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Examining the use of narrative constructs in data videos

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ABSTRACT

Data videos are a highly impactful method of communication and are becoming a prevalent medium for communicating information. While the majority of current research focuses on the cinematic aspects of data videos, very little is known about the narrative methodologies involved. This paper presents our insights derived from an initial exploration of this area. We present a taxonomy based on the analysis of 70 existing data videos examining their narrative and visual approaches. We propose that our taxonomy can be used to explain the characteristics or design of data videos. Applying this taxonomy, we present our observations, including the trend of popular technologies applied in current data videos, the under-utilization of promising methods, and highlight research opportunities in the field.

1. Introduction

Data Videos – videos telling data-driven stories – show tremendous potential for supporting narrative visualization tasks. Although data videos are prevalent in a diverse range of fields such as news and education, there is little theoretical grounding for the creation of these videos (Amini et al., 2015, 2017). This lack of theoretical grounding results in creators expending a significant amount of time and effort to create these videos, and consequently, the created videos do not always meet the designer's expectations. Driven by this problem, researchers have recently started to examine data videos with the goal of understanding their structures and creation methodologies. For example, Amini et al. (2015) focused on the constituent characteristics of data videos; and Amini et al. (2017) presented an authoring tool for data-driven videos. Typically, these examinations have focused on the cinematic aspects of data videos, such as camera techniques or applying categorizations commonly used in cinematography.

While the cinematic aspects of data videos have been explored, we still know very little about the *narrative* methodologies involved. In our work, we define narrative methodology as "the approach for building up a narrative", such as narrative structures. *This paper presents a theoretical framework examining narrative methodologies applied in data videos while including some basic cinematic methods.* As a method of narrative visualization, data videos use narrative constructs to communicate a given set of data in a more comprehensive, aesthetically pleasing, and palatable manner. As such, applying suitable narrative constructs is essential for the creation of data videos (Claes and Vande Moere, 2017). When discussing the constructs of narratives, a foundational understanding of narrative structures and genres that have evolved from the field of literature, drama, and movies is required. Such knowledge can be essential in helping a wider audience to design and craft better data videos, and in the future, aid the development of authoring tools to support the creation of compelling data videos.

To classify the genres and understand the use of narrative constructs in data videos, some formalizations is required. One manifestation of formalization is through taxonomies (Card and Mackinlay, 1997; Heer and Robertson, 2007; Broder, 2002). Using a taxonomy created by comparing different divisions or finding regular patterns within one division, analysts can gain an understanding of a complex topic by identifying the distinctive features of each division, and then determining the best fit use-cases for each technique. For instance, Chi (2000) presented a taxonomy of existing visualization techniques using the data state reference model, in which the authors extracted and listed the crucial operating steps in each visualization technique. The results of such a study can be the cornerstone for the design of complicated visualization systems. Another example of a taxonomy is the design space from Brehmer et al. (2017), which introduces different design strategies of timelines involved in data visualization.

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Our work is motivated by two significant narrative visualization research works. Segel and Heer (2010) presented a taxonomy of narrative visualization. Although the work introduced the technologies used in narrative visualization, their taxonomy only included four data videos. As such, we believe there are many applied methods used in data videos that were not addressed in their taxonomy. Amini et al. (2015) encoded 50 data videos and listed some popular authoring methods and structure patterns of data videos.

Motivated by those two papers, we provide a more detailed taxonomy that focuses on narrative methodologies in data videos. Focusing on narrative methods in data videos is necessary, as such work can help to understand the construction of a data video and contribute to other related research in this domain. In this paper, we encoded and analyzed 70 data videos (with two from Segel and Heer (2010)) for their visual and narrative approaches, and created a new taxonomy. Compared to the previous research, our taxonomy focuses on the narrative methods in data videos and highlights a larger variety of applied approaches.

The contribution of our work is: (1) providing a taxonomy of data videos that is supplementary to previous research. In contrast to the previous research, our taxonomy focuses on the narrative methods used. (2) highlighting the characteristics of current data videos, and (3) defining future research opportunities of data videos.

Following the review of related work and background, we present our taxonomy – including its composition and the validation process – at the end of which salient dimensions are discussed to highlight the features of existing data videos and suggest future research opportunities. We then provide five case studies to illustrate how we apply our taxonomy. We also present guidance on how to use our taxonomy. Finally, we discuss limitations and future work.

2. Background and related work

Defining data video genres is a critical process in our taxonomy. As such, we provide an overview of theories that are helpful for classifying genres in our work. We introduce two models that motivated our work. The section finishes with an exploration of the limitations of the models and how our work can overcome these limitations.

2.1. Narrative visualization

Narrative visualization – the use of storytelling elements to support information visualization – is a burgeoning field within the visualization community with practical applications (Satyanarayan and Heer, 2014; Bryan et al., 2017; Qu and Hullman, 2018; Wang et al., 2016; Yu et al., 2010). Designed to help people understand data, narrative visualization provides a compelling and empathetic way to communicate information in the form of a story. Unlike informal stories, narrative visualizations follow a formal narrative and visual structure (Baber et al., 2011). Gershon and Page (2001) first introduced the power of storytelling for information visualization, stating that "Storytelling allows visualization to reveal information as effectively and intuitively as if the viewers were watching a movie". Figueiras (2014) agreed that "if successfully being infused with narrative, visualizations can contribute to overcoming the limitations of both textual and visual representation".

The research surrounding narrative visualization provides an opportunity for understanding its constituent characteristics and the complementary relationship narratives bear to information visualization (Hullman and Diakopoulos, 2011a). Herman (2011) noted that there are four basic elements of a narrative: *Situatedness*, *Event sequencing*, *Worldmaking/world*, and *What it is like*. This provides us with a standard with which to review a narrative. Cohn (2013) introduced a structure of narrative, the core categories of which are: *Establisher (E), Initial (I), Prolongation (L), Peak (P),* and *Release (R)*. These categories build up the coherent pieces of a narrative structure, which they call the "phases of constituency". Bach et al. (2018) identified 18 narrative patterns after the analysis of a great number of data-driven stories, such as compare and speed-up/slow-down. Those narrative patterns can be applied as powerful methodologies for different purposes; they were categorized into five different groups: argumentation, narrative flow, framing, empathy and emotion, and engagement. They defined a narrative pattern as "a low-level narrative devices that serves a specific intent". Hullman and Diakopoulos (2011b) introduced seven rhetoric techniques and their benefits through the use of an analytical framework they presented. In order to validate the effects that sequencing choices might bring to narrative visualization, Hullman et al. (2013) conducted an analysis of 42 professional narrative visualizations and suggested a graph-driven approach which can automatically identify effective sequences in a set of linear visualizations.

2.2. Data videos

In 2010, Segel and Heer presented seven genres of narrative visualization, where "data video" is one of the genres (Segel and Heer, 2010). As suggested by the multimedia research (Mitra and McEligot, 2018; Mayer et al., 2001), information is easier to process when being provided in a multimedia environment where there is both visual and audio narration. Data videos are a form of multimedia; therefore, we believed they are an effective medium for delivering information.

Amini et al. (2015) describe data videos as "motion graphics that incorporate visualization about facts". In addition, they provided a selection criteria for their dataset that should be considered a part of the definition:

> "(1) it contains a core message and presents arguments supported by data; (2) it includes at least one data visualization, and; (3) it follows a narrative format which refers to the spoken or written account of connected events given in a sequence."

