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Visualizing Nonlinear Narratives with Story Curves

Nam Wook Kim, Benjamin Bach, Hyejin Im, Sasha Schriber, Markus Gross, Hanspeter Pfister

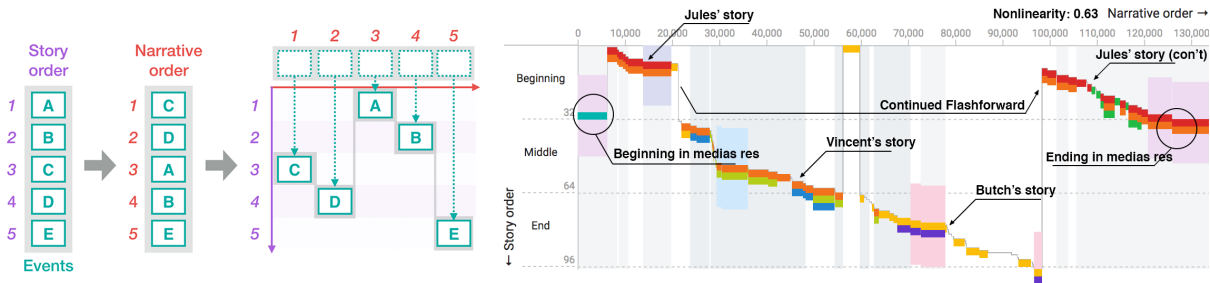


Fig. 1. A schematic diagram showing how to construct a story curve from a sequence of events in story and narrative order (left). An example of a story curve of the movie *Pulp Fiction* (right) showing characters (colored segments), location (colored bands), and day-time (gray backdrop). A nonlinearity index is calculated based on the degree of deviation of narrative order from actual story order.

Abstract—In this paper, we present *story curves*, a visualization technique for exploring and communicating nonlinear narratives in movies. A nonlinear narrative is a storytelling device that portrays events of a story out of chronological order, e.g., in reverse order or going back and forth between past and future events. Many acclaimed movies employ unique narrative patterns which in turn have inspired other movies and contributed to the broader analysis of narrative patterns in movies. However, understanding and communicating nonlinear narratives is a difficult task due to complex temporal disruptions in the order of events as well as no explicit records specifying the *actual* temporal order of the underlying story. Story curves visualize the nonlinear narrative of a movie by showing the order in which events are told in the movie and comparing them to their actual chronological order, resulting in possibly meandering visual patterns in the curve. We also present Story Explorer, an interactive tool that visualizes a story curve together with complementary information such as characters and settings. Story Explorer further provides a script curation interface that allows users to specify the chronological order of events in movies. We used Story Explorer to analyze 10 popular nonlinear movies and describe the spectrum of narrative patterns that we discovered, including some novel patterns not previously described in the literature. Feedback from experts highlights potential use cases in screenplay writing and analysis, education and film production. A controlled user study shows that users with no expertise are able to understand visual patterns of nonlinear narratives using story curves.

Index Terms—Nonlinear narrative, storytelling, visualization.

1 INTRODUCTION

A *narrative* specifies the way in which events in a story are told [26]. A *nonlinear* narrative is a narration technique portraying events in a story out of chronological order, such that the relationship among the events does not follow the original causality sequence. For example, a narrative can withhold information to maintain a sense of mystery, to keep tension high, and to keep the audience interested. Eventually, the narrative can flash back to the beginning of the story, releasing the tension. Such nonlinear narrative techniques are widely used in various types of storytelling genres, including literature, theater, movies, graphic novels, as well as hypertexts and other computer-mediated genres such as video games [11, 19, 24, 27].

Understanding the wealth of patterns in narratives as well as their respective effects has been an ongoing effort in the humanities and the domains associated with the production of narratives [14, 26, 45]. For example, the French literary theorist, Gérard Genette described a recurrent set of nonlinear narrative patterns including flashbacks,

flashforwards, and retrograde narratives [26]. Although there have been many computational approaches to analyze nonlinear patterns in stories [12, 22, 29, 37], there are relatively few studies that focus on the temporal aspect of narratives. One explanation may be that explicit data about the chronological order of events is typically not available and difficult to infer from the final narratives in film, theater, or video games [19, 26]. The complexity of temporal disorientation makes it not only hard to write a nonlinear narrative but also difficult to understand it [5]. In addition, there are no computational tools that can ease exploration and communication of intricate nonlinear narrative patterns.

In this paper, we present *story curves* (Fig. 1), a visualization technique to reveal nonlinear narrative patterns. We also describe Story Explorer (Fig. 2), a tool that allows users to curate the chronological order of scenes in a movie script and explore the nonlinear narrative of the movie using story curves. Story Explorer automatically parses movie scripts and extracts essential story elements such as scenes (the story's events taking place in a specific time and location) and characters as well as their semantic metadata such as dialog sentiment and scene settings. It displays the movie script text (Fig. 2b) alongside story curves with a set of visualizations of complementary information such as characters, times, and places (Fig. 2c).

Story curves are the core of Story Explorer and visualize events (scenes) as points in a 2-dimensional plot according to their order in the narrative (horizontally, left-to-right) and their chronological order in the story (vertically, top-down). As users rearrange scenes into their chronological order, nonlinear narrative patterns become evident through the meandering shape of the story curve that connects scenes in both narrative and story order. A similar visualization has been used by the New York Times to visualize the narration in movie

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Pulp Fiction -

Thriller, Crime | October 1994 | Directed by Quentin Tarantino | Nonlinearity 0.63 | [IMDB](#)



INT. LANCE'S HOUSE - NIGHT

EXT. LANCE'S HOUSE - NIGHT

INT. LANCE'S HOUSE NIGHT

INT. SPARE ROOM

INT. VINCENT'S MALIBU (MOVING) - NIGHT

EXT. FRONT OF MARSELLUS WALLACE'S HOUSE - NIGHT

Vincent

Well I'm of the opinion that Marsellus can live his whole life and never hear of this incident.

The Malibu pulls up to the front. Mia gets out without saying a word (still in a daze) and begins walking down the walkway toward her front door.

Mia

Don't worry about it. If Marsellus ever heard of this, I'd be in as much trouble as you.

Mia smiles.

She turns around. Vincent's out of the car, standing on the walkway, a big distance between the two.

Mia

What's yours?

Fig. 2. Overview of Story Explorer with three embedded views: (a) story curve view, (b) script view, and (c) metadata view. The story curve succinctly summarizes the nonlinear narrative of *Pulp Fiction* with additional metadata displayed along the story curve.

trailers [16]. Our story curves are the first scientific investigation and systematic exploration of this visualization technique. In addition, we encode additional story information such as characters, places, and periods of the day. Characters are represented using different colored curves, which communicate the number of characters in a scene through the thickness of the curve segment. Places are encoded using vertical backdrops in the background.

To demonstrate the usefulness of the visualization technique, we generated story curves for 10 popular nonlinear movies. We show that the story curves do not only reveal nonlinear narrative patterns mentioned in Genette's framework [26] but also show several novel patterns that have not been discussed in the literature before. In order to evaluate the readability and learnability of story curves, we conducted a user study asking participants to answer 20 questions of a pattern reading task (e.g., how many flashbacks are there in a story curve?). Some participants had difficulty in reading both story and narrative order at the same time. Overall, however, participants showed good performance, correctly answering 80% of the questions on average. We highlight potential use cases of Story Explorer in screenplay writing and analysis, education, and film production based on informal discussions with experts including professional writers and a literary scholar.

