DOI: 10.1111/cgf.14552
Eurographics Conference on Visualization (EuroVis) 2022
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(Guest Editors)

Volume 41 (2022), Number 3

DanmuVis: Visualizing Danmu Content Dynamics and Associated Viewer Behaviors in Online Videos

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Abstract

Danmu (Danmaku) is a unique social media service in online videos, especially popular in Japan and China, for viewers to write comments while watching videos. The danmu comments are overlaid on the video screen and synchronized to the associated video time, indicating viewers' thoughts of the video clip. This paper introduces an interactive visualization system to analyze danmu comments and associated viewer behaviors in a collection of videos and enable detailed exploration of one video on demand. The watching behaviors of viewers are identified by comparing video time and post time of viewers' danmu. The system supports analyzing danmu content and viewers' behaviors against both video time and post time to gain insights into viewers' online participation and perceived experience. Our evaluations, including usage scenarios and user interviews, demonstrate the effectiveness and usability of our system.

CCS Concepts

• ***Human-centered computing*** → ***Visual analytics;*** *Visualization systems and tools;*

1. Introduction

Danmu (Danmaku) is a unique social media service for online videos, especially popular on Asian video websites (e.g., Bilibili[†], iQIYI[‡]). Viewers can send danmu comments anonymously and see others' danmu while watching videos. These comments are overlaid on the video screen and aligned with the video timeline regardless of their post time, creating a co-viewing experience. As shown in Fig. 1, many viewers post the danmu "the highest order of a nonzero subexpression" in a teaching video. Compared with traditional video forums where comments are left asynchronously under the video or in separate communication channels, danmu comments enable seamless integration of textual commentary and the video frames. The danmu comments reveal viewers' instant thoughts and feelings of watching videos. This feedback can help video uploaders (like YouTubers) to improve their video creation [SHS*17]. However, according to our interviews with the video uploaders, currently, they can only browse danmu one by one in a list provided by the websites. It is time-consuming for them to gain insights from danmu comments.

Existing works focus on analyzing the motivation of posting danmu [CGR17], language features [MC17], sentiments [WSZH18], temporal distributions [HGC*18]. They are based on the aggregate method, which lacks interactive exploration of danmu data. VideoForest [SSCM16] summarizes video streams based on danmu data, which helps understand the keyframes with danmu comments. However, danmu is treated as complementary to the video data, lacking in-depth analysis of danmu content. Unlike common time-series data, danmu has two different time dimensions, i.e., video time (when danmu appears in the video) and post time (when viewers post danmu comments). Previous works mainly focus on aggregating the danmu comments against the video time, which neglects the dynamics of danmu data with post time. Our collaborated video uploaders want to know when their videos get popular and which video clips attract viewers. An interactive visualization that enables efficient analysis of danmu data with different time dimensions is demanded.

However, designing such a visualization system is nontrivial. First, danmu data is highly dynamic in time and content. Danmu, often posted by many viewers, can burst at any video clip or real-world time. These comments are relatively short and contain a large

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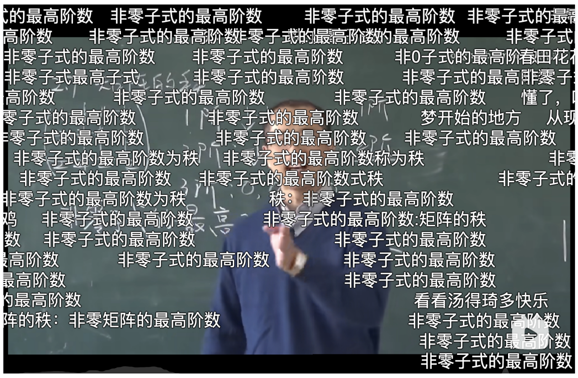

Figure 1: *Screenshot of danmu comments overlaid on a teaching video*¶*. The repeated comments read: "the highest order of a non-zero subexpression."*

number of buzzwords. Second, we need to consider two different time dimensions, which reveal two different types of danmu dynamics. Such consideration can demonstrate viewers' watching behaviors. How to visualize these watching behaviors is challenging. Third, a video uploader may have dozens or even hundreds of videos. Summarizing danmu dynamics in different levels of detail to facilitate exploration may be complex.

To fill the gap, we present DanmuVis, an interactive visualization system that enables users to analyze danmu comments and associated viewer behaviors in videos. We propose a behavior detection and classification method based on the viewer's danmu sequence in a video. Our system features three main views: a) a videos comparison view to compare danmu metrics in different videos from different dimensions; b) a time matrix view for users to analyze danmu data in one video; c) entity views to show popular danmu comments and active viewers. To evaluate the usefulness and effectiveness of DanmuVis, we present two use cases and collect feedback through interviews with users. The main contributions of this paper are as follows:

- An interactive visualization system to help analyze danmu data and associated viewer behaviors in a video collection. Our system supports users to compare danmu comments across different videos and drill down into one video for detailed analysis.
- A unique analysis perspective of danmu data from post time and video time. Our analysis of danmu data takes an integrated analysis of post time and video time, which shows correlations of the two time dimensions.
- A behavior identification method by comparing the two successive danmu comments of a viewer. This is the first study to deduce watching behaviors based on danmu data to the best of our knowledge. The results prove the effectiveness of the proposed method.

2. Related Work

In this section, the most relevant studies are surveyed, covering social media visualization, multimedia visual analytics, danmu and behaviors analysis.

¶ https://www.bilibili.com/video/BV1aW411Q7x1

Social Media Visualization Social media has changed the way of information sharing and social interactions between people. Different social media platforms have emerged, which generate a large amount of data. Researchers in visualization proposed many advanced methods and tools to analyze patterns on social media [CLY17, WCG*16]. These works focus on analyzing text content posted by users [CSL*10, CLT*11, CLWW14] or information diffusion process by users' interactions [CCW*16, CCL*17, CLCY20]. However, the existing visualization method can not support the analysis of danmu data directly. Firstly, danmu comments have two time dimensions while other social media data only have post time. Secondly, interactions between viewers are implicit in danmu, which is hard to construct the discussion thread of users automatically. Thirdly, danmu comments are very short and suffer from noise, which is challenging to make topics analysis [AYB20].