This definition plus the criteria from their study represents the first attempt to identify data videos from the immense pool of videos available. The selection of our data samples is based on this definition.

The creation of data videos is very difficult and time-consuming (Amini et al., 2017; Bulterman and Hardman, 2005), since it involves a great number of techniques and skills, such as movie-making, computer graphic technologies, and potentially even computer programming. Despite the complexity and the prevalence of data videos, there is relatively little research regarding data videos. Amini et al. (2015) studied the constituent characteristics of data videos. After researching 50 data videos, they found that the most common pattern of videos is the "E+I+PR+" structure, in Cohn's notation. Establisher (E) refers to "sequences that provide referential information without engaging them in the actions or events of a narrative". Initial (I) refers to "sequences that set the action or event in motion". Peak (P) means "sequences where the most important things happen; the culmination of an event or the confluence of numerous events". Release (R) refers to "sequences that show the aftermath of the Peak". The "+" sign indicates the repetition of the preceding element (one of E, I, P, and R). Subsequently, Amini et al. (2017) presented a web-based data video authoring tool, "DataClips", that allows users to import data and generates graphs automatically, a large component of what has become known as "infographics".

2.3. Genres

Creators and audiences of literature have benefited greatly from the defined set of genre classifications. We believe the classification of genres is also important in the field of data videos. Namely, a clear genre classification can help us more logically present our taxonomy and is beneficial in generating and reviewing future data videos.

The term *genre* (meaning "kind" or "class") has been widely utilized in rhetoric, literature, and film-related theories. Robert Allen stated:

> " For most of its 2000 years, genre study has been primarily nomological and typological in function. That is to say, it has taken as its principal task the division of the world of literature into types and the naming of those types — much as the botanist divides the realm of flora into varieties of plants (Allen, 1989)."

There are many theories regarding the definition of genres. Steve Neale declared that "genres are instances of repetition and difference" (Neale, 1990), while some other theorists prefer to describe genres concerning "family resemblances" among texts (Fairclough, 1995). In relation to television techniques, Abercrombie (1996) asserted that "the most important genre distinction is between fictional and non-fictional programming". Stam (2000) identified four key problems – *extension*, *normativism*, *monolithic definitions*, and *biologism* – which people should consider and address when defining genres. As noted by Chandler (1997), since the definition of genres is not a neutral and objective procedure, there is no common agreement for a specific genre definition; once a genre is given, people will argue it, redefine it, and thus more genre theories will appear.

2.4. Motivating models for our taxonomy

Our work is inspired by two models, a taxonomy model for narrative visualization and an encoding model for data videos. The first taxonomy is from Segel and Heer (2010); who analyzed 58 examples of narrative visualizations collected from multiple sources such as online journalism, blogs, and research papers. They then presented a taxonomy containing three divisions of features: genre, visual narrative, and narrative structure. These highlight the distinctive visualization methods that each narrative utilized. Based on the taxonomy, they suggested some effective methods regarding the creation of good narrative visualization. One such method involves providing a balance between author-driven elements (where the audience is provided with narrative without interactive ability) and reader-driven elements (where the audience is enabled to interact with the narrative). However, Segel and Heer's taxonomy only takes a cursory look at data videos, as only four of fifty sources investigated were data videos. Furthermore, they do not explore the narratological aspects of these data videos. Following the encoding methods from Segel and Heer's work, Hook (2018) recently provided a similar taxonomy including the analysis of 43 interactive videos however, this did not focus on data videos.

While the work of Amini et al. (2015) is not strictly a taxonomy, they investigated how to encode data videos. This is the first investigation into classifying data videos. Following Cohn (2013) theory on a narrative structure, Amini et al. collected 50 data videos and encoded the sequences regarding their narrative categories, by which they characterized the Narrative Structure of data videos from a cinematic perspective. By the use of small units (Establisher, Initial, Peak, and Release), they provided an effective and flexible way to build up the narrative structure for describing and creating data videos. However, their investigation into narrative aspects was quite brief, only identifying narrative structures. There are a great number of narrative techniques that need to be studied.

We developed a new taxonomy inspired by these two motivating models by studying a wider variety of narrative techniques utilized in data videos.

3. Design space of the taxonomy

In this section, we provide a detailed description of our taxonomy design space. In addition, we discuss the observations and research opportunities derived from this taxonomy. The taxonomy presents the design technologies of 70 existing data videos, emphasizing their applied narrative methodologies. By applying this taxonomy, we provide a method to describe the design of a data video and initial guidelines for the design options of data videos.

3.1. Method

To avoid subjectivity and provide a robust taxonomy, we followed the systematic methodology of Amini et al. (2015). We conducted both open (Glaser and Strauss, 2009) coding for creating the categories and close (Richards, 2014) coding for categorization and modification. We started by collecting the top-ranked videos from YouTube. Since there is no explicit "data video" classification on YouTube, we began the collection by using "data video(s)" as the keywords. From the results, we selected the top-ranked data videos and further added from related videos and channels. In order to get good coverage of topics, we selected data videos from various types of channels, such as entertainment, news, history, and education. For completeness, we also collected videos from the sources mentioned in our motivating models.

Twenty percent of the data videos collected were then sent to one of our authors (SD[1]) to characterize the content and plan the taxonomy, applying an open coding approach. The researcher's focus was on identifying narratological features that *could* be applied to data videos. These definitions were iteratively defined and refined through several discussions. Having received the initial version of the taxonomy, two of our researchers conducted a closed coding approach to finish coding the remaining data videos. The definitions were then further refined to resolve any ambiguity or misunderstanding.

It should be mentioned that due to the novelty of this work, the identification of valid data videos was difficult. We filtered and collected data videos strictly based on the definition presented by Amini et al. (2015). However, some videos were hard to classify clearly. For example, "Delta Airplane Safety Video[2]" is one of the videos included in the taxonomy of Segel and Heer (one of our motivating papers) (Segel and Heer, 2010), however, it cannot be classified as a data video based on the definition and criteria of Amini et al. In order to keep the uniformity of our dataset, we excluded this video from our taxonomy. However, this does reveal a possible need to modify the current definition of data videos. In order to recognize prominent features, data videos of high quality were collected. Although there are no established guidelines pertaining to what constitutes a data video of high quality, we determined that the number of viewers, the effective reach of the videos, and the video comments are effective indicators of a video's popularity. We believe that popularity (although not absolute) is our best measure for systematically judging data video quality. We collected the majority of our videos (81.43%)

1 SD has a background in narratology.

2 https://www.youtube.com/watch?v=IFG-XllVS7w.

from the top-ranked videos on YouTube, and the rest from professional data visualization and news websites.[3] We seek to enrich our dataset by including data videos that contain a diverse set of data video genres, narrative structures, and a range of narrative methods. In order to limit our research scope, we also filtered the data videos according to their length; videos that were shorter than 20 min were collected.

In summary, to be included in our dataset for analysis, a data video had to: (1) adhere to Amini's definition of what constitutes a data video; and (2) adhere to our duration guideline of less than 20 min. There was one exception "The Story of Stuff", which slightly over 20 min (21 min and 24 s). This exception was made as this data video inspired the taxonomy creation and encompasses a majority of attributes in our taxonomy design space, acting as an ideal exemplar. We do not claim that our dataset is exhaustive, but instead provides an informative overview of the criteria we have defined. The data videos included in our dataset for analysis and their URL are listed in Table A.1.

