravity) pulls them down while they also experience an upward dragging force, air resistance. According to Newton's second law, the acceleration of each bubble becomes, $a = (mg - 0.5C_d rV^2 A)/m$, where C_d is the drag coefficient, r is the density of air, V is the speed of the object relative to the air, A is the cross sectional area, m is the mass of the object, and g is the gravitational acceleration. Therefore, when the play rate of animation increases, not only does the occurrence of new bubbles increase, but also the acceleration of each bubble. Through the falling speed of the bubbles, users can more easily distinguish the changes in the rate of the animated visualization.

Focus+Context Timeline To build logical connections, raise users expectations, and keep their attention, we design an animated timeline to give an overview of the click events data. Timeline is a commonly used method to represent a time dimension. The audience can build visual anticipation and avoid short-term memory problems through the intuitive visual summary. We combine a simple bar chart design with the timeline.

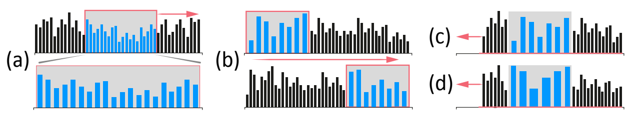

Figure 6: *Different styles of focus+context timeline design. (a) The context and focus view are placed side by side; (b) The focus window is moved from left to right; (c) The focus window is put in the center and the context moves from right to left; (d) The focus window with a fish eye design. The context moves from right to left.*

To make the users' attention more focused, we design a focus+context timeline. The focus part of the timeline shows the specific time of the animation while the context part of the timeline covers a long time range of all the click actions. Fig. 6 shows four design alternatives. The first choice is to move the sliding window from left to right and magnify the area inside the window (Fig. 6a). However, after implementing the design, we find this could be very distracting for the users, since they have to track the sliding window, the magnified area, and the falling of bubbles simultaneously. The second design reduces the distractions by embedding the magnified area into the timeline (Fig. 6b). However, users still have to track both the sliding window and the falling bubbles. To minimize users' visual load, the third and the fourth designs move the timeline instead of the window. In the third choice, the focus part is magnified (Fig. 6c). Users have a fixed position to focus on, liberating them from having to move their eyes along with the sliding window. The fourth choice (Fig. 6d) is the same as the third one except that it adopts a fish-eye focus. The fish eye further increases the bar width near the center. However, the distortion may confuse users about the true heights of the bars. Hence, we choose the third design.

5.3 Designs for Foreshadowing

Foreshadowing is an essential hint about information to be shown in a video. Specifically, our visual design of foreshadowing lies in two aspects: (1) The overview timeline foreshadows the distribution of click counts over the whole time span. (2) The stacked graph foreshadows the final click counts for each type of click and for each time stamp.

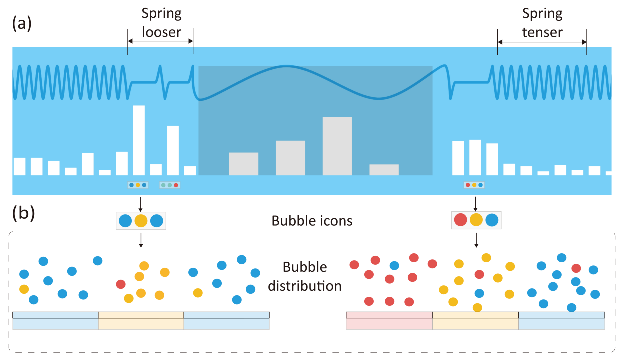

Figure 7: *Timeline Design: (a) A timeline with time Spring and a bar chart to give an overview of the animation; (b) Bubble icons. Two example foreshadowing cues on the timeline. The video timeline is divided into three parts. The three small dots shows the approximate distribution of different bubble colors (different colors indicate different types of clicks).*

Foreshadowing on Timeline Over a long time span, there might be some key events with important patterns that users need to pay attention to. Therefore, we want to alert the users so that they do not miss those key events. Three foreshadowing visual cues are added on the timeline:

- **Overview bar charts**: The bar chart on the timeline is an overview of the clickstream over the entire time range to indicate the number of clicks over time, as shown in Fig. 7a.
- **Time Spring**: We design a spring above the timeline to serve as a visual cue for the play rate of the animation. As shown in Fig. 7a, a tighter spring indicates a higher rate and a looser indicates a slower rate. Usually before and during the emergence of key patterns, the spring will get looser, meaning that the play rate has been tuned down for users to take a close look at the click events.
- **Bubble icons**: As shown in Fig. 7b, we use tiny bubbles on the timeline to present the approximate distributions over different types of clicks. To make it simple to understand, we divide the video timeline into three segments and use the color of the majority bubbles in each segment as the representative color.

We calculate the total number of click events in each time range unit, and use a normal distribution model to mark the time ranges. Many data mining techniques can also be used for pattern recognition. Data analysts can further define the patterns based on their own experience and domain knowledge about the video clickstream data.

Foreshadowing on Stacked Graphs We use a stacked graph to show the accumulation of video clickstream data. However, naively showing the stacked graph growing over time could confuse the users. To be more specific, since the baseline of one layer in the stacked graph depends on all layers below it, both the baselines and heights will vary over time in this design, compromising users' perception on the trends of each layer. In order to reveal the temporal pattern and provide a review of both what has happened and what will happen next, we design a stacked graph with *filling effects*. In other words, we indicate the final number of click events by showing a lighter color with small bubbles falling into the layers. The bubbles gradually filling and melting into the stacked graph layers are designed to indicate the past and future numbers of clickstreams at different stages (Fig. 8).

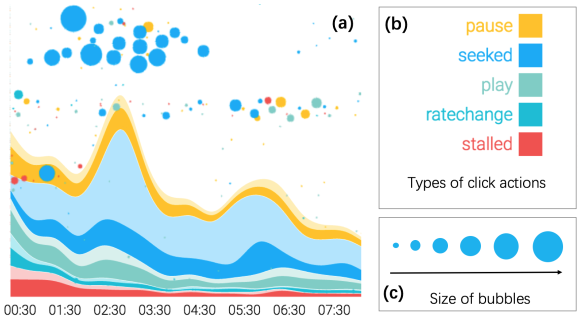

Figure 8: *The encoding of animated stacked graph design: the colors represent different types of click actions and the size indicates the number of click actions.*

5.4 Implementation

The front-end of our animated visualization system is implemented with D3.js, and we use the physics engine Box2DWeb (http://box2d.org/) to manage force-based animation. We deploy the back-end of the system into our server (with a 2.7GHz Intel Core i7 CPU, 8GB memory PC). The data are stored in a local database. We design the system as a web-based application, so that the authors and audience can easily access the animated visualization through a single web browser.

Transitions "Ease in and ease out" is a commonly used technique in animation to give a smooth transition and provide better user experience [Dragicevic et al. 2011]. We utilize this technique when switching the play rate of the animation. Moreover, if the play rate switches too frequently, the users may feel dizzy. Therefore, we merge adjacent highlighted parts on the timeline. For example, if two parts of the animation that are shown at slower speeds are too close to each other, we will combine them.

Control Panel On the left side of the system, a control panel is provided for users to choose the clickstream dataset and adjust the parameter settings. We also support the author mode and the user mode. Both authors (data analysts) and viewers (general audience) can perform their own adjustments. Authors can highlight the most important events and edit the animation iteratively while viewers can fine-tune the overall speed of the animated visualization. The control panel is hidden when not used.

6 Use Case

In this section, we demonstrate the system with a real dataset from edX[2]. We obtain the user clickstream data of a course offered by our university.