2 BACKGROUND

The terms *narrative* and *story* are often used interchangeably in informal settings, though the two are very different. A *story* is content (what is told) consisting of events (actions, happenings) and existents (characters and settings), while *narrative* is the expression (how it is told) concerning how the content is presented to readers (narrative voices, styles, plots) [19]. Strictly speaking, we only see the story through

narrative and thus it is the narrative that determines our perception of story. As both story and narration unfolding are time-dependent, events in a story "happen", while the narrative is narrated. Every narration encompasses two temporal sequences: *story time* is the chronological time in which the events happen (e.g., the year 1600, day 5 of the story, Monday, etc.), while *narrative time* is the time of the events being told (e.g. minute 4:21 of the movie, the beginning, middle, or end of a video game, etc.) [26].

Moreover, there are categories of narrative temporality: *order*, *duration*, and *frequency* [26]. Order describes the relation between the chronological sequence of the events of the story and the sequence within which the events are narrated to the audience. Duration compares the time an event spans in the story with the time it takes for it to be described in the narrative. And frequency contrasts the number of times an event occurs in the story to the number of times it is recounted in the narrative [48]. In this work, we are only concerned with order, i.e., the ordering of events in time, which is one of the most fundamental characteristics of any story [41, 44].

In a linear narrative, the order of events in narrative time is the same as in story time. Nonlinear narrative is a storytelling device that depicts events out of chronological order, often employed for the purpose of increasing the suspense of a story [21, 28]. Unlike a linear narrative, a nonlinear narrative does not have to follow direct causality patterns [20]. There may be more than one narrative describing the same story, such as leaving some events out to emphasize particular perspectives or rearranging events to create a sense of mystery [14].

According to Genette's typology [26], there are seven categories of the relationships between the temporal order of the events that are being told (story order) and the pseudo-temporal order of the narrative (narrative order). Montfort [41] concisely describes these patterns,

which we summarize as follows:

Chronicle: Events are narrated in chronological order, i.e., there is temporal agreement in the order of the events between story and narrative. A unique order may not be specified as some events can happen simultaneously; they may be arranged in any order, relative to each other. Most movies belong to this category (e.g., natural disaster or folklore movies).

Retrograde: Events are narrated in reverse chronological order. For example, colored scenes in Christopher Nolan’s movie *Memento* are portrayed backward, while black-and-white scenes are in the original order. Another historical example is *Iliad*, an ancient Greek epic poem, that begins in the middle of the Trojan War.

Zigzag: Events from a period are interleaved with those from another period as they are narrated in order, e.g., a narrative alternating between the past and present. The events that are paired must be semantically related, thus resulting in a temporal coordination similar to *Syllepsis* discussed later. For example, a past event is retrospective of a present event, and in the movie *Memento* chronological scenes are interleaved with reverse scenes.

Analepsis: Events are narrated that took place earlier than what is being narrated. It is more commonly referred as *flashbacks* that are used to recount events that occurred in the past to fill in crucial backstory [32]. For instance, flashbacks are a major part of the TV show *Lost*, portraying what happened in the life of the main characters before they were stranded on the island.

Prolepsis: Events are narrated that take place later than what is being narrated. It is more commonly referred as *flashforwards* that are used to allude to events projected to occur in the future. For example, the film *Arrival* extensively uses prolepsis to show events that occur in the future.

Syllepsis: Events are grouped based on some criteria (e.g., spatial, temporal, thematic kinship). Thematic groupings are often used in the classical episodic novel where multiple stories are inserted and justified by analogy or contrast. Similar groupings are also found in films like *Pulp Fiction* and *Love Actually* that use multiple plotlines.

Achrony: Events are randomly ordered; thus the relationship between the order in which events are narrated and the order in which they occur is difficult or impossible to establish, possibly due to lack of temporal information available from the narrative.

Others have gone on to further extend this taxonomy to address the temporal irony that prevails in postmodern narratives such as time forks (e.g., *Inception*) and time loops (e.g., *Interstellar*) [28,47].

3 RELATED WORK ON VISUALIZING NARRATIVES

Information visualization has been a valuable tool for humanities scholars, enhancing their interpretative activities for literary works [30,38]. Consequently, there are numerous works for visualizing narrative contents with a majority of them focusing on visualizing story content rather than narrative.

Visualization has been used to show character interactions (e.g., multiple protagonists or relationship developments, etc). Individual characters are represented as timelines that converge and diverge to indicate interactions or co-occurrences at the scene or event level [29,35,46,51,52]; similar visual encoding methods are found in other domains as well, such as the temporal dynamics of family relationships [33] and the evolution of network structures over time [39,54,55]. A potential drawback of the line representation is that a character’s absence is not encoded as the line persists from the start to the end of the narrative. Other visualizations have focused on the interplay between characters, employing matrix representations [4] or node-link diagrams [31]. Often, graph metrics for clustering and centrality are presented together.

Another line of examples focuses on visualizing metadata extracted from the movie script. Metadata includes character dialogs, sentiments (positive or negative) [6,10,15] and emotions (primary emotions such as joy, anger, sadness, fear, disgust) [22]. Existing script writing software also embeds visualizations to show narrative structures as well as semantic metadata such as character motivations and dramatic events that are manually annotated by screenplay writers themselves [9] by, e.g., showing the evolution of a character’s emotions through a line chart.

Some visualizations directly show character dialogs on top of visual summaries of characters and scenes, enabling qualitative interpretations for readers [50,53]. In addition, a few works visualize metadata that is not part of the narrative, such as character co-mention networks in Twitter [2] or movie reviews [42].

Yet, there is little work for visualizing nonlinear narratives. Most existing visualizations for nonlinear narratives are non-interactive and hand-crafted infographics for specific movies [1]. For example, Sharma and Rajamanickam [49] use a straight horizontal timeline to indicate the storyline and arcs to show nonlinear time jumps using manually crafted data for the film *500 Days of Summer*. A visualization published by Carter et al. [16] in the *New York Times* relates the order of scenes in movie trailers to their temporal position in the movie. However, it does not show story order of the actual scenes, but rather compares two narrative orders: the movie narrative and the trailer narrative. Thus, no narrative patterns are observable. While extending that technique to entire movies, we additionally visualize additional data such as characters, places, and times.

4 DESIGN GOALS

The overarching goal of this work is to develop a technique that facilitates the exploration, communication, and discovery of nonlinear narrative patterns.

Our work was inspired by Genette’s analysis on nonlinear narrative patterns which was purely based on close reading of short text [26]. For instance, Genette uses textual symbols to represent narrative order and story order, such as “A2[B1]C2[D1(E2)F1(G2)H1]I2”(A-I: narrated events, 1: present, 2: past). Brackets and parentheses indicate flashbacks and flashforwards respectively. While close reading (reading an actual part of a text), is a crucial part in literary research, we wanted to design a computer interface for distant reading that can reveal and communicate patterns visually to scale beyond a few sequence [30]. In order to design such a technique, we defined the following three design goals:

G1: Show events in both narrative and story order. Ordering of events is a key element for studying the temporal nonlinearity of narratives as highlighted by Genette [26]. Frequency and duration of events can only be considered after the order of the events is taken into account. Showing how narrated events are arranged in original story order demonstrates how the order of events has been dramatically manipulated into an engaging presentation of the story in the narrative.

G2: Present story metadata to reveal the semantic structure of narrative. The ordering of events in time alone does not provide a clear picture of what is told and how it is narrated. The raw material of a story, including not only actions but also actors, time, and location, is important for understanding the semantic structure of narrative [13]. Additional semantic metadata, such as character emotions (frown, fear, smile, etc) and traits (ambitious, charismatic, etc), could be also extremely useful. However, automatically extracting such high-level semantics from textual scripts is a challenging natural language processing problem and not the goal of our work.

G3: Let users access and read actual narrative texts. A traditional screenplay analysis involves closely reading scripts, similar to how humanities scholars analyze literary texts or text passages [30]. While a high-level, abstract visual summary of the narrative structure can be useful in discovering global patterns, it is still important to show the raw text. A close reading of the script can enable deeper analysis of the context of global patterns [30,38], e.g., reading actual conversations between two characters whose co-occurrence is prominent in the visual summary.