We present the taxonomy in Table A.2. Although we sought to include the four videos from Segel and Heer's work (Segel and Heer, 2010) into our dataset, one of the videos does not adhere to the current definition of data videos (described above) and another (''Mac Orientation Video'') cannot be found online.

3.2. Dimensions of the taxonomy design space

Our taxonomy design space includes four divisions of features: (1) time, (2) genres, (3) narrative approaches, and (4) visual approaches. The first division indicates the duration of a data video. The second identifies the genre of each data video, which will be introduced in the next section. The third division refers to the narrative approaches and is sub-divided into: (i) narrative structure, (ii) narrative attributes, and (iii) narrative tools. The fourth division refers to the visual approaches used in data videos.

3.2.1. Genres

We defined five genres of data videos based on narrative theory. We use the goal or intent (e.g. what the data video aims to do) as the primary condition to determine different genres, which is the same approach used by Ojo and Heravi (2017) and Kelliher and Slaney (2012). The reason we use the goal/intent is that we believe it is a data video's crucial and inherent attribute that cannot be easily changed once the data video has been created, and each data video typically only has one goal. By contrast, other features might be interchangeable. For example, Cao et al. (2017) used the forms of media (i.e. 2D, 2.5D, 3D, and Virtual Reality (VR)) to classify data videos. Using forms works well if we just discuss the naming of the type of data videos. However, in terms of genres, the use of forms has two main problems: (1) some data videos contain more than one form of content (e.g. 2D and 3D), and; (2) the form of a data video can be easily changed (e.g. a 3D data video can become a VR data video by simply being imported and played in a VR environment). At the same time, the goal of a data video is also an important key to decide where to play it and the intended audience, in-turn effecting its creation. That is, by knowing the goal of a data video beforehand, a designer can create a better data video.

Our genres are:

Factual Event: data videos visualizing historical events. We define *Factual Event* to refer to something that occurred in a certain place during a particular interval of time. For example, representing a known historical event would fit this description. *Factual Event* data videos aim to show or replay events and related information such as time, location, and people involved. Some examples are "The JFK Assassination in 4K 360° VR"[31], "Toddler survives 30ft fall through bleachers"[40], and "Toddler's brain damage reversed using oxygen treatment"[41].

Factual Knowledge: data videos visualizing and presenting facts. The purpose of the *Factual Knowledge* genre of data videos is providing knowledge or information about facts. Here, "facts" means some well-accepted knowledge (such as the law of gravity and the size of stars), and existing objects (such as countries, lands, and human bodies). For instance, the video "This incredible animation shows how deep the ocean really is"[32] depicts the depth of the ocean.

Hypothesis: data videos visualizing and presenting hypothetical situations or concepts. We adopt the philosophical meaning of hypothesis, which presumes a particular, sometimes counterfactual, truth, whether it be an incident or concept, that is taken to present a "what if" scenario. To illustrate, the video "How Folding Paper Can Get You to the Moon"[22] is classified in the genre of *Hypothesis* in our taxonomy, because the task it describes – going to the moon by folding paper – is impossible. However, the hypothesis this video provides is based on facts, such as the thickness of the paper and the distance between earth and moon.

Persuasion: data videos visualizing and presenting information supporting authors' opinions or point of view. The goal of *Persuasion* data videos is to communicate to audiences the authors' own point of view and attempt to persuade audiences to accept that view. Different from *Hypothesis*, which is using facts to support hypotheses that cannot be proven as yet, *Persuasion* presents a series of tangibles to support the authors' view regarding the facts. One of the common methods is first giving the author's points of view and then presenting sufficient information to support it. Examples videos are "Why can't we just print money to pay off debt?"[25] and "Why Some Countries Are Poor and Other Rich"[7].

Prediction: data videos visualizing and providing forecasts. *Prediction* data videos aim to provide predictions about the future. Similarly, those predictions have to be based on current facts or truth. Two typical examples in our dataset are "What Will The Earth Look Like In 100 Years?"[27] and "What Will the U.S. Economy Actually Look Like in 2017?"[15].

3.2.2. Narrative structures

Narrative structure represents the structural framework that underlies the order and manner in which a narrative is presented to a reader, listener, or viewer. The narrative text structures are the plot and the setting. It should be noted that ''plot'' and ''setting'' are the essential narrative structures with relation to fictional storytelling as we see in dramas and fiction movies. However, in our work, we are applying the concept of narrative structures to data videos which might lack the fictional drama that is the core to fiction movies and dramas. As such, we need to borrow from the conventional ideas of narrative structures and then build reasonable narrative structures that can explain the structures employed in data videos.

There is a clear difference between the narrative structures in the work of Amini et al. (2015). and our work. The narrative units and patterns from the work of Amini et al. (2015). focus on the construction of cinematic sequences and scenes, whilst our narrative structures are derived from the structures of data and information that are used to frame the narrative.

In our work, we define the following four narrative structures utilized in current data videos:

Chain of Facts: The *Chain of Facts* structure presents a series of facts and their related data, in order to support the main point or achieve the final goal. "Facts" refers to the same notion that is described in the definition of *Factual Knowledge* (Section 3.2.1). This

[3] The collection of our data samples were in two phases: (1) 6 December 2017: initial collection; (2) 13 August 2019: access re-checking and dataset refilling.

structure closely correlates to the Claim-Facts-Conclusion pattern previously identified by Kosara (2017). A typical demonstration of a *Chain of Facts* structured video is "$17 Trillion U.S.DEBT - A Visual Perspective"[2]. This video presents different amounts of money in sequential order (from 100 dollars to 17 trillion dollars) using computer-generated virtual objects (e.g. 3D models of US 100 dollar notes).

Chain of Hypothesis: The *Chain of Hypothesis* structure only contains a set of ordered hypotheses. Here, we adopt the same philosophical meaning of hypothesis as defined in the genre *Hypothesis* (Section 3.2.1). For example, "Census 2016: if Australia were 100 people"[28] consists of a set of hypotheses such as the possible population age range, in order to describe a hypothetical situation, i.e. if Australia was 100 people.

Chain of Events: Data videos utilizing the *Chain of Events* structure are made up of a series of events. We employ the term "events" in the same manner as that defined in *Factual Event* (Section 3.2.1). "Toddler survives 30ft fall through bleachers"[40] demonstrates this approach by presenting a series of events that comprise the whole video.

Chain of Arguments: Data videos utilizing the *Chain of Arguments* consist of sets of arguments and counter-arguments. For example, a data video may explore all sides of an argument and may attempt to convince the viewer of a particular view or leave the viewer to decide. An example is "Why the Moon Landing COULDN'T Have Been Faked"[43], which attempts to convince the viewer that the astronauts landed on the moon.

From our examination, we have found that compelling data videos have one prominent narrative structure, however, they may borrow elements from other structures. As a result, in our taxonomy, we focus on the prominent narrative structure presented by a data video.

3.2.3. Narrative attributes

We have identified six mandatory narrative attributes in our taxonomy. These attributes are binary in nature. For example, a data video must have an *Ending Type* attribute, and the *Ending Type* can either be *Open* or *Closed*. These attributes are summarized in Table 1.