Emily, a hard-working TA of the online course, browses through the clickstream data of the on-going course and tries to assess the students' performance, to see whether she can gain interesting and valuable insights from the clickstream data. She starts by loading the data for a lecture. Then, the system generates the clickstream animation for the loaded lecture. In the animation, bubbles of various colors (indicating different types of click actions) fall down from the timeline at the beginning of the course,. "It is difficult to tell what types of clicks are most frequent," she says. She notices that there is a bubble icon on the timeline, so she waits for the next event. Suddenly, a surge of green and yellow bubbles ('play' and 'pause' clicks) starts falling down (Fig. 9a). From the date and time shown, she is reminded that the surge of clicks happened when

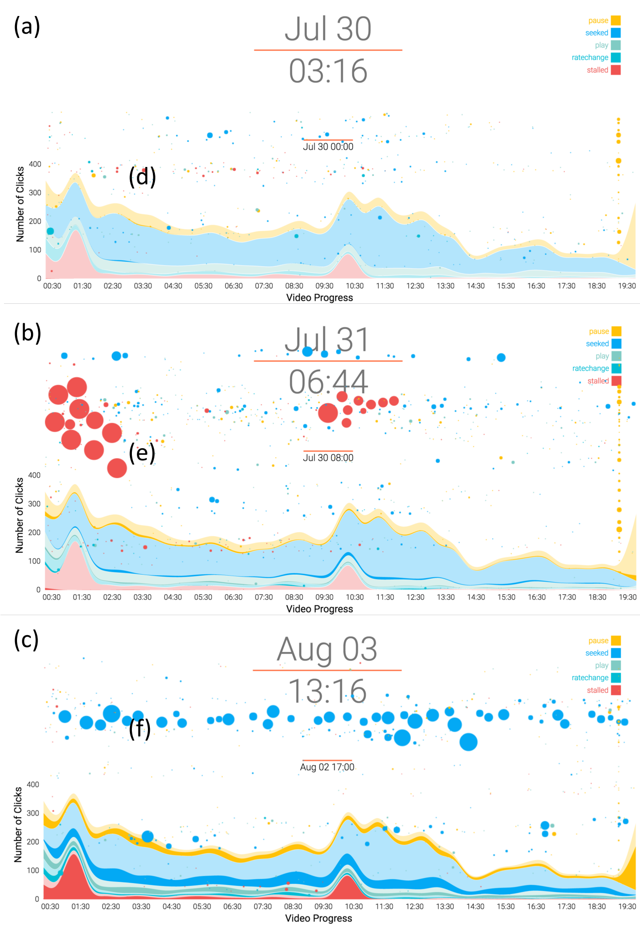

Figure 9: *Cases: (a) The start of a course, with many play and pause events, (b) concentrated emergence of stalled event, and (c) a large amount of seek events.*

the instructor was explaining about a rather obscure concept in the course. She therefore marks down the reasons for the events. Emily sometimes observes surges of red bubbles (Fig. 9b). Considering that the 'stalled' states are often caused by heavy network traffic and hence irrelevant to the course itself, she decides to ignore them. Although most of the other colors in the stacked graph are nearly filled up, the blue stream is still quite empty. She patiently watches the animation and waits. In an instant, another bunch of blue bubbles ('seek' clicks) attracts her attention (Fig. 9c). Wondering what the cause might be, Emily finds that the date of this phenomenon is around the final exam date. She suspects that the high occurrence of the 'seek' clicks is due to this lecture video being closely related to final exam, and therefore, students intensively review the lessons. Again, after taking corresponding notes, Emily carefully marks down the video positions that were frequently sought by the students, since those video contents may need further emphasis during class. On the next day, Emily takes the animation to the meeting room, plays the animation in the user mode at a constant rate of 0.8, slower than the original rate to synchronize with her oral explanation, and explains to the instructors what she had found. The instructors and the fellow TAs are greatly impressed and decide to discuss more about the difficult concepts found by the system in the next term.