Based on these design goals, we infer four main visualization tasks. These tasks involve not only drilling down into a single character’s progression across scenes but also making sense of the overall nonlinear structure.

T1: Identify nonlinear narrative patterns, i.e., identify how the order of the scenes in a film unfolds in story order. An example task is to find a flashback scene or a retrograde pattern [G1].

T2: Identify and compare character occurrences across different scenes in both story and narrative order [G1, G2].

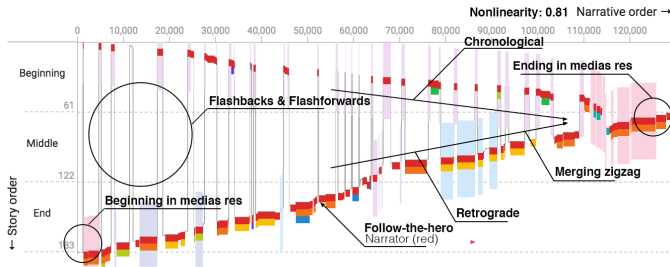


Fig. 3. *Memento* with characters and scene locations superimposed onto the story curve.

T3: Compare the character occurrences in different scene settings including location and time [G1, G2].

T4: Read character dialogs and actions in a specific scene and identify the position of the scene in the global context [G1, G3].

These tasks are mostly in line with existing story visualizations outlined in Section Sect. 3, except that we focus on the temporal nonlinearity of narratives. To support these tasks, we developed story curves and Story Explorer, facilitating the visual exploration and communication of nonlinear narratives. We first describe the story curves visualization technique (Section Sect. 5) and discuss the interactive exploration tool Story Explorer (Section Sect. 6).

5 STORY CURVES

5.1 Revealing Nonlinear Patterns

A story curve provides a succinct visual summary of the order of events in a nonlinear narrative. Fig. 1 shows a schematic diagram of how a story curve is constructed from a sequence of events in both story and narrative order (Fig. 1 (left)). In the story curve (Fig. 1 (right)) the events are arranged from the left to right (i.e., reading order in Western cultures) following the progression of the film narrative, while their story order is encoded from the top to bottom.

Story events are connected to form a curve such that the up-and-down movements of the curve’s trajectory reveal nonlinear narrative patterns (T1). The duration of each event is encoded using the horizontal length of the corresponding visual mark. The length can also remain uniform across the events if necessary to facilitate the analysis of order alone (Fig. 10b). The visual pattern of the story curve can be perceived by reading how much the curve deviates from the diagonal that represents the chronological timeline. For instance, the first scene and the last scene in the movie *Pulp Fiction* is located in the middle of the story (Fig. 2), indicating that the narrative begins and ends at the same point of the story. An indexing degree of nonlinearity is calculated from the sum of distances of the events to the diagonal and shown above the story curve in Fig. 2.

Another example, *Memento*, shows a completely different pattern (Fig. 3). The narrative begins with the last event, and routinely flashes back to the beginning of the story. As a result, the story curve frequently moves up and down, creating a zigzag pattern. More interestingly, the flashback scenes are narrated in chronological order, while the flashforward scenes are narrated in reverse order. The two distinctive lines of scenes merge towards the end of the narrative. Surprisingly, this one movie contains almost all the patterns from Genette’s framework, including chronology, retrograde, flashback, flashforward, and zigzag. A user can opt to flip the curve along the diagonal to read story order from left to right (Fig. 4).

5.2 Visualizing Metadata on Story Curves

A story curve alone only communicates the nonlinear temporality of a narrative. To show a more comprehensive overview of the narrative structure, additional story metadata can be visualized along the curve. The goal is to selectively superimpose the metadata onto the curve while not overloading the user with too much information.

Individual characters are represented as colored segments placed on the curve to support understanding of character occurrences and their interactions (T2). The density of the color communicates who

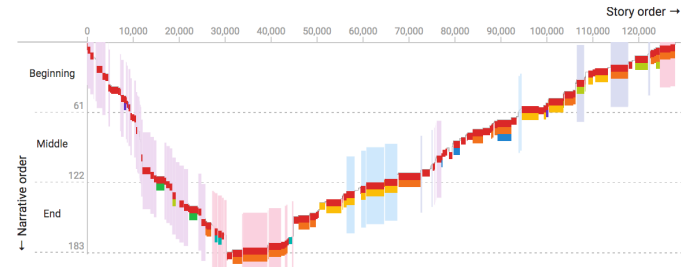


Fig. 4. *Memento* with reverted axes showing the events in story order from the left to right.

are prominent characters in the story based on the frequency of their appearances, while the thickness of the curve communicates how many characters co-occur in each scene. For example, in *Memento* (Fig. 3), the red color shows that the main protagonist is the only character appearing in the flashback scenes (parts of the curve “spiking” upwards), while he interacts with other characters in the flashforward scenes.

Additional scene information, such as locations and periods of the day, can be added to the story curve as well (T3). Locations are represented as a band surrounding character segments. Where information is available, periods of the day are communicated through gray backdrops in the background (Fig. 1). While not as prominent as characters, the setting information can also reveal interesting patterns. For example, the movie *Memento* begins and ends in the same location, shown by the red band surrounding the curve in Fig. 3.

5.3 Design Alternatives

We considered different design alternatives for showing the temporal relationship between story and narrative (Fig. 5). Our arc diagram (Fig. 5a) is similar to the visualization by Sharma et al. [49]. It consists of a straight line from left to right representing story time, and circular arcs to different points along the story line to represent narrative time. Forward time jumps are represented in the upper part and backward jumps are located in the lower part of the diagram. The bipartite graph (Fig. 5c) is similar to the infographic by Syed [1]. It has also two lines representing story time (bottom) and narrative time (top), respectively. Connecting edges are drawn to communicate the temporal connections between events in story and narrative times.

While visually interesting at a glance, both alternatives suffer from line crossings that can generate visual clutter in a complex narrative (Fig. 5 bottom). In addition, following the narrative timeline and reading temporal patterns can be harder as they require frequent and longer eye movements, e.g., following the arcs back and forth or moving eyes up and down to find corresponding story points.

6 STORY EXPLORER

Story Explorer (Fig. 2) processes a movie script, extracts story elements (scenes, characters, settings), and visualizes the narrative of the movie alongside the script text. It supports the curation of the chronological order of scenes and enables close reading of the script in both story and narrative order.

6.1 Extracting Narratives from Movie Scripts

6.1.1 Movie Script

A script, or screenplay, is written and intended for producing a movie or television program. It is usually formatted according to industrial standards [8] that stipulates how script elements are presented (Fig. 6). The script elements include scene headings, actions, character names, dialogs, and other extra information (e.g., movie editing instructions).

A scene heading, also called slugline, introduces a scene by usually providing three pieces of information including whether the scene is inside (INT.) or outside (EXT.), and a location and time in which the scene takes place. An action describes the setting of the scene in more detail or often introduces characters if necessary. A character name specifies who speaks the dialog that comes after the name. A

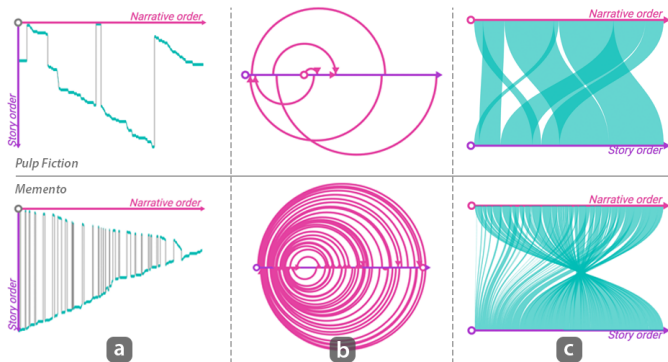


Fig. 5. Story curves (a) compared to design alternatives (b,c) for *Pulp Fiction* (top) and *Memento* (bottom).

parenthetical remark is used to describe an attitude of the character; it is not used as frequently as other elements, though.