In shaping a primary taxonomy of data videos, we have used two terms: narrative structure and narrative attributes. Based on the 70 data videos we have analyzed, we posit that the narrative structure cannot be sufficiently described by using terms like *Linear/Non-Linear* or *Interactive/Non-Interactive*. While some of these terms are often used to describe narrative structures, a finer study of the data videos shows the discrimination — two data videos can both be *Linear* and still differ in the structuring of their narrative. Therefore, we have used the term narrative structures for the inherent structuring of the video and narrative attributes for the characteristics that a data video might show.

It should be pointed out that narrative structures and narrative attributes as we posit both have the fundamental purpose of teasing out the manner in which narration takes place in a data video and how they can be classified. We acknowledge that we have not identified exemplar videos comprising some of the narrative attributes that we have defined. For example, there is no data video utilizing *Unrestricted* narrative. In this case, we will introduce possible reasons for the lack and the research opportunities it may present in the **Observation** section.

3.2.4. Narrative tools

Narrative structures rely on a number of underlying techniques and tools to convey information to an audience (Orehovec and Alley, 2003). We identified six divisions under Narrative Tools. A data video can utilize an arbitrary number of those tools.

Symbolic Visuals: In a data video, there might be a need to illustrate an object from the real world (e.g. a human, car, or weapon), which could be represented by using a virtual object (e.g. a virtual character, 2D graph, or 3D model). We call this virtual object *Symbolic Visuals*. *2D* refers to 2D style visual content (e.g. 2D graphs), while *3D* indicates a 3D style visual content. *VR* means the content of a data video can be viewed using VR technologies.

Event Creation: Another requirement of a data video might be presenting or reproducing an event (e.g. a timeline of crime, meetings, and classes). This process is named *Event Creation*. According to the format of the content, we further divide it into *2D*, *3D*, and *VR*. *2D* refers to replaying events using the 2D visual content without 3D camera movement. *3D* refers to replaying events using 3D visual content with 3D camera movement. *VR* means that the content of videos can be viewed using VR technologies. Importantly, we found there are two types of videos, that might be confusing. The first one is videos applying 2D visual content while using 3D camera techniques (e.g. moving the camera from the back of an object to its front). The other one is videos utilizing 3D visual content but not applying any camera movement — all scenes are shown from one perspective. We define both of those approaches to be *2D*.

Real Visual Cues: As well as *2D*, *3D*, and *VR* content, we identified that some data videos also contain real visual elements, such as real images and video pieces. We classify the real visual content as *Real Visual Cues*. There is a special case, where some data videos are produced as real films. Namely, they use real actors and actresses, and environments for the duration of the videos. We classify this style of video as applying *Real Visual Cues*.

Voice Over: *Voice Over* is a known production technique. Where a real voice is applied to a data video, normally, as a background voice for the purpose of the introduction.

Annotations: *Annotations* are those notes or comments appearing in a data video, applied for further explanation of the data, graphs, or concepts presented in the data video. They can appear anywhere and at any time during a data video.

Music: *Music* refers to any music being played during a data video. It can be background music across the whole video or serve for part of the video.

3.2.5. Highlighting

Highlighting is one of the basic viewing control mechanisms to guide viewers' attention (Liang and Huang, 2010). In our research, we identified four major types of visual effects used for highlighting:

Close-Ups: *Close-Ups* indicates a position of the camera where the majority of the camera's frame captures the object of interest.

Zooming (in/out): *Zoom (in/out)* refers to the motion of the camera moving in our away from the object of interest, effectively enlarging or shrinking the object in the camera's frame.

Contrast/Affinity: *Contrast/Affinity* indicates the discrimination of colors between different objects within a scene in order to highlight the main body.

Motion/Animation: *Motion/Animation* refers to the action of character or animated objects, which guide viewers' attention.

3.2.6. Transition effect

Transition effect is an important method of changing from one scene to another scene (Beaver, 1983). As there are a large array of transition effects utilized in the video-editing field, we listed some of the more common effects such as *Cuts*, *Viewer Motion*, *Fade (in/out)*, *Dissolve*, *Wipe*, *Slide*, and *Iris*, and provide one column named *Others* for the techniques that fall outside of those mentioned.

Table 1
Narrative attributes.

Attribute	Options	Description
Ending Type	Open	In an *Open* narrative, there is no clear conclusion at the end of the data video and the viewers are left to draw their own conclusions.
	Closed	*Closed* narrative has a structured ending including a specific conclusion.
Story Strand	Single Strand	A *Single Strand* data video only has one storyline. In literary, dramatic work, and cinematic work, the term storyline refers to the plot and development of a story. In our work, we define a storyline as a thread for presenting data and its stories.
	Multi-Strand	*Multi-Strand* data video have several storylines.
Investigation	Investigative	Focusing on seeking an answer to a question, an *Investigative* narrative shows a set of systematic motions or processes investigating data, after which – depending on the ending type – an end with/without conclusion is shown.
	Non-Investigative	Without showing the actions or processes of investigation, *Non-Investigative* narrative data videos simply present data or tell stories
Order	Linear	In a *Linear* narrative, the events play out in a clear linear fashion (e.g. obvious time-line, headings, or causality cues).
	Non-Linear	In a *Non-Linear* narrative the events are presented out of order and does not have a clear linear cues.
Storyteller	Restricted	A *Restricted* narrative presents a story from one person's perspective.
	Unrestricted	In an *Unrestricted* narrative a story is told from the many characters' point of view.
Interactivity	Interactive	A data video is equipped with interactive functions.
	Non-Interactive	A data video has no interactive abilities.

3.3. Observation and discussion

In this section, we discuss our findings from the observation of each dimension in our design space against our sample data set, including characteristics and research opportunities. This is undertaken with the intention of providing a detailed understanding of current data videos, in turn, benefiting the design and use of data videos for future research. It should be noted that the insights we gained are based on the observation of short data videos in our dataset (shorter than 20 min). We assert that our insights might not be valid for long data videos.

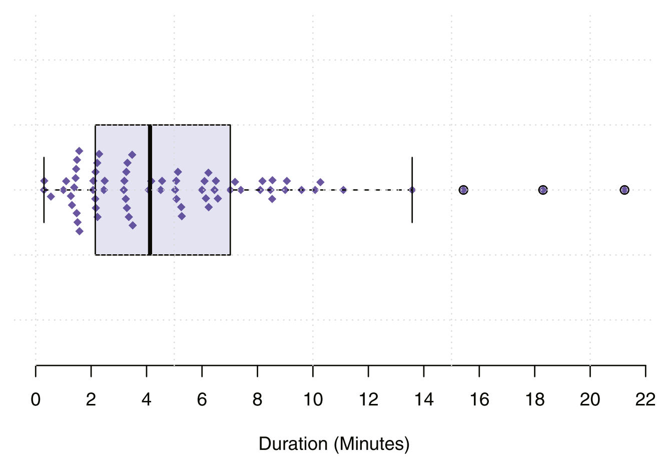

Fig. 1. Swarm plot of the duration of the data videos in our taxonomy. A majority of the videos we examined fell in the 2–7 min range.