Multimedia Visual Analytics Many works have been proposed to assist in multimedia analysis and knowledge discovery. They are classified into two categories: image-based and abstract approaches. Image-based approaches extract key frames in the video to help users gain a quick overview of the video content. For instance, Kim et al. [KGS*14] proposed a video thumbnail technique to automatically summarize dynamic objects within a video clip. Nguyen et al. [NNL12] visualized a video in a 3D cube, enabling quick navigation. Abstract approaches extract and visualize multimodal information in the videos. These videos cover different topics, like sports [SJL*17, AAA*21], talks [WQ20, ZWW*20], meetings [GMSW15, CBS*19]. Kurzhals et al. [KJH*16] proposed a multi-level visual analytics method to visualize the structures of a movie, which combines scenes, script and subtitle text of the movie. Kim et al. [KBI*17] further analyzed the narrative structure by story curves.

Different from these works, we focus on the analysis of viewers' interaction data in videos. Besides visualizing multimodal information in one single video, analyzing video collections has attracted researchers' attention. Renoust et al. [RLS16] designed a graph to visualize the concurrence relations of people in the videos. Matejka, Grossman and Fitzmaurice [MGF14] proposed a framework allowing users to visualize and explore a large collection of sports videos and associated metadata. The pixel-based timelines let users quickly find relevant sections within the videos. Our work also focuses on video collections, which enables users to compare danmu in different videos and then focus on videos of interest for further analysis.

Danmu Analysis and Visualization The increasing popularity of danmu has attracted the interest of social media researchers. Chen et al. [CGR17] first explored the motivations of Danmu viewing. Danmu provides viewers a desired co-viewing experience, and the comments satisfy viewers' information and entertainment needs. They designed a danmu posting interface to facilitate discussion among MOOC learners and instructors [CGYT19]. Ma and Cao [MC17] found that humor, sarcasm and happiness are three primary emotions that evoke the impulse to post danmu. Besides, existing works make further statistical analysis about danmu information [LZW*22, HGC*18, WSH19]. Lv et al. [LZW*22] analyzed the unique attributes of danmu, including the color, display type, emoji. He et al. [HGC*18] found a strong herding effect in

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danmu posting. Viewers who write danmu comments can be easily affected by the observed danmu, so danmu often gather together at several time points. Wu et al. [WSH19] found that there are more active viewers in posting danmu than commenting in forums. The sentiment of danmu comments is significantly more negative than forum comments.

While these studies provide analysis about danmu, they only use some basic representations and none of them dig deep into the analysis of danmu content within a video. VideoForest [SSCM16] presents the relationships between video content and danmu comments with the metaphor of a tree. Key frames of the video are clustered and visualized in scene trees, with roots showing the corresponding danmu comments. Sung et al. [SHS*17] visualize the dynamics of different types of time-anchored comments on the online video with a river metaphor. StreamWiki [LHW18] summarizes danmu by keywords to improve the learning experience of live stream viewers. Although these works provide insight into the dynamics of danmu content, only the video time dimension is considered. Also, behaviors hidden in the danmu data are ignored.

Behaviors Analytics in Videos When a viewer watches a video, different actions can be taken to control the playback of the video, including play, pause, seek, rate change, open, and close [LBYC17]. These behaviors are typically recorded as a sequence of clickstreams. The analysis of clickstreams can help to gain insights into online watching behaviors. PeakVizor [CCL*16] helps education experts to analyze video clickstreams peaks from different aspects. The system visualizes spatio-temporal information about clickstream peaks and the correlation between different learner groups and clickstream peaks. To convey the patterns in video clickstream data, Wang et al. [WCL*16] propose an animated narrative visualization based on non-linear time mapping and foreshadowing techniques. By sampling a collection of videos, Kim et al. [KGS*14] summarized which parts in lecture videos lead to more frequent and sharper peaks. The clickstreams can be used as a measurement of engagement in online course studies. Lan et al. [LBYC17] use clickstreams to determine learner engagement. Yu et al. [YWL19] predict learning outcomes of MOOCs based on clickstreams.

However, these studies focus on aggregate behaviors, ignoring the difference between them for video content analysis. Chorianopoulos assumed that GoBackward/GoForward behaviors were different indicators of viewer's interest in videos [Cho13]. The viewers replay a video segment because something is exciting or challenging to understand. They skip forward a video segment because there is nothing of interest. Based on the two behaviors, he proposed a viewer-based approach to detecting attractive video segments. Similarly, Shi et al. [SFCQ15] found that a larger percentage of backward seek behaviors happening around video segments with a more complicated question in MOOC platforms. We extract viewers' possible behaviors from their danmu comments by comparing the difference between post time and video time. To the best of our knowledge, this is the first such study. Unlike the behavior data recorded in logs, these extracted viewers' behaviors in this study are uncertain, but they can also provide users insight into viewers' watching patterns.

3. Problem Characterization

This section introduces the characteristics of danmu data and discusses how to extract viewers' behaviors extracted from danmu data. Then, we summarize the design requirements for the system.

3.1. Data Description

In this study, the data is obtained by the API from Bilibili, a famous danmu website in China. For a danmu comment posted by a viewer, it has the following attributes:

- **Comment** is the text content of danmu viewers send out. The comment indicates the viewer's experience about the video, which is often short and contains buzzwords, such as "666" (great) and "hhh" (haha).
- **Video time** is the playback time around which the viewer sends out the danmu comment. Once a viewer writes a danmu comment and sends it out, it will be synchronized to the associated video time and immediately displayed onto the video. All video viewers might see the text next time when watching the video around the associated video time.
- **Post time** is the natural time when viewers send out a danmu comment, e.g., at 8:00:00 a.m., on Jan. 1, 2022. The post time of danmu is always later than the uploading time of the video. When viewers watch one video on Bilibili, recent danmu comments are always displayed first, and older danmu comments might be hidden due to limited display space.
- **UID** is the ID of the viewer who posts the danmu. With UID, we can extract danmu comments posted by the same viewer, which helps further identify the viewer's watching behaviors when posting danmu.

Different from comments in other social media, each danmu comment is associated with two timestamps, i.e., video time and post time. After having an initial analysis of danmu data, we found that the watching behaviors of viewers could be derived by post time and video time of danmu. Since we can not get the exact watching behaviors of viewers from the API, this indirect method provides a new perspective of danmu analysis. We first use an example to explain how the watching behaviors of viewers affect the time of danmu comments.