6.1.2 Processing Movie Scripts

To process movie scripts to extract story elements (scenes, characters, etc.) we implemented a parser for segmenting a script into script elements. We developed a similar method as Pavel et al. [43] that extracts scene headings, actions, character names, dialogs, and parentheticals. We ignore other elements, such as transitions (e.g., CUT TO, FADE TO) and shots (e.g., ANGLE ON), that are technical notes for directing a movie.

Our parser first segments a script into individual lines. It then computes features for each line, including whether the line is in all capital letters (e.g., character names, scene headings, transitions etc), contains a special marker such as *INT.* or *EXT.*, or is enclosed by parentheses. We also detect the left margin of the line. We also maintains a list of words indicating transitions and shots and ignore lines that contain such words.

Next, we separate the segmented script lines into two groups, where the first group contains the lines with all capital letters and the second group contains the rest (actions, dialogs, parentheticals). Using k-means clustering based on the left margin of the lines, it classifies scene headings and character names in the first group, and actions, character dialogs, and parentheticals in the second group. We further make use of the remaining features (i.e., interior/exterior, enclosing parenthesis) to resolve the tag for each line.

Unfortunately, not all scripts are well formatted. Some scripts deviate from the formatting standard (e.g., inconsistent left margins, non-capital letters for some character names, etc.). To work around this problem, we developed a tagging interface to fix the labels of the lines that are incorrectly tagged by the parser using a dropdown menu in the interface (Fig. 6).

6.1.3 Extracting Story Metadata

Once scene and character information is parsed, our system further extracts semantic metadata from the script. From each scene heading, it retrieves the name of the location, the time of day, and whether the scene is inside/outside. The length of each scene is determined based on the amount of text in the scene. The system also derives the sentiment (negative, positive) of characters based on the sentiment of their dialogs in each scene using a simple Naive Bayes classifier trained on movie reviews [36].

Our system requests data from a public movie database [7] using the movie title as a query, and merges the movie metadata (e.g., ratings, genres, director, cast, etc.) with the script data. To derive the gender of each character, we use the gender of the actor as the gender of the character.

6.2 Exploring Movie Narratives

When a user selects a movie in Story Explorer, it retrieves the preprocessed movie narrative data and presents three views: 1) story curves



Fig. 6. The tagging interface that shows a parsed script for *Eternal Sunshine of the Spotless Mind*. A user can modify the tag of each line using the dropdown selection on the right side.

showing the arrangement of scenes in story and narrative order, 2) metadata view aligned with story curves displaying characters, locations, and periods of the day, and 3) script text as a list of segmented scenes (Fig. 2).

6.2.1 Navigating Visualizations

The set of visualizations shows an overview of the narrative structure of the movie. The story curve view communicates the nonlinear temporal pattern of the narrative (**T1**), as can be seen in the top-left corner of Fig. 2. Various modes of operations related to story curves are exposed through interface components. They include flipping axes to read the script in story order, switching to a rich view to place metadata on top of a story curve, and encoding scene length as the number of letters in the scene text. In addition, a user can choose different color encodings of the curve segments to display characters, character gender (Fig. 2 a), and dialog sentiments (Fig. 7).

To avoid visual clutter, scene setting information is initially displayed in the metadata view, separately from the story curve. The metadata view is vertically aligned with the story curves so that each column is a scene in both visualizations. A user can selectively project each character, location, or time onto the curve (Fig. 2). This enables analysis of the story metadata in the context of the nonlinear timeline of the narrative (**T2**, **T3**). Instead of superimposing additional visual elements, the segments of the story curve are highlighted to show the co-occurrence of the metadata when a rich-view mode is not enabled, e.g., co-appearance of characters in a specific time and location (Fig. 8).

6.2.2 Reading Movie Scripts

In addition to quickly grasping the narrative structure of the movie through the visualizations, a user can read the actual movie script in order to inspect the details of each scene (**T4**). The purpose of the script view is to supplement the visualizations by enabling close reading.

The script is shown as a segmented list of scenes, each of which corresponds to a column in the visualizations (Fig. 2b). Both the visualizations and script reading interface are coordinated so that a user



Fig. 7. *Pulp Fiction*'s story curve showing character dialog sentiment; red: negative, gray: neutral, green: positive.

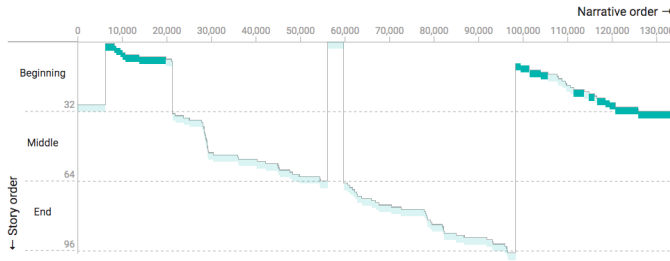


Fig. 8. *Pulp Fiction*'s story curve showing the co-occurrence of the two main characters, Jules and Vincent in the morning.

can dig into the script of each scene from the curve, and vice versa. While the scenes are initially arranged in the movie's narrative order, the user can read the script in story order by flipping the axes of the narrative curve.

6.2.3 Rearranging Scenes in Story Order

The original script does contain the story order of the scenes. In order to reconstruct the arrangement of the scenes in chronological order, a user can drag and drop each scene segment in the script reading interface (Fig. 9). This manual reordering can be cognitively demanding when lack of temporal information is available. For example, it took us 30 to 60 minutes on average to complete the rearrangement for each of the 10 selected movies that we analyze in Sect. 7.

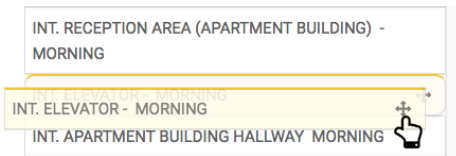


Fig. 9. Arranging scenes in story order in the script reading interface.

7 STORY CURVE PATTERNS FOR NONLINEAR FILMS

We now report on narrative patterns that we could observe using story curves. Our intent here is threefold. We want to demonstrate how to generally read story curves; we want to show how the basic set of narrative patterns is represented (Sect. 2); and finally we want to demonstrate the power of story curve visual patterns that led us to the discovery of additional narrative patterns that may have not been described in the literature.

We created story curves for a selected set of popular nonlinear narrative movies: *Memento*, *Pulp Fiction*, *Eternal Sunshine of the Spotless Mind*, *The Usual Suspects*, *Reservoir Dogs*, *Annie Hall*, *500 Days of Summer*, *12 Monkeys*, *Fight Club*, and *Prestige*. We gathered the movie scripts from a public database [3] and manually restored the story order of the scenes in each movie using our interface (Sect. 6.2.3). The following description of our analysis refers to Fig. 10.

7.1 Genette's Basic Structural Patterns

All the movies we considered contain at least a couple of Genette's basic patterns. In our analysis, we considered six patterns: chronological, retrograde, flashbacks (analepsis), flashforwards (prolepsis), zigzag, and syllepsis (Sect. 2).

Flashbacks and flashforwards are most commonly observed in the movies, which can be easily identified by the up-and-down movements of the trajectory of the corresponding story curves. For instance, *Fight Club* begins with the last event and quickly flashes back to the beginning of the story; similar flashback patterns can be observed in *Annie Hall*, *500 Days of Summer*, and *12 Monkeys*.

A more extreme use of flashbacks and flashforwards are found in *Memento* and *Eternal Sunshine of the Spotless Mind*, eventually creating a prominent zigzag pattern. Similarly, *The Usual Suspects* also shows a zigzag pattern interweaving two time periods. Other interesting cases

can be found in *500 Days of Summer* and *Prestige* that both show multiple short zigzags.