3.3.1. Time

As shown in Fig. 1, a majority of the data videos in our taxonomy are from two to eight minutes long. This finding may serve as a reference for those wanting to create data videos. Furthermore, it is not clear whether the length of data videos will affect people's understanding and engagement. If so, to what extent does it impact understanding? Further research is needed to characterize the time attribute of data videos. Such studies could also provide insights for the arrangement of the content, such as the detail level of the story and the pace of the videos.

3.3.2. Genres and narrative structure

A summary of the usage of genres and narrative structures classified within our taxonomy is depicted in Fig. 2. From the figure, we can see that most existing data videos belong to the genre of *Factual Knowledge* (62.86%) and the most popular narrative structure is *Chain of Facts* (82.86%). We believe one of the possible reasons is the inherent intention of data videos — presenting a set of data in an audio-visual narrative, which is mostly dominated by the need to present facts. In addition, during the encoding and analysis of data videos, we found that the narrative structures that current data videos apply are quite simple. As a result, we only identified four narrative structures, all of which are the simple chain of data and information. It is not clear if this is due to the insufficiency of established research and techniques in this domain, or due to the use of only short videos in our dataset.

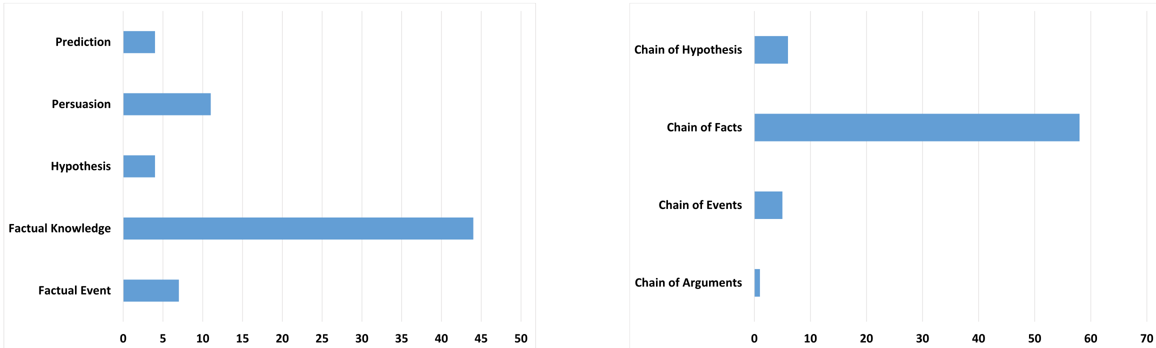

Fig. 2. The application of Genres (left) and Narrative Structures (right).

Either way, we do not deny the possible application of other narrative structures for data videos, such as Three-Act Structure.

3.3.3. Narrative attributes

According to our analysis, a summary of narrative attributes is shown in Fig. 3. While *Linear* and *Non-Linear* are found equally applied, most attributes have an obvious difference between the application of each option. Especially in *Story Strand* and *Storyteller*, we did not find any videos utilizing *Multi-Strand* and *Unrestricted*. We believe one of the reasons is those attributes were developed from a narratological background and are only now starting to be applied to data videos. The absence of those attributes does not mean that they do not exist but is indicative of the early stages of data video research. This suggests that it is worth developing these missing attributes as they are accepted in narrative theory. We will introduce the observation of narrative attributes in more detail.

In exploring endings, 81.43% of data videos have a *Closed Ending*. Only 18.57% of data videos do not provide the viewer with certain conclusions at the end.

Regarding story strands, all the data videos utilized *Single Strand*, meaning they only had one storyline. The complexity of *Multi-Strand* narrative might be one of the reasons for this. Despite the under-utilization, we believe multi-storylines can potentially enrich the content of a data video and support complicated storytelling such as depictions of criminal cases in the law enforcement domain. However, more related experiments are required to support this. Furthermore, since we have not seen a *Multi-Strand* data video, it is still not clear what a *Multi-Strand* data video may be like and how one would create it. The answers to these questions can be significantly beneficial to the research of data video authoring tools.

Non-Investigative data videos dominated, with 92.86%. This, in some sense, was due to the lack of video-related interactive techniques. Another phenomenon we observed from our taxonomy is that only a few data videos applied interactive techniques (2.86%). We believe that despite the reduced usage in current data videos, the popularity of interactive and investigative data videos will increase with research and improvements in interactive techniques, such as VR.

Like *Story Strand*, we cannot find any *Unrestricted* data videos; all the data videos we found tell stories from a single perspective. Like applying *Multi-Strand* narrative, utilizing *Unrestricted* narrative also brings many complex issues, the methods of which are still unclear. For example, if a data video uses two or more perspectives, how can we arrange and balance those perspectives to avoid possible confusion and redundancy? What is the intent of the video? Most importantly, is unrestricted storytelling truly superior? Only after those questions are fully explored, can we determine whether an *Unrestricted* narrative should be applied to data videos.

Only 41.43% of videos were *Linear* in nature compared to 58.87% being *Non-Linear*. This is interesting, given that in movies, dramas, or other narrative mediums, *Linear* narrative is the most common form (Rayner and Wall, 2008). In contrast, *Linear* and *Non-Linear* narrative are somewhat equally applied in data videos.

3.3.4. Narrative tools

The most common narrative tool is *Voice Over* — 61 data videos (87.14%) utilize *Voice Over*. The second most common is *Music* (82.86%). Some of the data videos even use the lyrics of the music as *Voice Over* for messaging.

As for the format of data videos, most current data videos are in *2D*, while a few videos apply *3D* techniques, and only one uses *VR*. In addition, the VR data video had a very low level of interactivity, with only the function of moving the field-of-view. Whilst we believe 2D techniques are clearly suited to specific types of applications, the advantages offered by 3D and VR could potentially provide a compelling medium to convey certain narratives. Supporting this, Bastiras and Thomas (2017) examined combining narrative visualizations with VR techniques. Although their results show no quantitative difference between VR and non-VR narratives, participant questionnaires indicate that VR enhanced the subjective experience.

3.3.5. Other observations

During the creation of our taxonomy and its validation, we have watched more than 200 data videos, from which we have gained some other observations about *Subjectivity* and *Animations*. We will present them and related potential research opportunities in this section.

Subjectivity: During our review, we found several videos aiming to introduce the same data. However the stories they present differ. From this, we observed the *Subjectivity* involved in the creation of data videos. Thudt et al. (2017) asserted that "subjective perspectives can be introduced at every step of visualization creation — data collection and processing, visual encoding, and presentation". This subjectivity can have either a positive or negative impact on the effectiveness of the data video, which depends on the purposes of the narratives and how it is used. For example, in a data video of a criminal case, in order to maintain the fairness, there should not be any subjective point of view, while an entertaining data video might have many personal perspectives, which, if well designed, will make the data video even more engaging. However, we have not found any research about subjectivity design regarding data videos. Future research directions in this domain include identifying the creation phases where subjectivity could be introduced, the effects of subjectivity on audience's causal understanding, and the methods to reduce the interference of subjectivity or increase the benefits of subjectivity if any.