Imagine that Jack, an online video viewer, opens a video on Bilibili at 08:00:00. As shown in Fig. 2, the x-axis represents the post time of danmu comments, while the y-axis is video time. Twenty seconds later, he posts one danmu (D_1), which appears at 08:00:20 of the x-axis and the 20th second of the y-axis. At 08:00:40, another danmu D_2 is sent out. Jack has no intervention on the playback of the video, so D_2 is at the 40th second in the video. Since each pixel of the x-axis and y-axis represents the same time length, the slope of the line connecting D_1 and D_2 is 45°against the y-axis. Next, Jack drags the seek bar in the video forward and posts D_3. D_3 marches a longer distance on the y-axis than the x-axis. The angle of the line connecting D_3 and D_2 is less than 45°. Jack slows the playback rate of the video and then posts D_4. The slope of the line connecting D_4 and D_3 is more than 45°. Later, Jack drags the seek bar backward and posts D_5. In contrast, it appears earlier in the video than D_4. The slope of the line connecting D_5 and D_4 is over 90°. After finishing the video, Jack reopens the video in the

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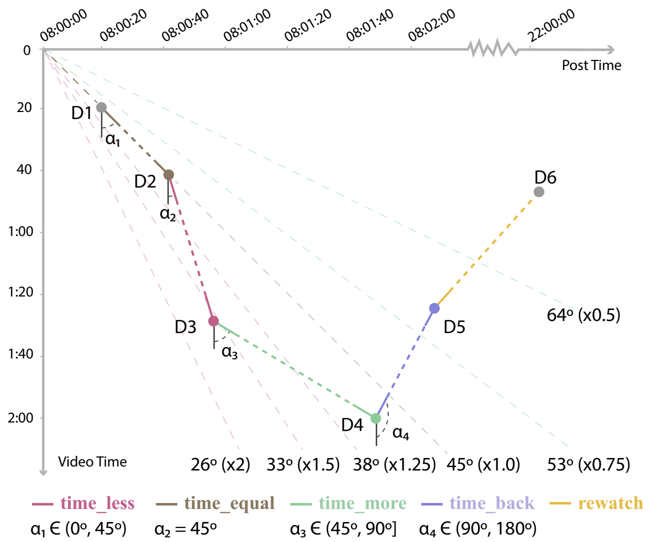

Figure 2: *Illustration of a viewer's danmu sequence and associated behaviors in a video. We calculate the angle of the line connecting two successive danmu comments, reflecting the viewer's possible behaviors of watching videos. Special angles related to different playback rates of videos are marked with dashed lines. To reduce visual clutter, only colored short tails are used to represent these behaviors while middle dashed lines are ignored in the final visualization.*

Table 1: *Identification and explanation of different viewer behaviors*

Relation	Behavior	Term
$0^\circ < \alpha < 45^\circ$	rate increase	**time_less**
	forward	
$\alpha = 45^\circ$	normal	**time_equal**
$45^\circ < \alpha <= 90^\circ$	uncertain	**time_more**
$90^\circ < \alpha < 180^\circ$	backward	**time_back**
$I_{pt} >> v\_length$	rewatch	**rewatch**

evening and posts danmu D_6. The post time of D_6 is much later than that of the previous danmu comments.

From the above example, it is clear that viewers' interactions with the video controls influence the video time interval and post time interval of two successive danmu comments. The difference of the two intervals will result in lines with different slopes on the 2D plot, with the x-axis and y-axis representing post time and video time, respectively. Next, we introduce how to determine a viewer's possible behavior by comparing post time and video time of the viewer's two successive danmu comments.

3.2. Behaviors Identification

For two successive danmu comments posted by one viewer, they are denoted as D_i and D_{i+1}, respectively. Here, "successive" means the viewer sends out D_{i+1} after D_i, and there are no danmu comments posted between them by the viewer. The time interval of D_i and D_{i+1} in post time and video time are calculated, respectively.

$$I_{pt} = D_{i+1}.post\_time - D_i.post\_time, \tag{1}$$

$$I_{vt} = D_{i+1}.video\_time - D_i.video\_time, \tag{2}$$

Then the angle of the line $\overline{D_iD_{i+1}}$ (Fig. 2) against the y-axis (video time) is calculated by the following equation.

$$\alpha = (\operatorname{arccot} I_{vt}/I_{pt}) \times 180/\pi, \tag{3}$$

Based on events in course videos by Shi et al. [SFCQ15], we summarize how these events affect the value of α.

- $0^\circ < \alpha < 45^\circ$ The later danmu D_{i+1} goes further along the y-axis (video time) than the x-axis (post time). Viewers must seek the video forward or increase the playback rate of the video so that they spend less time from the video time point of D_i to the time point of D_{i+1}. This pattern is denoted as **time_less** behavior.
- $\alpha = 45^\circ$ The time viewers spend is the same as the video time interval between D_i and D_{i+1}. It is probable that viewers watch the video at a normal rate and take no interventions of the video controls. This pattern is denoted as **time_equal** behavior.
- $45^\circ < \alpha <= 90^\circ$ It takes viewers a longer time from the video time point of D_i to that of D_{i+1}. All possible behaviors could happen between the post time intervals of D_i and D_{i+1}. For example, viewers could pause the video for a while and then post D_{i+1}. They can also slow the playback rate of video or finish watching and then post D_{i+1}. So, the behaviors are quite uncertain. Especially, if viewers paused the video and post D_i and D_{i+1}, the two danmu comments would have the same video time, which makes α equal 90°on the plot. This pattern is denoted as **time_more** behavior.
- $90^\circ < \alpha < 180^\circ$ It means that viewers seek the video backward or watch the video again. Then, they post danmu D_{i+1}. Although posted later, D_{i+1} may be ahead of D_i in the video. This pattern is denoted as **time_back** behavior.
- $I_{pt} >> v\_length$ If the post time interval of D_{i+1} and D_i is much larger than the video length, they do not belong to the same time of watching. Viewers could watch the video several times. The happening time of each watching could be quite different. We set a threshold to determine such behaviors. The current threshold of the post time interval is ten times the video length. This pattern is denoted as **rewatch** behavior.

The value of α has a continuous range between $0^\circ$and 180°. Each part of the value space is mapped to different watching behaviors (Table 1). Except for **time_more** behaviors, other classified behaviors can be mapped to one or multiple viewers' actual watching behaviors on online video websites. However, the identification method can not determine that no other watching behaviors happen. Also, no behaviors can be derived for viewers who only post one danmu in a video.