Syllepsis (groupings) are difficult to observe in the movies. Two notable cases are Quentin Tarantino's movies *Pulp Fiction* and *Reservoir Dogs*. For instance, *Pulp Fiction* has three main interrelated stories with multiple protagonists (Vincent, Butch, and Jules). Based on the colors of the characters, it is easy to see that two groups of scenes belong to Jules (red color), one group belongs to Vincent (orange), and another group belongs to Butch (yellow).

7.2 Extensions to Genette's Structural Patterns

Genette's patterns mostly describe local patterns in the narratives, often spanning only a small set of scenes. Combining basic patterns can lead to higher-level structural patterns being composed of multiple other patterns that eventually can characterize an entire movie. Using story curves we were able to discern the following extended (global) patterns:

Beginning/ending in medias res: All the movies we had showed this narrative pattern. They begin at either the middle (e.g., *Pulp Fiction*, *Reservoir Dogs*) or the end (e.g., *Annie Hall*, *Fight Club*) of the story, and subsequently use flashbacks to explain earlier events in order to fill in the backstory. Most movies end at the last event of the story, except *Pulp Fiction* and *Memento*.

Continued flashbacks/flashforwards: These take the narrative back to the moment where an earlier flashback/flashforward ended, connecting disjointed, yet related groups of events that are separated apart in the narrative. For example, in *Pulp Fiction*, Jules story consists of two parts of scenes that are disconnected by the interjected stories of Vincent and Butch; the second part is continued after Butch's story through a flashback. A similar case can be found in *Eternal Sunshine of the Spotless Mind*, where the narrative flashes back to explain why Joel and Clementine's memories were removed, and then jumps back to where it left off.

Staged flashback/flashforward: A flashback or flashforward followed by the same one and leading to a stepwise narration of events. For instance, *500 Days of Summer* shows this pattern using a series of explanatory flashbacks to show different points in the romantic relationship, creating a staircase-like pattern. Similarly, in the same movie, multiple flashforwards are used to come back to the most recent time. This is common in movies that have multiple time periods such as *The Prestige* and *Annie Hall*.

Bidirectional flashes: Flashbacks and flashforwards are intertwined with one another to reveal past and future events back and forth. This pattern is also commonly found in narratives that involves multiple time periods. It is similar to a zigzag pattern spanning more than two time periods, but the visual pattern is somewhat unique. The most prominent patterns of this category can be observed in *Annie Hall* and *500 Days of Summer*, e.g., the narrative travels through time to show the changes in characters' emotions or objectives, which are not necessarily temporally dependent.

Merging/diverging zigzags: This pattern shows that multiple groups of scenes create sub-narratives that diverge or converge. For example, in *Memento*, the flashback scenes and the flashforward scenes meet at the end of the movie, creating a converging visual pattern. On the other hand, *Eternal Sunshine of the Spotless Mind* shows the opposite pattern. While less unique than the two movies, *The Usual Suspects* and *12 Monkeys* also show similar patterns.

7.3 Semantic Patterns

So far, we have discussed structural patterns. Structural patterns represent how narrative order alters and jumps between story order. Semantic patterns include additional information about the movie, such as persons, places, and time of the day.

Follow-the-hero: This pattern jumps around in story order but always follows the main character in the story. It is found in many movies, including *Fight Club*, *Annie Hall*, and *Memento*. A common characteristic of these movies is that they have a single protagonist usually as a narrator, and begin the narrative with the most recent event followed by explanatory flashbacks. For instance, *Annie Hall* opens with a monologue by Alvy regretting breaking up with a former girlfriend

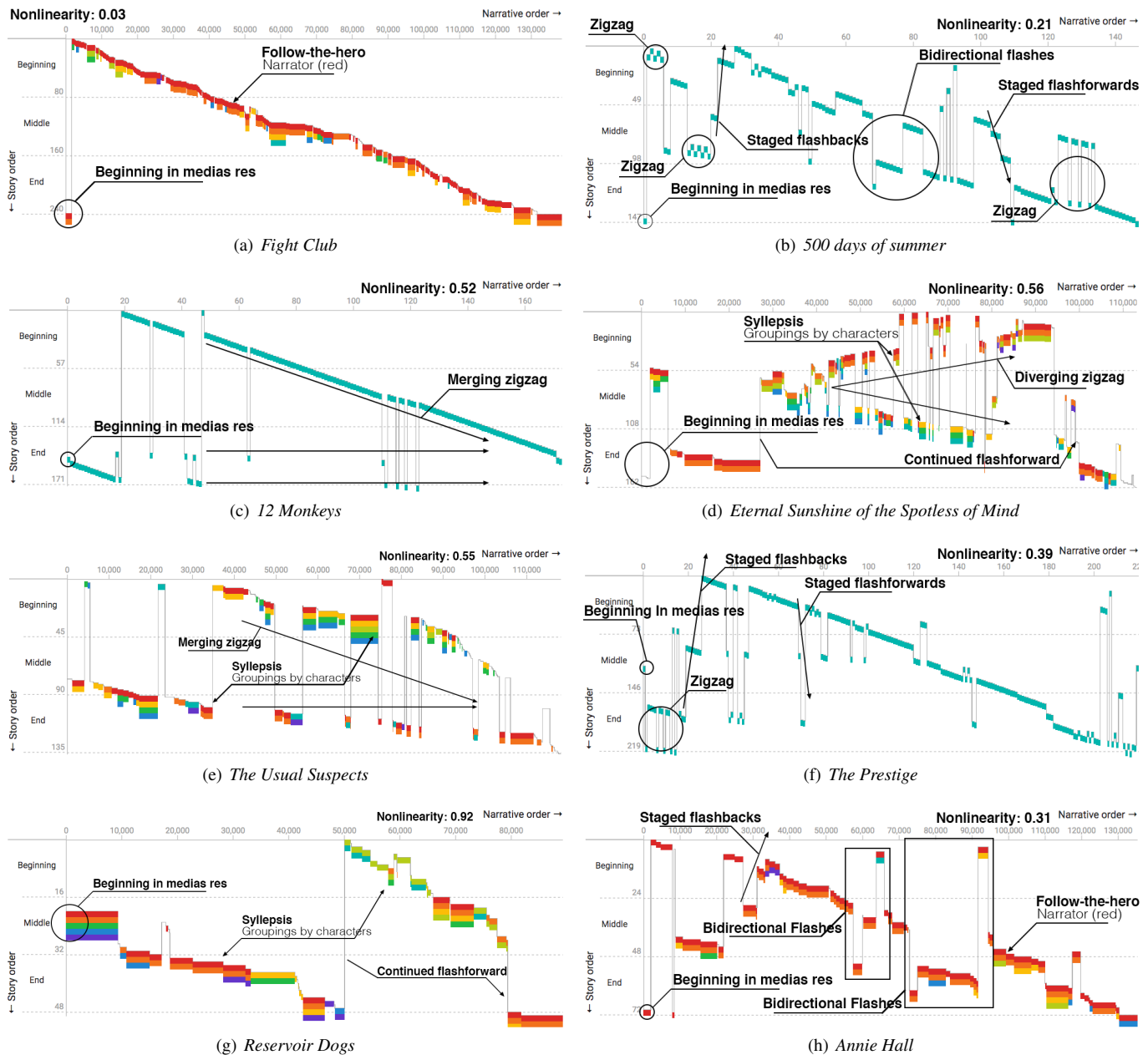


Fig. 10. Examples of story curves for selected movies with nonlinear narratives. Narrative order advances horizontally from left to right, story order vertically from top to bottom. Colors on the curve indicate the presence of characters. The nonlinearity value is computed by the degree of deviation from the diagonal line (chronological timeline).

Annie, and Alvy narrates his past relationship with Annie throughout the movie.

Grouped-by-character: As the narrative changes in story time so do the characters. The change of characters often reveal interesting patterns. For example, character occurrences in different events reveal the multiplot structure of *Pulp Fiction*, which is further accentuated by locations and time of day (i.e., a kind of syllepsis). *Eternal Sunshine of the Spotless Mind*, *Memento*, and *The Usual Suspects* also show interesting character groupings separated in two different time periods in a zigzag pattern.