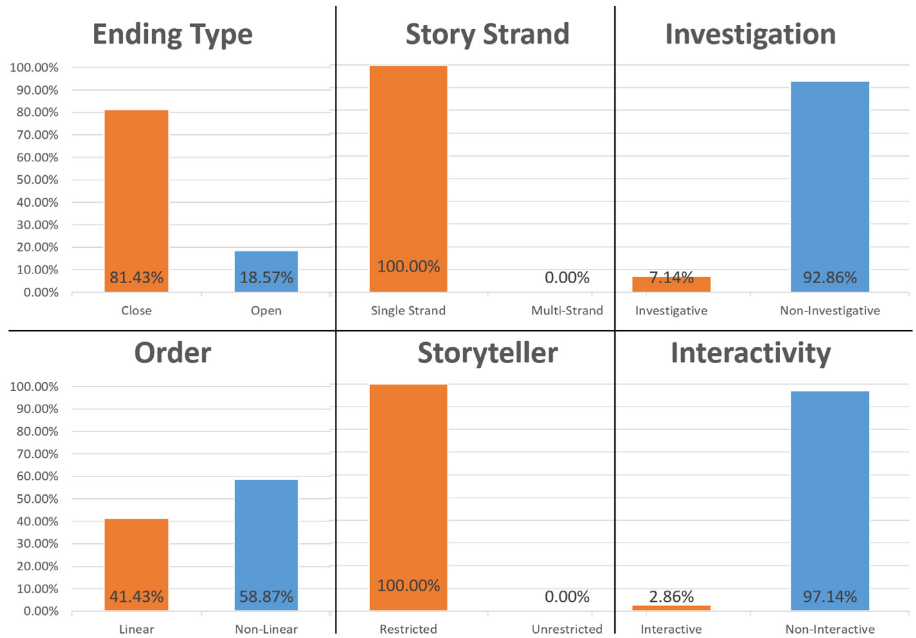

Fig. 3. The percentages of Narrative Attributes: each percentage indicates the number of the videos utilizing a specific narrative attribute.

Animations: We found *Animation* is a common tool applied in data videos; almost all data videos we collected have animations either in 2D, 3D, or VR format. *Animations* can bring many benefits to data videos. In traditional data visualization, many of the key elements of the stories are not presented, such as characters, a plot, a beginning, and an end (Marcengo and Rapp, 2014). *Animations* can greatly support visualizing those missing elements, which efficiently enhance the power of data videos. Chevalier et al. (2016) further presented 23 benefits of animations, such as staying oriented during navigation and keeping the user engaged. Amini et al. (2018) recently proved that animation as a design technique can significantly increase the focused attention of data videos and keep the viewers engaged. However, this work only focused on infographics. There is still no evidence indicating the power of *Animation* in other types of data videos. This suggests more research is needed in this space.

4. Case studies of data videos

In this section, we present five data video case studies. Each of the five examples is aligned with each of our five genres, which indicate the preferred narrative and visual methodologies. Our goal is to provide the readers with a detailed sense of how the design space of our new taxonomy is employed. Throughout, the design classifications involved will be marked in *monospace*. We have received author permissions to use the snapshots from these videos.

4.1. Powers of Ten (1977)

"Powers of Ten"[4] is a famous video introducing magnitudes in an intuitive way. This video has been posted on various websites for different purposes since it was created, most of which have a great number of viewers and positive comments (Until now, it has 5,261,233 viewers and 3658 comments on YouTube within the past 6 years). Depicted in Fig. 4, the video starts at a picnic by a lakeside in Chicago, transports the view to outer edges of the

[4] Powers of Ten (1977), a film by Charles and Ray Eames is © 1977, 2018 Eames Office, LLC (eamesoffice.com).

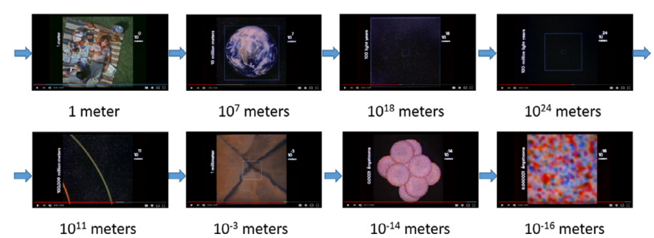

Fig. 4. The "Power of Ten" data video. Each scene represents a progressive magnitude of scale depicting a real-world entity, such as the Earth or a human cell. Each scale is contrasted to the previous due to the narrative ordering, which we identify as *Chain of Facts* structure.

universe, then moves inward into the hand of the sleeping picnic attendee, and finally ends inside a proton of a carbon atom within a DNA molecule in a white blood cell. The view moves the power of ten farther/closer every ten seconds.

The intent of this video is to introduce viewers to the relative size of things in the universe. In the sense that there are no procedural skills being taught. As such, we classify this video into the genre of *Factual Knowledge*. In order to provide the viewer with an intuitive perception, the video simply shows different facts – the size of the things in the universe – in order (As shown in Fig. 4, the size is from 1 meter to 100 million light-years, then back to 10^{-16} meters). Therefore, we define its narrative structure as *Chain of Facts*. Based on this structure, there is only one storyline and one voice using different objects in the universe to visualize different sizes. The application of the taxonomy to the features of this video is listed in Table 2.

4.2. The JFK assassination in 4K 360° VR

The video is describing a historical incident — the assassination of John F. Kennedy, by embedding historical footage into a 360° view. Viewers are allowed to control their field-of-view and observe the whole environment in 360° from multiple angles (as shown in Fig. 5), with digital overlays in 3D space for the bullet paths, which enhance the ability to understand the positional information of this case. This interactive function (although a very

Table 2
Features of "Powers of Ten (1977)".

Time		9:00
Genre		Factual knowledge
Narrative approaches	Narrative structure	Chain of Facts
	Narrative attributes	Ending Type: Closed Story Strand: Single Strand Investigation: Non-Investigative Order: Linear Storyteller: Restricted Interactivity: Non-Interactive
	Narrative tools	Real Visual Cues Voice Over Annotations Music
Visual approaches	Highlighting	Close-Ups Contrast/Affinity
	Transition effect	Cuts Viewer (camera) Motion Fade (in/out) Dissolve

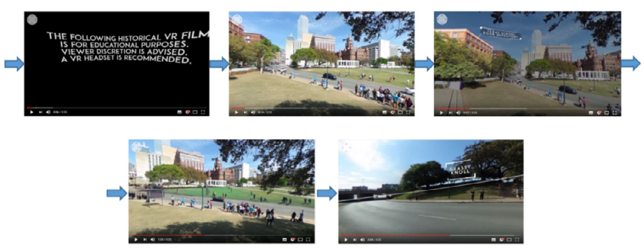

Fig. 5. "The JFK Assassination in 4K 360° VR" video. Each example scene illustrates different field-of-view, which can be changed by viewers.

low level of interaction) makes the video very attractive. Viewers gave comments including "[Felt] like [I] time travelled".

As the purpose of this data video is to visualize and show people the historical case of the assassination, its genre is *Factual Event*. A natural method to present this information is to simply present a set of facts, with film footage spatially embedded. As such, we define its narrative structure as *Chain of Facts*. All the attributes of the taxonomy for this video are listed in Table 3.