Based on the above analysis, we further make statistics of angles in different videos. Fig. 3 shows the distribution of behavior angles in one online video. There are several peaks in the histogram, which are highly related to play controls of online video websites. On Bilibili, viewers can control the playback rate of videos. The

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playback rates include x2, x1.5, x1.25, x1.0, x0.75, x0.5. The rates over x1.0 accelerate the playback of the video and vice versa. If one viewer posted multiple danmu comments with a fixed playback rate of the video, the line connecting these danmu would be a straight line with a specific angle. Rate x2 is mapped to 26°, x1.5 to 33°, x1.25 to 38°, x1.0 to 45°, x0.75 to 53°, x0.5 to 64°, in our detection method, respectively. If viewers pause the video and post danmu comments, the behavior angle will be 90°. We make statistics of viewer behaviors in different videos with the proposed method. There are always peaks in these special angles.

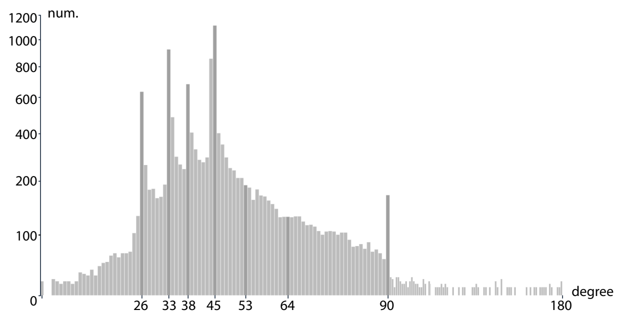

Figure 3: *Statistics of danmu angles in a video. There are peaks in the angles less than 45°, corresponding to different accelerating rates on the website. 45°means viewers watch the video at the normal rate. 90°means viewers pause the video and post danmu comments. **time_back** behaviors are much fewer than other behaviors. The x-axis is nonlinear to emphasize special angles between 0°and 90°.*

3.3. Task Analysis

Our system was designed to meet the real-world requirements for video uploaders to analyze danmu. We interviewed two video uploaders (E1, E2) to survey their detailed requirements. E1 has shared over 100 videos about learning advanced mathematics on Bilibili since 2018. E2 is a games videos creator and has uploaded 37 videos since 2019. The uploaders reported that the website only provides quantitative statistics of their videos, e.g., how many viewers watch their videos each day. The danmu comments are only shown in a list, but viewers' watching behaviors are not displayed. Often they need to check the comments left by viewers manually to get feedback. They are eager to have a more efficient analysis tool. We reported our initial analysis to them, especially how to derive the watching behaviors of viewers according to their danmu. They were surprised by our initial results since they could not get information on viewers' watching behaviors. Based on their feedback and literature review of previous works on danmu [SSCM16, SHS*17, LHW18], and watching behaviors analysis [SFCQ15, CCL*16, XWX*19], we distilled the following design requirements.

- **R1 Support analysis of danmu in a video collection.** The uploaders requested to analyze danmu data in an entire video collection instead of only one video. They often uploaded dozens of videos to the website, and they hoped to get an overview of what viewers post when watching these videos. The summary of the video collection can help the uploaders compare different videos and make effective exploration.
- **R2 Summarize and analyze danmu from multiple aspects.** Besides danmu content, the uploaders were interested in viewers' watching behaviors. For example, if viewers seek the video from an earlier point to a later one, they skip some content not interesting. The uploaders may reduce such content in the video since viewers pay less attention to them. Some viewers are active in posting danmu comments. The uploaders were very interested in how they engaged in the videos.
- **R3 Reveal temporal patterns of danmu data.** The uploaders mentioned the desire to know how danmu comments and viewers' behaviors change with the video content. The temporal patterns with video time help them locate video clips attracting viewers' attention. Moreover, they hoped to see the danmu data from the perspective of post time to monitor the popularity of their videos.
- **R4 Enable multilevel analysis.** One uploader's video collection has dozens or possibly hundreds of videos, including different danmu comments and viewers. The system should facilitate the analysis of these entities from the collection to each video.
- **R5 Provide easy interaction and intuitive visual designs.** It is essential to provide convenient interactions with the system to support the exploration of danmu data at different levels. Also, our target users may not have a background in data visualization. Simple visual designs are easier for them to understand.

4. DanmuVis

In this section, we introduce DanmuVis, an interactive visual analytics system for danmu content dynamics and associated viewer behaviors in online videos. This section first gives an overview of DanmuVis and then describes each view of the visualization system in detail.

4.1. System Overview

Our system contains a data processing step and a visual exploration phase, as shown in Fig. 5. We first build a danmu sequence for each viewer in each video. Then, behaviors for each viewer in the video are identified by the proposed method in section 3.2. In the processing step, the aggregation of danmu data against video time, post time, and danmu content are also finished. The visual exploration phase is divided into two levels. For collection level exploration, videos are compared by aligning each video against different time dimensions (Fig. 4c) to show their difference in temporal dynamics (R1, R2, R3). After such comparison, users can select videos of interest, and the videos comparison view is replaced by the time matrix view (Fig. 6) for video level exploration of the chosen video (R3, R4, R5). Users can also select a viewer or a danmu comment in the collection level exploration and observe its distribution in different videos (Fig. 8). In the video level exploration, users can have an overview of danmu comments and behaviors. Then, they can select behaviors, danmu comments, or viewers of interest for further investigation.

4.2. Exploring Danmu in a Video Collection

DanmuVis enables analysis of danmu in a video collection. The videos comparison view (Fig. 4c) summarizes the dynamics of