8 USE CASES

In this section, we briefly describe potential use cases for story curves and Story Explorer that we identified through interviews with three professional writers (W1, W2, W3) and one literary scholar (L1). During

the interviews, we introduced Story Explorer as well as the patterns we discovered. All experts had years of experience in writing, were very familiar with nonlinear narratives, and thus were easily able to grasp the overall idea of story curves.

All participants agreed that being able to see the overall temporal structure of a narrative is interesting and useful; e.g., W1: “*The visuals look like musical notes. A literary work has also rhythm. It is fantastic to see the narrative structure in this way.*”, and L1: “*Finding patterns indicating differences between directors and even different storytelling styles is valuable*”, W3: “*Very interesting, I think that Woody Allen’s stand up comedy career might have influenced the bi-directional flashes in Annie Hall*”.

Although the writers said that the tool may not be useful within the writing process (W2: “*When I write, I just write, everything else gets in the way*”, W3: “*Some writers outline events in advance, but I usually*

don't"), they all commented that it can be useful at a later stage such as revision or analysis; W1: "As I refine my script, I rearrange scenes very frequently. I really like the rearranging interface", W2: "I often have to read and reorganize more than 70 pages and it is helpful to visually see the overview of a narrative.", W3: "With this kind of tool, reading existing scripts can be easier and entertaining". This in part correlates with our prior assumption that writers often use markers to annotate different points in time [19, 21].¹

Two writers particularly commented on the potential usefulness of our work for students in film studies; W1: "students often have a hard time writing a good narrative even if they have a good story. Writers are all about narratives, however. They especially don't know how to use time well and often overuse flashbacks. This tool can visually teach how time is manipulated in a narrative", and W3: "Being able to quickly see different narrative patterns in existing literature could be useful for them to visualize their own narratives". Based on this feedback, we later found a course material that specifically teaches nonlinear narrative, where our tool can be useful as a teaching aid [23].

Two participants also commented that our work can be useful at the production stage; W2: "if the scenes are arranged in chronological order, it is easier for the director to decide which scenes to shoot together", and L1: "In a TV series, people could use it to help visualize the amount and type of nonlinearity that is typical in early episodes. Similarly, it could help someone who rearrange the rendered scenes and compare different arrangements of events".

9 READABILITY STUDY

We were interested in assessing the readability and learnability of story curves. We conducted an online user study to see whether people with no expertise in visualization and narrative theory can learn to read story curves to perform low-level pattern reading tasks. As the result of this study, we also wanted to extract a systematically developed set of pattern reading questions (Table 1) appropriate for a literacy assessment test of story curves, inspired by Lee et al [34].

We recruited a total of 13 participants through various university mailing lists. We showed them story curves that we had created from actual movies and asked 20 questions that required correct interpretation of story curves. Participants were aged between 18 and 35 (8 female, 5 male) and were pursuing, or had pursued, a higher education degree in engineering or design. 12 were graduates, 1 was an undergraduate. The average proficiency in English was 4.69 on a 5-point Likert scale (5: native, 1: elementary).

9.1 Procedures

First, participants were introduced to basic nonlinear narrative patterns including flashbacks and flashforwards as well as how they are represented through story curves. Participants were also shown how story curves are constructed, and then were required to complete two tasks.

A first task asked them to read a plot summary of the movie *Pulp Fiction* containing 13 events, each of which was described by a few sentences. Then, participants had to arrange these events in their chronological order, which is often used in teaching film studies [23]. Participants were then required to draw a corresponding story curve into a canvas with a grid in the background; the grid size was set to the number of events. The time limit for the entire reading-and-sketching task was set to 20 minutes. We expected this task to serve as active learning of story curves and only wanted to see how difficult the reordering task was.

After the sketching, participants were presented with individual story curves (without movie names) and a total of 20 multiple-choice questions, some of which are stated in Table 1. Most questions had 5 choices, while some had 3 choices. Questions required to understand and read patterns in the story curves for *Pulp Fiction*, *Memento*, *Eternal Sunshine of the Spotless Mind*, *12 Monkeys*, and *Fight Club* (Fig. 10). Time limit for each question was 2 minutes.

9.2 Measures

We measured the task performance for the second task based on time and accuracy of the responses. The purpose of this measurement was to see if participants are able to read patterns from story curves even with relatively short learning time (i.e., reading the tutorial and completing the sketching task).

The accuracy score per participant was calculated based on the number of correct responses out of 20 questions. The score was corrected for guessing [25]. I.e., a participant had a 1/5 chance of getting a 5-choice question correct due to random guessing:

$$CS = R - \frac{W}{K - 1},$$

where R is the number of correct responses, W is the number of wrong responses, and K is the number of choices for a question.

In order to judge performance, we also needed to consider the appropriateness of the questions we asked. Similar to the visualization literacy test by Lee et al. [34], we derived an *item difficulty index* (DF) and an *item discrimination index* (DC) for each question. The difficulty index ranges from 0.0 to 1.0 and is equal to the average ratio of correct responses per question:

$$DF_i = \frac{C_i}{N},$$

where C_i is the number of correct responses and N is the number of participants. The discrimination index shows how well the question distinguishes between high-scoring participants and low-scoring participants. The index ranges from -1.0 to 1.0 and is computed using:

$$DC_i = \frac{H_i - L_i}{N},$$

where H_i is the number of participants who answered the i -th question correctly in the high-scoring group, and L_i is the same number in the low-scoring group.

9.3 Results

The average score per participant for the pattern reading task was 16 ($\sigma=3.37$). The raw scores ranged from 9 to 20. The corrected score was 14.74 ($\sigma=4.39$). The average time taken to complete the whole task was 7.49 minutes per participant ($\sigma=1.83$, min=4.21, max=9.76). The learning time was around 17 minutes on average (reading the tutorial: 2.21 and completing the sketching task: 15.14 minutes). The overall task performance was a success, and participants were able to correctly answer 80% of the questions on average.

When we looked at individual questions, each question took 22.48 sec ($\sigma = 9.78$) on average per participant, showing that the time limit (2 minutes per question) was appropriate. The average difficulty index (or the percentage of participants who answered each question correctly) was 0.80 ($\sigma=0.80$, min=0.46, max=1.0). Based on the classification scheme used by Lee et al. [34], we had 6 easy ($DF_i > 0.85$), 12 moderate ($0.50 < DF_i \leq 0.85$), and 2 hard ($DF_i \leq 0.50$) questions. As with the overall performance, the results suggest that participants were able to fairly easily and quickly answer the pattern reading questions.

The discrimination index ranged from -0.08 to 0.31. We had 2 high-discriminative ($DC_i > 0.3$), 5 medium-discriminative ($0.1 < DC_i \leq 0.3$), and 13 low-discriminative questions ($DC_i < 0.1$) [34]. We had four negative discrimination values ($DC_i < 0.0$), indicating that the corresponding questions may not be desirable and could be misinterpreted by participants. I.e., the low-scoring group would answer the question correctly but the high-scoring group would not. The rest of low-discriminative questions ($0.0 \leq DC_i < 0.1$) suggests that all the participants performed well on the questions, thus less discriminative.

Based on these results, we selected representative questions summarized in Table 1 based on performance diversity (DF), question quality (DC), and question diversity (some questions were reused across different movies). This set of questions provides a basis for future readability studies regarding story curves and may allow researchers to compare other techniques.