[2] https://www.edx.org/

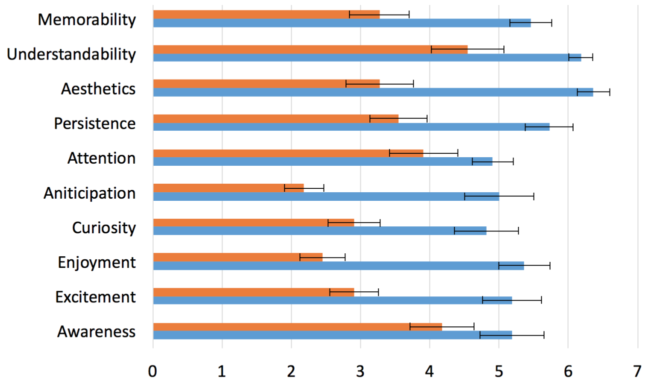

Figure 10: *The scores of our designs (the bottom columns) wins the baseline design (the top columns) in all the aspects of engaging experience. Error bars show standard errors.*

7 User Study

Our system is tailored to guide the general audience to understand data in a more engaging way. Through manipulating time dimensions based on the importance of temporal events recognized by data analysts, we are able to provide a more intuitive form of representation for the temporal data. To confirm this, we ran a pre-study where we asked an expert data analyst to ensure that the events identified were reasonable from the viewpoint of their domain knowledge. After that, a formal study was conducted to compare the effects of showing the animation of video clickstream data with and without time compression and foreshadowing designs.

Study Design For the qualitative study, we recruited 12 participants (7 males and 5 females) between the age of 21 and 29. Their educational background ranged from computer science, electrical engineering, to arts. We started our user study by introducing the dataset background and the encoding scheme of the proposed visualization. Then, two animated visualizations with different datasets were provided to them. The participants could watch the whole animation without pause and take notes on a white paper. Both animated visualization designs could be viewed only once. After that, they were asked to finish four task-specific multiple-choice questions (two for each video) about when and what happened on a certain day regarding some patterns. We also gave the subjects a questionnaire with fifteen subjective questions to answer after watching the video clickstream data with and without time compressing and foreshadowing designs. These questions evaluated our system on a 7-point Likert scale. The questions covered two important aspects: the workload analysis and engagement experience compared with the baseline system. Additionally, we concluded every session by asking semi-structured questions to collect detailed feedback and suggestions for future improvements. The order of the evaluation on our system and the baseline are also counterbalanced.

Results and Discussion Overall, all of our participants chose our design with nonlinear time mapping and foreshadowing as their preferred presentation style. Their responses were: "The visual design made observing the video clickstream data more engaging and interesting." In the questionnaire, participants were asked about their workload when completing the tasks by watching the animation of video clickstream data with and without our designs. The workload was further explained in terms of *mental*, *physical*, *temporal*, *effort* and *frustration*. The average level of workload in our design was 2.63 on a 7-point scale, and that of the baseline design was 4.05 on average (Table 1). All participants were convinced that our time compressing and foreshadowing designs would greatly reduce their perception load.

Task load	Mean (a)	Mean (b)	SD (a)	SD (b)
Mental load	2.92	4.08	1.68	2.15
Temporal cost	2.67	4.42	1.72	1.83
Efforts	2.42	3.92	1.73	1.93
Frustration level	2.25	4.08	1.29	1.51

Table 1: *The scores of workload measurement from a 7-point Likert scale questionnaire. (a) shows the rates of our design while (b) shows the results of a baseline design*

In addition to evaluating the perception stress and workload, we also wanted to find out how much users engage in the animation when watching the clickstream data. The engagement was refined in the following aspects: *awareness*, *excitement*, *enjoyment*, *curiosity*, *anticipation*, *attention*, *persistence*, *aesthetics*, *understandability*, and *memorability* on a 7-point scale ranging from the worst (1) to the best (7) experience. Fig. 10 displays the results of our measurement, which shows the participants found our designs more engaging, especially in the case of *excitement*, *enjoyment*, *anticipation*, and *aesthetics*.