According to our observations, the application of VR technologies increases the appeal and attraction of data videos. However, current VR techniques applied to videos are relatively simple, such as the change of viewing angles. Potentially, more powerful interactions could be utilized to significantly enhance the videos. This requires further research as the cinematic skills required for authoring VR data videos are complicated. Specifically, in "The JFK Assassination in 4K 360° VR", there is only *Fade (in/out)* transition effect applied. From our perspective, a possible reason for this is still the lack of knowledge regarding utilizing VR into videos. Some suggestions such as "Can you make it more immersive?" are offered by the viewers in the comments, indicating that the use of VR does not automatically increase the level of immersion.

4.3. How Folding Paper Can Get You to the Moon

This three minutes and 48 s video presents an interesting concept – going to the moon by folding paper – by the use of a stylized 2D animation. As the content is fictional, we define it in the genre of *Hypothesis*. In the video, the author presents several hypothetical situations first. For example, we have an almost infinitely large sheet of paper that is 10^{-3}cm thick and big enough, and most importantly, we can fold this paper as many times as we wish. Based on these assumptions, several facts are

Table 3
Features of "The JFK Assassination in 4K 360° VR".

Time		3:25
Genre		Factual event
Narrative approaches	Narrative structure	Chain of Facts
	Narrative attributes	Ending Type: Closed Story Strand: Single Strand Investigation: Non-Investigative Order: Non-Linear Storyteller: Restricted Interactivity: Interactive
	Narrative tools	Symbolic Visuals: VR Event Creation: VR Real Visual Cues Voice Over Annotations Music
Visual approaches	Highlighting	Contrast/Affinity
	Transition effect	Fade (in/out)

Table 4
Features of "How Folding Paper Can Get You to the Moon".

Time		3:48
Genre		Hypothesis
Narrative approaches	Narrative structure	Chain of Hypothesis
	Narrative attributes	Ending Type: Closed Story Strand: Single Strand Investigation: Non-Investigative Order: Linear Storyteller: Restricted Interactivity: Non-Interactive
	Narrative tools	Symbolic Visuals: 2D Event Creation: 2D Voice Over Annotations
Visual approaches	Highlighting	Contrast/Affinity Motion/Animation
	Transition effect	Others

then presented, such as the paper being 0.33 km high after 25 folds, 10.73 km by 30 folds, and finally getting to the moon by 45 times folds. We name this structure as *Chain of Hypothesis*, which is also the dominating narrative structure in this genre, according to our taxonomy. This data video is similar to the "Powers of Ten" data video, as both videos are explaining mathematical concept of increasing exponential powers. The taxonomy attributes of this video are listed in Table 4.

4.4. What Will The Earth Look Like In 100 Years?

Generated by Life Noggin,[5] this video explores several ideas of what the future will be like (as shown in Fig. 6), which is aligned with a genre of *Prediction*. Following our taxonomy, there are two structures of relevance applied in this genre: *Chain of Facts* and *Chain of Hypothesis*. The difference between these two structures is whether the video presents a real fact (e.g. the speed of light) or a hypothetical (e.g. in the future, we may move faster than the speed of light). For the purpose of describing "what will the earth look like in 100 years", this video presents many speculations, such as the concept of "neural lace" (a technology to build a wireless interface between human brains and computers). Although this technology may exist in the future, it does not currently exist. As such, the structure of this video is *Chain of Hypothesis*. The taxonomy features of this video are described in Table 5.

5 https://www.youtube.com/user/lifenoggin.

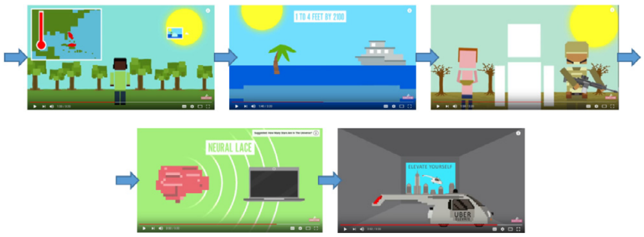

Fig. 6. "What Will The Earth Look Like In 100 Years?" video. This video is consist of a series of hypotheses regarding the future, which we define as *Chain of Hypothesis* structure.

Table 5
Features of "What Will The Earth Look Like In 100 Years?".

Time		3:20
Genre		Prediction
Narrative approaches	Narrative structure	Chain of Hypothesis
	Narrative attributes	Ending Type: Closed Story Strand: Single Strand Investigation: Non-Investigative Order: Non-Linear Storyteller: Restricted Interactivity: Non-Interactive
	Narrative tools	Symbolic Visuals: 2D Event Creation: 2D Voice Over Annotations Music
Visual approaches	Highlighting	Close-Ups Zooming (in/out) Contrast/Affinity
	Transition effect	Wipe Slide Others

4.5. *Why Some Countries Are Poor and Others Rich*

The reason why some countries are rich and others poor is the result of many factors. That means there must be various ideas about this question from different people. The video "Why Some Countries Are Poor and Others Rich" introduces some of the author's opinions by the use of 2D animations with real images and videos included. As such, it is obvious that the intent of this video is to communicate a number of influencing factors ideas and try to convince viewers to agree. We place this video in the genre of *Persuasion*. The video achieves the author's goals by visualizing and presenting many related facts, such as the quality of the institutions, the cultures, and geography. Therefore, as with most other *Persuasion* data videos, this video utilizes a structure of *Chain of Facts*. All the taxonomy attributes of this video are found in Table 6.

5. Using the taxonomy

With this taxonomy, we provide a formalization of data videos that may benefit both the research in related fields and the development of relevant techniques. In this section, we present our guidance for where our taxonomy can be applied.

5.1. *An easier and consistent language to describe and compare data videos*

As data videos become more prevalent, researchers and practitioners need a consistent language to support development, discussion, and analysis of these data videos. However, a data

Table 6
Features of "Why Some Countries Are Poor and Others Rich".

Time		8:47
Genre		Persuasion
Narrative approaches	Narrative structure	Chain of Facts
	Narrative attributes	Ending Type: Closed Story Strand: Single Strand Investigation: Non-Investigative Order: Linear Storyteller: Restricted Interactivity: Non-Interactive
	Narrative tools	Symbolic Visuals: 2D Event Creation: 2D Real Visual Cues Voice Over Annotations Music
Visual approaches	Highlighting	Close-Ups Zooming (in/out) Contrast/Affinity Motion/Animation
	Transition effect	Cuts Dissolve Slide Iris Others

video is complex, consisting of multiple types of data visualization, various images, video footage, and other elements. The dynamic form of data videos for presenting information further complicates the characterization. As a result, it can be difficult to describe a data video in a concise and systematic manner. Specifically in our work, we found that the lack of a consistent language to describe data videos required us to spend more time and effort on the communication and discussion about our dataset. Our taxonomy provides a consistent and clear language of describing data videos. We hope it will result in more effective communication for related research and development activities. Examples are as the descriptions in Section 4.

5.2. *A method to classify data videos*

We believe a clear classification of data videos would benefit their research and development. To the best of the authors' knowledge, there is no classification method specifically for data videos and existing data video sources (online and offline) are not well organized. This complicates and limits the work involving data videos. We envision our taxonomy could be one of the first attempts to support the classification of data videos. Following our taxonomy, a data video can be classified by its genre, narrative structure, or other narrative techniques. A better-classified data video source could bring benefits to practical activities in many ways. For example, individuals could easily locate a specific type of data videos, developers could have a better idea of what category of data videos they want their work to fit, and researchers could organize and study their data video samples in a more systematic way. Comparison activities could also get benefits; our taxonomy could also help to answer questions such as "are these data videos the same?" and "how are they different?". Based on this, more measurements specifically for data videos can be developed. Following this work, we plan to develop an online source that collects and provides the well-classified data videos.