Around half of the participants ($DF_{20} = 0.46$) were able to correctly answer the last question that is designed to measure the success of the sketching task. It was one of the most discriminative question

¹<https://cgblake.wordpress.com/2011/12/06/linear-vs-non-linear-narrative/>

Table 1. A selected set of questions from the pattern reading task in the usability study with 13 participants; i.e., less discriminative and overlapping questions are not included. DF shows the difficulty of each question, i.e., a percentage of correct responds, while DC indicates how discriminative each question is in terms of distinguishing the high scoring and low-scoring participants.

| Movie | Question | AVG.TIME | DF | DC |
|---------------------------|---|----------|------|------|
| <i>Pulp Fiction</i> | 1. How many flashbacks are there? | 13 sec | 0.85 | 0.08 |
| <i>Pulp Fiction</i> | 2. How many flashforwards are there? | 10 sec | 0.85 | 0.08 |
| <i>Memento</i> | 5. Among five basic nonlinear patterns, how many of them do you seen in this story curve? | 32 sec | 0.75 | 0.15 |
| <i>Memento</i> | 6. What is the overall pattern of the events belonging to the beginning of the story? | 30 sec | 0.54 | 0.23 |
| <i>Memento</i> | 8. In which range of narrative order can you find the longest retrograde? | 23 sec | 0.85 | 0.08 |
| <i>Fight Club</i> | 10. At which point of the story does the narrative start? | 12 sec | 0.46 | 0.15 |
| <i>12 Monkeys</i> | 12. In which range of narrative order can you find the flashback that goes farthest back in story time? | 33 sec | 0.77 | 0.15 |
| <i>500 Days of Summer</i> | 16. In which range of narrative order can you find a short zigzag jumping within the middle of the story? | 20 sec | 0.85 | 0.08 |

($DC_{20} = 0.31$). When we looked at the difference between participants who answered the last question correctly or incorrectly, the overall score was significantly different ($p < 0.05$). This suggests that the sketching had a positive effect on learning the mechanics of story curves.

In a follow-up survey with 5-point Likert scale questions (1-strongly disagree, 5-strongly agree), participants indicated that they are able to read story curves (mean=4.08, $\sigma=0.64$) and to apply story curves to represent nonlinear narratives in movies they had watched or will watch in the future (mean=4.00, $\sigma=0.78$).

In terms of the difficulty of the tasks (1-very easy, 5-very difficult), participants rated the sketching task slightly difficult (mean=3.90, $\sigma=0.94$). They indicated that figuring out the chronological order of events ($\mu=3.91$, $\sigma=0.54$) is more difficult than the drawing of story curves ($\mu=2.27$, $\sigma=0.90$). Most participants found the pattern reading tasks rather easy ($\mu=2.09$, $\sigma=0.54$).

10 DISCUSSION

10.1 Lessons Learned from the Readability Study

The results of our user study indicate that story curves are easily graspable. A number of participants commented that it is fun and enjoyable to learn about story curves; e.g., P5: “[...] a lot of fun!”, P10: “[...] an interesting experiment to understand narrative and story in graphics.”, and P11: “I was able to recognize *Memento*’s curve. It is a totally fascinating idea.”. Some participants struggled to understand the design of story curves; e.g., P3: “Putting the origin at the upper left corner was initially disorientating”, P9: “I needed to remind myself that one thing is narrative and the other is chronological.” These comments suggest that being able to control the origin of the axes and a visual aid for reading two axes (e.g., double crossline in Story Explorer) could be useful for reading story curves. Inspecting the responses, we also found that some participants were confused between flashforwards and flashbacks. One option to resolve that confusion might be arrows indicating the direction of time jumps.

One participant particularly commented on the sketching task that “I thought it was very interesting, specially the part of drawing the story curve” (E13). The overall results indicate that reconstructing original order of events is not easy even for such short narrative text. One participant suggested to provide a notepad and being able to directly drag events into the canvas, which we consider a useful future extension.

10.2 Extending Story Curves and Story Explorer

Story curves were developed mainly based on Genette’s analysis on event order in narratives. Genette discussed other dimensions of temporal nonlinearity, such as frequency (e.g., repetitive descriptions of a single story event) and duration (e.g., time taken to narrate a story event). For example, in *Pulp Fiction*, a flashback scene explains an incident that happened several decades ago, while the story curve currently does not accurately communicate this amount of time. One could enrich story curves with additional temporal information instead of

using event order alone. E.g., one could be using a log scale for story time while keeping a linear scale in narrative time.

There are some extensions to Genette’s patterns in the literature [28,47]. While Genette’s framework is mostly applicable to nonfictional narratives or realistic fictions, it may not generalize well to ones that contain numerous violations of realistic temporality [47]. Richardson describes various temporal paradoxes that can exist in narratives, including time loops and parallel timelines and there are several movies that have such temporal structures, e.g., *Looper* or *Inception*. Story curves can potentially be extended to represent such parallel, branching, and repeating patterns. However specific challenges may arise (e.g., layout, clutter, visual encoding) that require a careful visual design.

Eventually, given the challenges of restoring the actual chronological order of events, we plan to automatically assist the ordering of events in Story Explorer. While there are preliminary works on automatically inferring the causal relationship between events [17, 18], an ideal solution would be a mixed initiative system leveraging human cognition.

10.3 Generalizations to Other Domains

Though our examples in this paper exclusively involved movies, story curves and Story Explorer are generalizable to other genres such as theater plays, novels, poems, and song lyrics. Of course, each of these genres may introduce specific structural patterns and information to visualize. Beyond the domain of story narratives, story curves could be applied to other problem that involves the comparison of two orderings for the same set of elements. The data structure underlying story curves is essentially a bipartite graph with an ordering in both node sets and an identity relation as links. Examples include the comparison of rankings in sports analytics and demographics, or the visualization of a chromosome rearrangement in which the order of nucleotides is modified in the structure of the chromosome [40].

11 CONCLUSIONS

Nonlinear narratives are often complex to understand due to the disruption of the direct causal relationship between events in order to increase suspense. We developed story curves, a visualization technique for communicating nonlinear narratives. Based on the technique we built Story Explorer, an interactive system that allows users to curate the chronological sequence of scenes in a movie script and explore the nonlinear narrative of the movie using story curves. We illustrated several examples of story curves using popular nonlinear movies, evaluated the readability of story curves through a user study, and highlighted potential use cases in screenplay analysis and story production.