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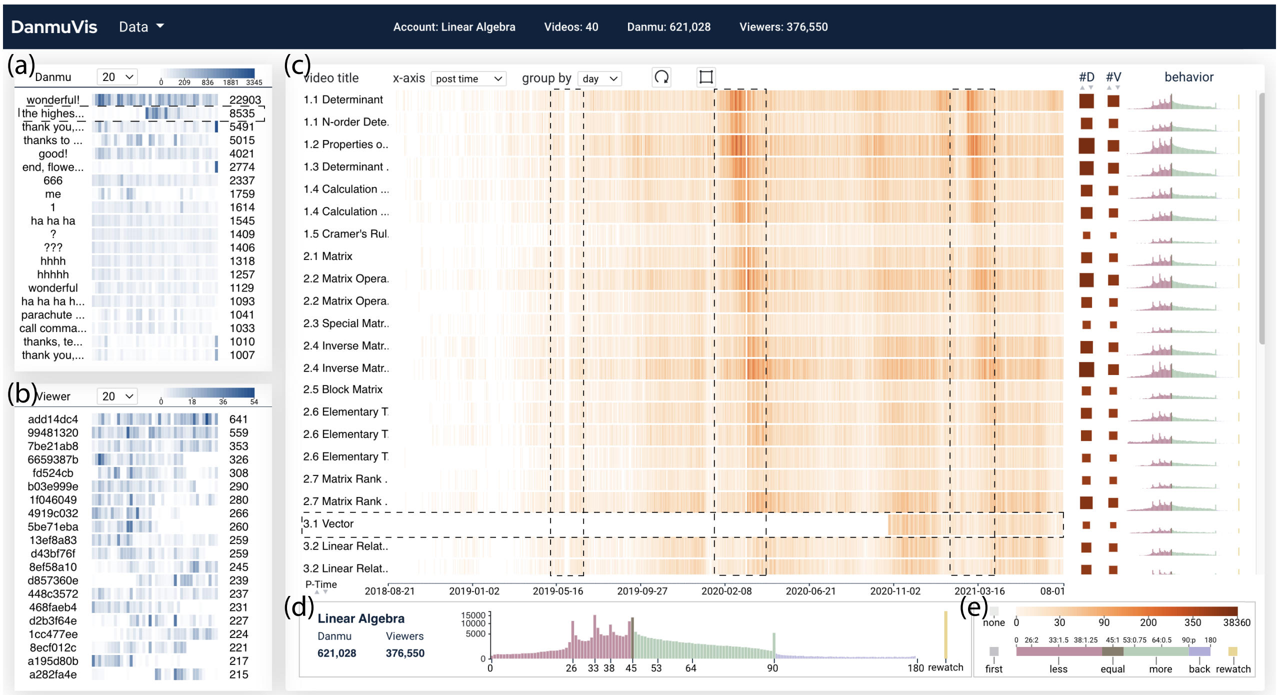

Figure 4: *The video corpus exploration interface supports danmu analysis across different videos. Top danmu comments are listed in the comments view (a), while the viewers view (b) displays active viewers in the video collection. The videos comparison view (c) compares metrics of danmu in different videos against the selected time dimension (post time). The behavior statistic view (d) shows the behaviors information of the video corpus. The legend view (e) demonstrates the color encoding method of the interface. For the convenience of non-Chinese readers, danmu texts and video titles are translated from Chinese to English.*

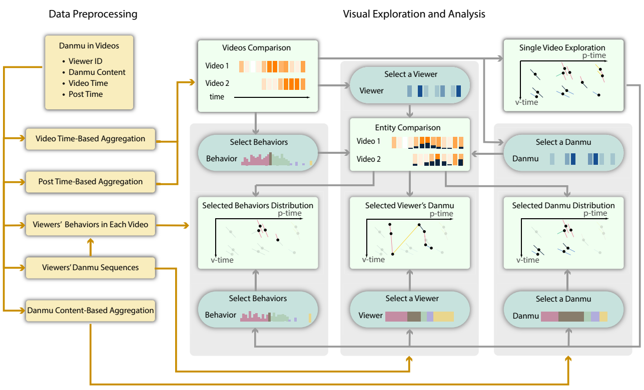

Figure 5: *System pipeline. Our system supports exploring danmu comments from a video collection to one single video from different paths.*

danmu data in each video and provides an easy comparison of different videos (R1). Each row represents one video in this view, showing the changes in the number of danmu comments with post time or video time (R3). Each cell in the row represents one time block, and the saturation of color encodes the number of danmu comments posted within the time block. White blocks indicate no danmu comments posted. A light gray block in each row indicates when the video is uploaded or when the video ends. The size of each block can be adjusted to different time granularity, e.g., one week or one day for post time, one second or ten seconds for video time.

At the right side of each video, two rectangles are used with size and color to encode the total number of danmu comments and viewers in each video, respectively. Then, a histogram is used to show the distribution of behavior angles. Different color represents different types of behaviors. The number of **rewatch** behavior is encoded separately with a bar (R2). After hovering on one video row, the behavior histogram will be enlarged at the bottom view (Fig. 4d). Information about the color scheme is presented in Fig. 4e. By default, the videos in the collection are arranged according to their uploading time from top to bottom. Besides, different sorting methods are provided. These videos can be sorted according to video length, danmu number, or viewers number. After selecting the behaviors angles histogram of one video, other videos will be sorted according to the distribution similarity of behavior angles. The similarity is calculated by the chi-squared distance between histograms of two videos [JNK19].

Top danmu comments (Fig. 4a) and active viewers (Fig. 4b) in the video collection help summarize the video collection. Colored bars with different saturation encode the frequency of the entity in different videos. After selecting an entity, its distribution in different videos will be overlaid on each video row (Fig. 8). The height of each dark blue bar encodes the frequency of the selected entity appearing in each time block (R3).

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4.3. Inspecting Danmu in One Video

After selecting one video in the video collection interface, details of one video can be explored in the time matrix view (Fig. 6). The two time dimensions, i.e., post time and video time are both important features of danmu data. Analyzing one time dimension alone will lose the correlations between them. A 2d visualization is proposed, with the horizontal x-axis representing post time and the vertical y-axis representing video time, respectively (R5). The horizontal x-axis can also represent relative post time to inspect viewers' watching behaviors. In the relative time mode, the x coordinate of one danmu represents the delay time compared to the first danmu posted by the same viewer. Since each pixel in the x-axis and y-axis represents the same time interval, the slope of the line connecting two successive danmu by one user indicates the behavior, as illustrated in Fig. 2.

Each danmu comment is encoded as a circle on the canvas, with the position to represent time information. The heatmap along each time axis summarizes the temporal dynamics of the danmu number (R3). In the initial design, we connected danmu comments of the same viewer to reveal their danmu posting sequences and associated behaviors. However, it brings heavy visual clutter due to line overlappings and crossings. We took a similar design in origin-destination visualization [AAFW17, TC21], which only encodes the edge direction with a short tail. The tails are simplified from lines to reduce visual clutter. One short tail at the left of the danmu circle encodes the behavior between this danmu and its previous danmu. By this analogy, one short tail at the right of the danmu circle encodes the behavior between this danmu and its succeeding danmu. If one user posts only one danmu in the video, the danmu circle has no tails attached . If one danmu is the first danmu in the danmu sequence, no left tail is attached . If one danmu is the last danmu in the danmu sequence, no right tail is attached . The color of the danmu circle is consistent with the behavior encoding to strengthen the perception of behavior patterns. For the danmu with two associated behaviors, we use the color of its previous behavior. All the first danmu posted by viewers in the video is colored gray. Danmu comments indicating rewatch behaviors are colored yellow. Top danmu comments are placed on the canvas to help users gain an overview of semantics. We use the Mean Shift [Che95] algorithm to calculate the position of one danmu comment according to its distribution on the canvas. Danmu comments with higher frequency are placed first. The size of a danmu comment encodes its frequency.