In the open-ended feedback session, participants particularly valued the time-compressing design (spring) and also found the timeline with foreshadowing designs, as well as the falling bubbles useful to anticipate and stress patterns. They appreciated the overall aesthetic design of our system. One participant said: "the system with time compressing and foreshadowing design is better than the baseline system in terms of its ability to draw my attention." Regarding the information obtained from the two animated designs, most of the participants wrote down the dates they observed to help answer the follow-up questions of the tasks after watching without much detailed descriptions of the corresponding patterns. Compared with the baseline system, most participants took about half the amount of notes when using our system.

8 Conclusion

We have proposed an animated narrative visualization system to present temporal video clickstream data, which enable the audience to understand data and the underlying patterns in a more engaging way. Specifically, we make use of the time remapping and foreshadowing techniques in the film field. To help users build up their anticipation of the coming events, we design an animated timeline and an animated stacked graph with foreshadowing visual cues. In addition, we evaluate the system through a real world clickstream dataset. To validate the perception of the temporal remapping and foreshadowing cues, we design and conduct a user study to evaluate the subjective engagement level of our design, showing that the audience is engaged with the animation.

Our work opens up new possibilities for future work in animation-based narrative visualization with data. Moreover, the animation design should not just be limited to video data. They can also be applied to general temporal data. In the future, we plan to conduct a more detailed quantitative study for different visual elements. We will expand our design choices by including considerations of more possible narrative elements.

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References

AGUIAR, E., NAGRECHA, S., AND CHAWLA, N. V. 2015. Predicting online video engagement using clickstreams. In *Data Science and Advanced Analytics (DSAA), 2015. 36678 2015. IEEE International Conference on*, IEEE, 1–10.

AIGNER, W., MIKSCH, S., MÜLLER, W., SCHUMANN, H., AND TOMINSKI, C. 2007. Visualizing time-oriented dataa systematic view. *Computers & Graphics 31*, 3, 401–409.

AMINI, F., HENRY RICHE, N., LEE, B., HURTER, C., AND IRANI, P. 2015. Understanding data videos: Looking at narrative visualization through the cinematography lens. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, ACM, 1459–1468.

BACH, B., PIETRIGA, E., AND FEKETE, J.-D. 2014. Graphdiaries: animated transitions andtemporal navigation for dynamic networks. *Visualization and Computer Graphics, IEEE Transactions on 20*, 5, 740–754.

BEAL, C. R., AND COHEN, P. R. 2008. Temporal data mining for educational applications. In *PRICAI 2008: Trends in Artificial Intelligence*. Springer, 66–77.

BORDWELL, D., THOMPSON, K., AND ASHTON, J. 1997. *Film art: An introduction*, vol. 7. McGraw-Hill New York.

CHORIANOPOULOS, K. 2013. Collective intelligence within web video. *Human-centric Computing and Information Sciences 3*, 1, 1–16.

DACHSELT, R., AND WEILAND, M. 2006. Timezoom: a flexible detail and context timeline. In *CHI'06 Extended Abstracts on Human Factors in Computing Systems*, ACM, 682–687.

DRAGICEVIC, P., BEZERIANOS, A., JAVED, W., ELMQVIST, N., AND FEKETE, J.-D. 2011. Temporal distortion for animated transitions. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, ACM, 2009–2018.

FORESHADOWING.ORG, 2016. Types of foreshadowing. http://foreshadowing.org/types-of-foreshadowing.html. Retrived on April 27th, 2016.

FULDA, J., BREHMER, M., AND MUNZNER, T. 2016. Timelinecurator: Interactive authoring of visual timelines from unstructured text. *Visualization and Computer Graphics, IEEE Transactions on 22*, 1, 300–309.

GRATZL, S., LEX, A., GEHLENBORG, N., COSGROVE, N., AND STREIT, M. 2016. From visual exploration to storytelling and back again. *bioRxiv*, 049585.