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REFERENCES

- [1] 16 complicated movie plots explained with infographic timelines. <http://www.scribblelive.com/blog/2013/08/26/16-movie-timeline-infographics/>. Accessed: 2017-03-31.
- [2] How every #gameofthrones episode has been discussed on twitter. <https://interactive.twitter.com/game-of-thrones/>. Accessed: 2017-03-31.
- [3] The internet movie script database. www.imsdb.com/. Accessed: 2017-03-31.
- [4] Les misrables co-occurrence. <https://bost.ocks.org/mike/miserables/>. Accessed: 2017-03-31.
- [5] Linear vs. non-linear narrative. <https://cgblake.wordpress.com/2011/12/06/linear-vs-non-linear-narrative/>. Accessed: 2017-06-24.
- [6] Lostalgic. <http://intuitionanalytics.com/other/lostalgic/>. Accessed: 2017-03-31.
- [7] The movie database. <https://www.themoviedb.org/>. Accessed: 2017-03-31.
- [8] Screenplay format guide. <http://www.storysense.com/SPFormat.pdf>. Accessed: 2017-03-31.
- [9] Story touch - scriptwriting tools. <http://www.storytouch.com/o-que-e.html>. Accessed: 2017-03-31.
- [10] Visualizing star wars movie scripts. <http://labs.precognox.com/star-wars-visualization/>. Accessed: 2017-03-31.
- [11] E. Aarseth. A narrative theory of games. In *Proceedings of the international conference on the foundations of digital Games*, pp. 129–133. ACM, 2012.
- [12] J. Abello, P. Broadwell, and T. R. Tangherlini. Computational folkloristics. *Communications of the ACM*, 55(7):60–70, 2012.
- [13] M. Bal. *Narratology: Introduction to the theory of narrative*. University of Toronto Press, 2009.
- [14] R. Barthes. *S/z*, trans. *Richard Miller (New York: Hill and Wang, 1974)*, 76, 1974.
- [15] N. Bilenko. The narrative explorer. Master’s thesis, EECS Department, University of California, Berkeley, May 2016.
- [16] S. Carter, A. Cox, and M. Bostock. Dissecting a trailer: The parts of the film that make the cut. *The New York Times*, 2013.
- [17] N. Chambers and D. Jurafsky. Unsupervised learning of narrative event chains. Citeseer, 2008.
- [18] N. Chambers, S. Wang, and D. Jurafsky. Classifying temporal relations between events. In *Proceedings of the 45th Annual Meeting of the ACL on Interactive Poster and Demonstration Sessions*, pp. 173–176. Association for Computational Linguistics, 2007.
- [19] S. B. Chatman. *Story and discourse: Narrative structure in fiction and film*. Cornell University Press, 1980.
- [20] K. Dancyger. *The technique of film and video editing: history, theory, and practice*. CRC Press, 2014.
- [21] K. Dancyger and J. Rush. *Alternative scriptwriting: Beyond the Hollywood formula*. CRC Press, 2013.
- [22] A. Denis, S. Cruz-Lara, N. Bellalem, and L. Bellalem. Visualization of affect in movie scripts. In *Empatex, 1st International Workshop on Empathic Television Experiences at TVX 2014*, 2014.
- [23] A. Dharwadker, V. Dharwadker, S. Harrison, T. Lemaster, and H. D. Bourenane. Teaching the god of small things in wisconsin: A guide for educators, 2012.
- [24] J. ECKEL. Twisted times. *(Dis) Orienting Media and Narrative Mazes*, p. 275, 2014.
- [25] R. B. Frary. Formula scoring of multiple-choice tests (correction for guessing). *Educational Measurement: Issues and Practice*, 7(2):33–38, 1988.
- [26] G. Genette. *Narrative discourse: An essay in method*. Cornell University Press, 1983.
- [27] S. Göbel, L. Salvatore, and R. Konrad. Storytec: A digital storytelling platform for the authoring and experiencing of interactive and non-linear stories. In *Automated solutions for Cross Media Content and Multi-channel Distribution, 2008. AXMEDIS’08. International Conference on*, pp. 103–110. Ieee, 2008.
- [28] U. K. Heise. *Chronoschisms: Time, narrative, and postmodernism*, vol. 23. Cambridge University Press, 1997.
- [29] E. Hoyt, K. Ponto, and C. Roy. Visualizing and analyzing the hollywood screenplay with scripthreads. *Digital Humanities Quarterly*, 8(2), 2014.
- [30] S. Jänick, G. Franzini, M. F. Cheema, and G. Scheuermann. On close and distant reading in digital humanities: A survey and future challenges.
- [31] J. Kaminski, M. Schober, R. Albaladejo, O. Zastupailo, and C. Hidalgo. Moviegalaxies - social networks in movies. Dec 2012.
- [32] R. Kenny. *Teaching TV production in a digital world: Integrating media literacy*. Libraries Unlimited, 2004.
- [33] N. W. Kim, S. K. Card, and J. Heer. Tracing genealogical data with timenets. In *Proceedings of the International Conference on Advanced Visual Interfaces, AVI ’10*, pp. 241–248. ACM, New York, NY, USA, 2010. doi: 10.1145/1842993.1843035
- [34] S. Lee, S. H. Kim, and B. C. Kwon. Vlat: Development of a visualization literacy assessment test. *IEEE Transactions on Visualization and Computer Graphics*, 23(1):551–560, Jan 2017. doi: 10.1109/TVCG.2016.2598920
- [35] S. Liu, Y. Wu, E. Wei, M. Liu, and Y. Liu. Storyflow: Tracking the evolution of stories. *IEEE Transactions on Visualization and Computer Graphics*, 19(12):2436–2445, Dec. 2013. doi: 10.1109/TVCG.2013.196
- [36] S. Loria. Textblob: simplified text processing. *Secondary TextBlob: Simplified Text Processing*, 2014.
- [37] I. Mani. Computational modeling of narrative. *Synthesis Lectures on Human Language Technologies*, 5(3):1–142, 2012.
- [38] N. McCurdy, J. Lein, K. Coles, and M. Meyer. Poemage: Visualizing the sonic topology of a poem. *IEEE Transactions on Visualization and Computer Graphics*, 22(1):439–448, Jan 2016. doi: 10.1109/TVCG.2015.2467811
- [39] A. Meidiana and S.-H. Hong. Multistory: Visual analytics of dynamic multi-relational networks. In *2015 IEEE Pacific Visualization Symposium (PacificVis)*, pp. 75–79, April 2015. doi: 10.1109/PACIFICVIS.2015.7156359
- [40] M. Meyer, T. Munzner, and H. Pfister. Mizbee: A multiscale synteny browser. *IEEE Transactions on Visualization and Computer Graphics*, 15(6):897–904, Nov 2009. doi: 10.1109/TVCG.2009.167
- [41] N. Montfort. Ordering events in interactive fiction narratives. In *Proceedings of the AAAI Fall Symposium on Intelligent Narrative Technologies*, pp. 87–94, 2007.
- [42] J.-C. Na, T. T. Thet, C. S. Khoo, and W. Y. M. Kyaing. Visual sentiment summarization of movie reviews. In *International Conference on Asian Digital Libraries*, pp. 277–287. Springer, 2011.
- [43] A. Pavel, D. B. Goldman, B. Hartmann, and M. Agrawala. Sceniskim: Searching and browsing movies using synchronized captions, scripts and plot summaries. In *Proceedings of the 28th Annual ACM Symposium on User Interface Software & Technology*, pp. 181–190. ACM, 2015.
- [44] G. Prince. *A grammar of stories: An introduction*, vol. 13. Walter de Gruyter, 1974.
- [45] V. Propp. *Morphology of the Folktale*, vol. 9. University of Texas Press, 2010.
- [46] L. Qiang, C. Bingjie, and Z. Haibo. Storytelling by the storycake visualization. *The Visual Computer*, 2017. doi: 10.1007/s00371-017-1409-2
- [47] B. Richardson. Beyond story and discourse: Narrative time in postmodern and nonmimetic fiction. *Narrative dynamics: Essays on time, plot, closure, and frames*, pp. 47–63, 2002.
- [48] B. Richardson. *Narrative dynamics: essays on time, plot, closure, and frames*. Ohio State University Press, 2002.
- [49] R. Sharma and V. Rajamanickam. Using interactive data visualization to explore non-linear movie narratives. *Parsons Journal for Information Mapping*, 2013.
- [50] S. Sinclair and S. Ruecker. The digital play book: An environment for interacting with play scripts. *Canadian Theatre Review*, 127:38–41, 2006.
- [51] Y. Tanahashi and K.-L. Ma. Design considerations for optimizing story-line visualizations. *IEEE Transactions on Visualization and Computer Graphics*, 18(12):2679–2688, 2012.
- [52] M. Tapaswi, M. Bauml, and R. Stiefelhamen. Storygraphs: visualizing character interactions as a timeline. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pp. 827–834, 2014.
- [53] T. Wilhelm, M. Burghardt, and C. Wolff. To see or not to see-an interactive tool for the visualization and analysis of shakespeare plays. 2013.
- [54] Y. Wu, N. Pitipornvivat, J. Zhao, S. Yang, G. Huang, and H. Qu. egoslider: Visual analysis of egocentric network evolution. *IEEE Transactions on Visualization and Computer Graphics*, 22(1):260–269, Jan 2016. doi: 10.1109/TVCG.2015.2468151
- [55] J. Zhao, M. Glueck, F. Chevalier, Y. Wu, and A. Khan. Egocentric analysis of dynamic networks with egolines. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems, CHI ’16*, pp. 5003–5014. ACM, New York, NY, USA, 2016. doi: 10.1145/2858036.2858488