Design alternatives of the time matrix view have been considered. ThemeRiver [HHN00] is popular for showing the dynamics of the dataset with multiple attributes. But it is not suitable for identifying the correlation between two temporal attributes. We also experimented with aggregating danmu comments into matrix cells. The matrix cells design needs to divide the video content into different clips and post time into different stages. The division methods and the size of each cell will affect the final results. Finally, we took the tail-based design. The tail design is a design trade-off between clutter and angle encoding. The tails are already simplified from original lines to reduce visual clutter.

Various interactions are supported to help users explore danmu flexibly on the time matrix view (R5).

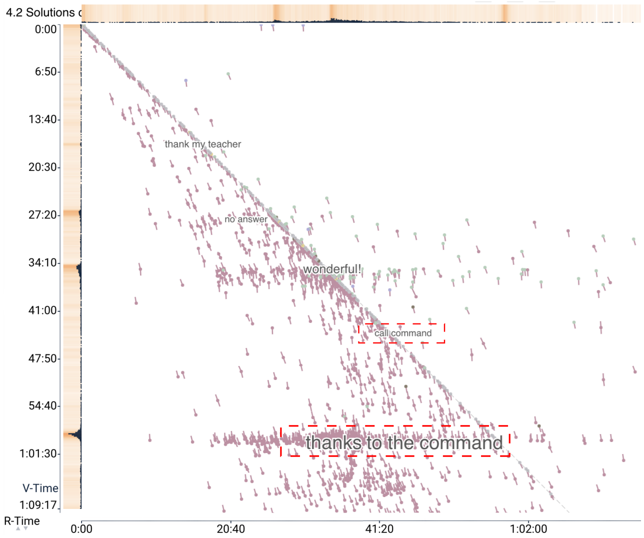

Figure 6: *Time Matrix View. Short tails around a circle are drawn to represent associated behaviors instead of connecting two successive danmu comments directly. The behaviors with an angle less than 26° are filtered out in this view, and the highlighted damnu comments indicate why these behaviors happen more. The x-axis represents relative post time in this view.*

- **Brushing** Users can brush areas on the time matrix view, post time heatmap, or video time heatmap to investigate danmu comments by viewers within the selected time range. After brushing, a popup window will be shown to display the brush time range and popular danmu comments. The video is also provided so that users can check how these comments are related to video content.
- **Filtering** Danmu comments are associated with rich viewer behaviors. Users can filter danmu comments according to different types of behaviors or behaviors angles. Once users click a danmu comment in the danmu comments view, its distribution in the time matrix view will be highlighted. Selecting a viewer will show the danmu posting sequence.
- **Clicking** A popup window including danmu content, the associated behavior, post time and video time will be shown after clicking on a danmu circle on the time matrix view. Double-clicking a danmu circle will highlight the danmu posting sequence of the viewer.

5. Usage Scenario

In this section, we present two usage scenarios conducted together with our collaborated video uploaders to demonstrate the effectiveness and usefulness of DanmuVis in analyzing danmu data.

5.1. Scenario 1: How to engage viewers

In this scenario, a college teacher who shares videos about linear algebra online wants to understand online learners' feedback and their learning status. The course has 40 videos. There are a total of 621,028 danmu comments sent by 376,550 viewers until Aug. 1st, 2021.

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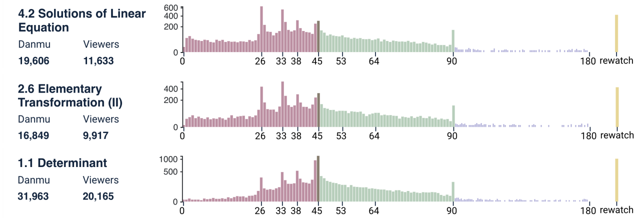

Figure 7: *Behaviors comparison in different videos. The first two videos have very similar behavior distributions. They both have more* ***time_less*** *behaviors with the angle below 26°.*

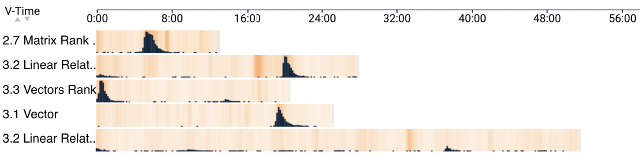

Figure 8: *Danmu comments are highly related to video content. After selecting the danmu comment "the highest order of a non-zero subdivision", videos are sorted and the overlaid dark histogram shows the selected danmu distribution in each video (the x-axis encodes video time).*

After loading the video collection, the teacher finds that the videos were all uploaded on Aug. 21st, 2018 (Fig. 4c). There are few danmu comments posted by viewers in the initial months after these videos were uploaded. However, these videos become popular after 2018 and have remained hot until now. He finds two peaks appearing almost after the Spring Festival in 2020 and 2021, respectively. He thinks that this periodic phenomenon is highly possible that students preparing for the graduate entrance examination begin to review linear algebra after the break of the Spring Festival holiday. Besides, the teacher observes that some blank blocks suddenly appear in all the videos simultaneously, which means there are no danmu comments posted during this time. He thinks that viewers could not post danmu due to website maintenance. There is also a row that is almost blank ("Video 3.1 Vector"). After checking this video content, it reminds him that it has been re-made. The historical danmu comments are not recorded.

The teacher is interested in how viewers watch his videos. He finds that many viewers prefer to change the playback rate of videos as the peaks at these angles are very obvious (Fig. 4d). He thinks that viewers prefer to accelerate the playback rate to save watching time. They will not miss important content in the video with this watching method. By browsing the behavior angle histogram accompanying each row, the teacher finds that behaviors distribution in the video "4.2 Solutions of Linear Equations" (referred to as "4.2" below) is quite different. In this video, there are more behaviors with angles less than 26°, which means the forward seek behaviors happen more frequently. By sorting all the other videos by behavior distribution similarity to this video, the most similar one is video 2.6, while the most different one is video 1.1 (Fig. 7). The teacher wants to know why viewers skip some content in the video. He selects video 4.2, and the video row expands in the vertical direction, as shown in Fig. 6. Only behaviors with an angle less than 26° are shown after filtering. Two buzzwords, "call command" and "thanks to the command" are very popular in the video. "call command" means that viewers are not interested in current video content. In contrast, "thanks to the command" means that viewers jump to a specific time point according to the danmu guidance of other viewers. So, viewers' watching behaviors are consistent with what they post. The teacher checks the video content and finds that he is talking about something irrelevant to the course, so some viewers skip this part by seeking the video controller forward.