HEER, J., AND ROBERTSON, G. G. 2007. Animated transitions in statistical data graphics. *Visualization and Computer Graphics, IEEE Transactions on 13*, 6, 1240–1247.

HOU, X., AND ZHANG, L. 2007. Saliency detection: A spectral residual approach. In *Computer Vision and Pattern Recognition, 2007. CVPR'07. IEEE Conference on*, IEEE, 1–8.

HURON, S., VUILLEMOT, R., AND FEKETE, J.-D. 2013. Visual sedimentation. *Visualization and Computer Graphics, IEEE Transactions on 19*, 12, 2446–2455.

LEE, J., PODLASECK, M., SCHONBERG, E., AND HOCH, R. 2001. Visualization and analysis of clickstream data of online stores for understanding web merchandising. In *Applications of Data Mining to Electronic Commerce*. Springer, 59–84.

MCKEE, R. 1997. *Substance, Structure, Style, and the Principles of Screenwriting*. New York: HarperCollins.

MEDIACOLLEGE, 2016. Manipulating time in video production. http://www.mediacollege.com/video/editing/. Retrieved on March 10th, 2016.

MONTGOMERY, A. L., LI, S., SRINIVASAN, K., AND LIECHTY, J. C. 2004. Modeling online browsing and path analysis using clickstream data. *Marketing Science 23*, 4, 579–595.

NGUYEN, P. H., XU, K., WALKER, R., AND WONG, B. 2014. Schemaline: Timeline visualization for sensemaking. In *Information Visualisation (IV), 2014 18th International Conference on*, IEEE, 225–233.

RIEDL, M. O., AND YOUNG, R. M. 2010. Narrative planning: Balancing plot and character. *Journal of Artificial Intelligence Research 39*, 1, 217–268.

ROBERTSON, G., FERNANDEZ, R., FISHER, D., LEE, B., AND STASKO, J. 2008. Effectiveness of animation in trend visualization. *Visualization and Computer Graphics, IEEE Transactions on 14*, 6, 1325–1332.

ROSLING, H. 2009. Gapminder. *GapMinder Foundation http://www. gapminder. org*, 91.

SEGEL, E., AND HEER, J. 2010. Narrative visualization: Telling stories with data. *Visualization and Computer Graphics, IEEE Transactions on 16*, 6, 1139–1148.

SHI, C., FU, S., CHEN, Q., AND QU, H. 2015. Vismooc: Visualizing video clickstream data from massive open online courses. In *Visualization Symposium (PacificVis), 2015 IEEE Pacific*, IEEE, 159–166.

SIGOVAN, C., MUELDER, C. W., AND MA, K.-L. 2013. Visualizing large-scale parallel communication traces using a particle animation technique. In *Computer Graphics Forum*, vol. 32, Wiley Online Library, 141–150.

THOMAS, F., JOHNSTON, O., AND THOMAS, F. 1995. *The illusion of life: Disney animation*. Hyperion New York.

TVERSKY, B., MORRISON, J. B., AND BETRANCOURT, M. 2002. Animation: can it facilitate? *International journal of human-computer studies 57*, 4, 247–262.

WALDNER, M., LE MUZIC, M., BERNHARD, M., PURGATHOFER, W., AND VIOLA, I. 2014. Attractive flicker - guiding attention in dynamic narrative visualizations. *Visualization and Computer Graphics, IEEE Transactions on 20*, 12, 2456–2465.

WEI, J., SHEN, Z., SUNDARESAN, N., AND MA, K.-L. 2012. Visual cluster exploration of web clickstream data. In *Visual Analytics Science and Technology (VAST), 2012 IEEE Conference on*, IEEE, 3–12.

ZHAO, J., DRUCKER, S. M., FISHER, D., AND BRINKMAN, D. 2012. Timeslice: Interactive faceted browsing of timeline data. In *Proceedings of the International Working Conference on Advanced Visual Interfaces*, ACM, 433–436.