Next, the teacher wants to know what viewers post in the video collection. He observers that besides some buzzwords, positive danmu like "wonderful", "thank you, teacher" are very popular in the videos (Fig. 4a). The danmu "the highest order of a non-zero subdivision" is highly related to the video content, which shows a quite uneven distribution in the videos. He hypothesizes that viewers post this danmu when he is teaching about the rank of matrices. To verify his hypothesis, the teacher selects this danmu, and all the videos are sorted according to the number of this danmu appearing in them (Fig. 8). The overlaid histogram indicates that this danmu concentrates on particular video clips. He selects the first video "2.7 Matrix Rank" and brushes the corresponding video clips. The popup video interface shows that he is teaching the concept "the rank of a matrix equals to the highest order of a non-zero subexpression of the matrix". As an important concept in linear algebra, he often asks the question, "what is the rank of a matrix?" in the video. In response, the viewers will post the danmu "the highest order of a non-zero subexpression".

In summary, the teacher finds his videos may be more popular among students for the graduate entrance examination. Asking questions in the teaching video can engage more students to post danmu, which increases the video's popularity.

5.2. Scenario 2: Which videos are popular

In this scenario, an uploader shares videos about her daily life and how to keep fit. By Aug. 1st, 2021, she has uploaded 73 videos. After loading her videos into DanmuVis, she sorts these videos by the number of danmu in descending order. She selects the first video about "High-intensity interval training (HIIT)" to check why viewers post more danmu in this video.

In the time matrix view, the uploader discovers that **rewatch** behaviors are dominant, which means many viewers watch this video multiple times (Fig. 9). She notices that there are three peaks of danmu comments in the video. Danmu comments posted by viewers are about tags like "day 1" "day 2", which marks how many times the viewers watch this video. She thinks that viewers post these danmu comments to encourage themselves to exercise regularly. In addition, she is interested in why there are three peaks in the video. She finds that between the first and second peaks, the video content is about the steps of high-intensity interval training. The video content is the relaxation stage between the second and third peaks. Some viewers prefer to post danmu at the beginning of the video, some at the end of the training and some at the end of the video. This pattern is verified further by exploring the danmu comments of individual viewers (Fig. 10). These viewers watch the video dozens of times at different time. Especially, the viewer in

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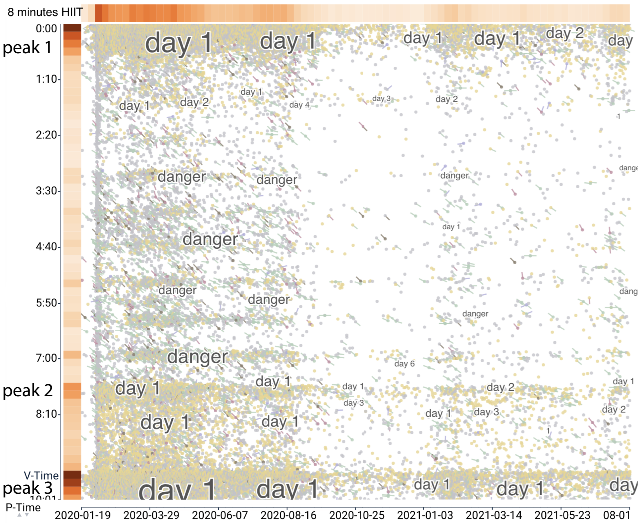

Figure 9: *There are many **rewatch** behaviors in this video. Three peaks are about tags of viewers watching the training steps in the video. Danmu "danger" in the middle of the video indicates that viewers are surprised at the intensity of training in the video.*

(Fig. 10d) posts two danmu at the beginning and end of the video while watching the video, respectively.

There are much fewer danmu comments posted by viewers in the video, except the three clips with a peak. The uploader considers that many viewers follow the training steps in the video, so they watch the video without posting danmu. She is inspired since viewers take part in the training with her. The most danmu is "danger" during the training, indicating viewers might be surprised at the intensity of the activity. They can not follow the training steps in the video, so they stop to express feelings by posting this danmu.

Overall, the uploader thinks that her videos about fitness attract more viewers. Many viewers prefer to post danmu comments as marks of their watching. Considering the danmu comments like "danger" posted by viewers, she might reduce the level of training intensity in the future.

6. User Interview

We interviewed six video uploaders (E1-6). E1 and E2 have been working with us through the design process while the other four just explored the system for the first time.

Procedure. Each interview lasted for about an hour. First, we introduced how we derived viewers' watching behaviors from danmu. We explained the workflow and visual encoding of DanmuVis through the case in Section 5.1 (15 mins). Second, we invited the participants to explore danmu in their own videos with our system to complete three tasks: (1) tell the video with most danmu, when the video is most popular and which clips in the video that viewers are most interested in (10 mins); (2) report one representative danmu and explain why viewers post it in a video (10 mins); (3) report one representative behavior and explain why viewers are with this behavior in a video (10 mins). During the task time, participants should record findings by taking screenshots of the system. Finally, we collected their feedback on watching behaviors, usability, effectiveness, visual design and interactions (15 mins). Their reported results and feedback are summarized from the following aspects.

Watching Behaviors. All the participants confirmed that viewers' watching behaviors derived from danmu data provided more insight into how viewers engage in video watching. Currently, online websites provide no information about viewers' watching behaviors to these participants. With our system, participants could explore watching behaviors in the videos. For example, in Task 3 (behaviors analysis), E3 and E4 found that many viewers in their videos paused the playback of videos to post multiple danmu comments. E1 was more interested in **time_less** behaviors and commented, "If many viewers increased the playback rate while watching my video, I would consider adjusting the rhythm of videos next time."

Usability. The participants confirmed that DanmuVis was easy to use and could facilitate the analysis of danmu data. For example, in Task 1 (popularity analysis), all of them could find the most popular video by sorting videos with the number of danmu. They could answer when the video was popular and which clips were popular by the timeline heatmap. E4 and E6 found that many danmu were posted by viewers at the beginning or end of the videos. "By switching the horizontal timeline to represent video time, I found more saturated color blocks appear at the end of the videos. The viewers prefer to post danmu as ending of watching the videos." (E4). As for Task 2, E1 and E2 agreed that DanmuVis helped them summarize danmu posted by viewers. E1 said, "I seldom inspected danmu in the video because it took me much time. The top danmu comments list tells me what viewers post in my videos at a glance." E2 stated, "Danmu comments are directly related to the video clips. The analysis functions provided by DanmuVis system help me reduce the burden of manually checking different videos to find similar video clips."

Effectiveness. All the participants could finish the tasks within the given time and provided the rationales of their answers. For example, E5, as a game video creator, found the videos about collections of game highlights were more popular among viewers. Viewers prefer to post the danmu "666" (great) in these videos. He also found an active viewer, who posted over 100 danmu comments in one video within 2 days.

Visual Designs and Interactions. Although most participants lacked the fundamental background of data visualization, they reported that the visual design was easy to understand and informative. E1 liked the aligned videos view design and mentioned, "It is easy to compare the metrics of different videos, and different sort methods are helpful to find the videos of interest." He also stated that the time matrix view is intuitive with danmu text overlapped. E3 and E5 echoed this point. All the participants agreed that the tails-based method to encode behaviors angles reduces visual clutter. E4 mentioned the limitation of the short tail, "It is hard to determine the playback rate directly by the short tail from the overview. I need to hover over the short tail to know the angle or playback rate exactly". The participants appreciated the rich sorting and filtering interactions supported by the system. According to our observation,

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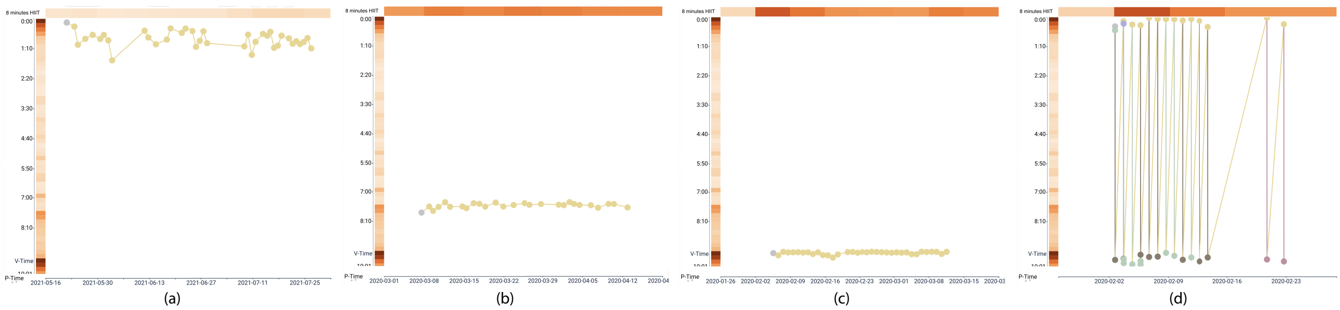

Figure 10: *Different danmu posting preferences, at the beginning (a), at the end of training (b), at the end of the video (c), and both at the beginning and end of the video (d).*

they could make use of the filtering methods to check each type of behaviors in the video.

7. Discussion and Limitation

In this section, we discuss the limitations of our system and propose directions for future study.

Uncertainty of Behaviors. We categorize five types of behaviors according to danmu comments. However, these behaviors can not directly be mapped to viewers' real watching behaviors. The classified behaviors have different uncertainties. For example, the appearance of time_more behaviors may be due to all possible viewer behaviors. However, when the video time of two danmu comments is the same, it is highly probable that viewers pause the video and then post danmu. The proposed method determines possible actual watching behaviors but can not exclude the probability of other watching behaviors. Also, the angle-based determination method does not consider the time intervals of two danmu comments. Their uncertainties should be different for behaviors with the same angle but different related time intervals. The proposed method can not determine when these behaviors start and end. Therefore, we plan to consider the uncertainty of behaviors in the future.

Semantics of Danmu Content. We find that many danmu comments have the same semantics but with different types of expression methods, e.g., "thanks", "thanks a lot", and "thank you". We regard them as different danmu comments in the current system. Further computational analysis of danmu comments, such as clustering, can improve content analysis. Bag-Of-Word or TF-IDF [Cho17] are usually good at modeling long documents. However, they are not suitable for danmu comments analysis, which is often short with buzzwords. Another choice is extracting keywords from danmu text. The extraction results might be misleading and hide the original semantics of the danmu comments. In the future, we plan to collaborate with natural language processing experts to improve the semantics preprocessing of danmu comments.

Visual Designs. The current visual designs of our system list all videos row by row. Users can scroll to view videos out of the current screen. Although we provide abundant methods to help users explore videos, users can hardly overview the corpus, especially for large datasets. One way to improve the scalability of the system is to compare each video row with a pixel-based method, like TABLE LENS [RC94]. In the time matrix view, we simplified the original lines as short tails to reduce visual clutter. However, for the dense danmu area, the overdrawing is server. We currently enable users to select interested danmu, viewers or behaviors to show on the canvas on demand. Although the novelty concerning visualization or interaction is limited, the proposed system applies visualization techniques to the danmu domain, resulting in previously unknown insights.

Generalizability. It is better to involve more video uploaders to improve and evaluate our system further. In addition, DanmuVis is proposed for analyzing danmu comments, which are with two timestamps. But it is not limited to danmu and can be extended to other time-based comments on videos, such as comments in YouTube Live. However, we may not derive viewers' watching behaviors from these comments.

8. Conclusion

This paper proposes DanmuVis, an interactive visualization system to analyze danmu dynamics and associated viewer behaviors in online videos. Based on danmu comments, interesting viewer behaviors are identified by the proposed method. Our system supports users in exploring the difference of danmu features between videos and investigating the dynamics of danmu comments and viewing behaviors in one video. It supports smooth transitions between collection level and video level exploration. Two usage scenarios and interviews with users demonstrate the effectiveness of our system.

In the future, we plan to improve the behavior detection method and further show the behavior uncertainties in our system. Moreover, we plan to cooperate with NLP experts to improve the semantic analysis of danmu comments. Besides, we will design a more structured evaluation with different danmu data for more users to rate the usability of the system.

Acknowledgement

This work is supported by NSFC No. 61872013. We would like to thank Dr. Tao Wang and other members of iQIYI, as well as the members of Bilibili for their discussions on DanmuVis.

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