5.3. *A clear and easy-to-follow strategy to design data videos*

Another usage of our taxonomy is to help individuals to design and develop data videos. Bastiras and Thomas (2017) defined four steps for creating a narrative visualization: (1) data collection, (2) data analysis/narrative construction, (3) modeling data, and (4) narrative integration. Based on these steps, our taxonomy provides a clear and easy-to-follow strategy that supports the design work from step two to step four. Our genres, narrative structures, and narrative attributes can help people to construct their narrative, while narrative tools and visual approaches can lead people to model their data and finalize the data videos. In the future, we will enrich the techniques in our taxonomy, and provide more method options for people to design data videos. Following this, we also envision our taxonomy to be a fundamental structure for data video authoring tools.

6. Limitations

We sought a variety of videos when collecting data videos for examination; however, no dataset is completely comprehensive. Although we filtered data videos by their number of viewers, we cannot assume the actual "quality" of the videos (e.g. the engagement of viewers and effectiveness). In light of this, applying our taxonomy to more data videos would be beneficial.

As mentioned earlier, the videos collected in this work are shorter than 20 min. As such, we do not claim that the taxonomy must be valid for long videos. By contrast, we acknowledge this is a limitation of our work. We treat our taxonomy as a starting point of the formalization of data videos' narrative construction, and future work needs to be conducted to further evaluate and modify this taxonomy.

We also acknowledge there may be inevitable subjective bias when recognizing and categorizing a diverse set of features from data videos. We were able to identify different features, our goal is to provide an approach to explain the characteristics or design of data videos. As with the development of all taxonomies, this is a generative process, and additions to the taxonomy are anticipated and welcomed.

7. Areas to be explored

Although the concept of data videos is not new, their research is still in its infancy. In this section, we present some of the unexplored areas we have identified in the field of data videos with the hope of providing suggestions for future work in the domain.

7.1. Measurement

During our video collection phase, we continuously posed the question "what constitutes a good data video?". The measurement of data videos is not well developed. To the best of the authors knowledge, there is only one set of questions specifically developed for data videos (Amini et al., 2018), however, the question set only focuses on viewer engagement. It is still not clear if there are other aspects that need to be measured, and if so, what are the metrics? Understanding "what constitutes a good data video" is important for guiding the development of data videos and their relevant quantitative studies. In light of this, testing and developing measurements for data videos is necessary.

7.2. Authoring tools

The authoring process of data videos is another fruitful yet not well-explored area. Amini et al. (2015) conducted a study and firstly had a brief understanding of the creation of data videos. They characterized the storyboarding processes of data videos and identified four main *Non-Linear* and *Iterative* processes (i.e. reading and interpreting data, selecting data, crafting the narrative structure, and integrating strategies to engage viewers). Consequently, Amini et al. (2017) created an authoring tool for data-driven videos, which allows users to semi-automatically create a short data video with a wide variety of abstract data visualizations. The forms of the available data visualizations, however, are pre-defined, which monotonize the created videos. In fact, the creation of current data videos still relies on general video editing tools such as Adobe Premiere,[6] and other graphic editing tools such as Unity.[7] In some sense, the use of those tools complicates the generation of data videos and therefore limits their application. More effort on the research and development of authoring tools for data videos is therefore necessary. By providing a taxonomy of data videos, we hope to identify the narrative construction of data videos and contribute to this domain.

7.3. New display technologies

The capability of storytelling always relies on its medium. While traditional screens are still the main technique by which to view data videos, it is worth exploring different and new display technologies. The power of VR for data analytics has already been proven (for an overview see Marriott et al., 2018). The use of VR for data videos has great potential. We have already observed some attempts of VR data videos in our taxonomy. Further work, however, is necessary in order to understand data videos in VR, that is, capitalizing on VR' advantages and overcoming its disadvantages. Research in this domain draw from the work in other related domains such as Cinematic Virtual Reality (CVR) and immersive data analytics. Other potential new technologies for data videos include Augmented Reality (AR), Mixed Reality (MR), and Spatial Augmented Reality (SAR).

7.4. Data visualization

In addition to the narrative aspects that we explored in our taxonomy, data visualization is another indispensable component of data videos. While the research of traditional data visualization is abundant (see Friendly, 2008; Borkin et al., 2013 for a review), the inherent features of data videos such as dynamic visuals could bring new challenges for effectively visualizing data. There is still much in this space that has not been explored, and the related research would be more challenging when new display techniques are utilized. Relevant work includes the measurement of traditional data visualization's capability in data videos, the methods of presenting data visualization in data videos, and the development of new ways of visualizing data in data videos and new displays.

8. Conclusions

Data videos are a new medium for storytelling with data. This paper presents a taxonomy derived from analyzing 70 data videos based on current narrative visualization theories. Specifically, we define five distinct genres, four narrative structures, and six narrative attributes involved in the design of data videos. In addition, we list popular visual tools such as *Close-Ups* and *Zooming* for Highlighting and *Cuts* for Transition. Our analysis highlights the salient characteristics and suggests several potential research opportunities for data videos from a narrative perspective. Whilst helping to understand narrative methodologies in data videos, using the taxonomy, we hope to provide an initial framework to characterize the narrative constructions of data videos and contribute to their authoring tools.

6 www.adobe.com.

7 https://unity.com/.

Table A.1
Data videos and URLs used in the taxonomy.

#	Name of data videos	URL
1	The Story of Stuff	https://www.youtube.com/watch?v=9GorqroigqM
2	$17 Trilion U.S.DEBT - A Visual Perspective	https://www.youtube.com/watch?v=WFP-2_iDYMU
3	Price Comparison (World Most Expensive Things)	https://www.youtube.com/watch?v=j8qwb6IHrZk
4	USA and India traffic rules	https://www.youtube.com/watch?v=tPLk9rDl_Wk
5	This animation puts the entire US population into perspective	https://www.youtube.com/watch?v=mCTaiKxpWSA
6	Wealth Inequality in America	https://www.youtube.com/watch?v=QPKKQnijnsM
7	Why Some Countries Are Poor and Others Rich	https://www.youtube.com/watch?v=9-4V3HR696k
8	How to Make a Country Rich	https://www.youtube.com/watch?v=Y9zThcMJzQU
9	Which Countries Have The Fastest Growing Populations?	https://www.youtube.com/watch?v=3nnbd1b_tKQ
10	Winners & Losers - Episode 1: Countries	https://www.youtube.com/watch?v=C4whvUxeG88
11	Japan's Debt Problem Visualized	https://www.youtube.com/watch?v=Njp8bKpi-vg
12	Why the Strong U.S. Economy Is Not Making Americans Happy	https://hbr.org/video/5118087677001/why-the-strong-us-economy-is-not-making-americans-happy
13	Western Middle Classes Have Been Left Out of Global Growth	https://hbr.org/video/5078117043001/western-middle-classes-have-been-left-out-of-global-growth
14	Where the Digital Economy Is Moving the Fastest	https://hbr.org/video/4443548302001/where-the-digital-economy-is-moving-the-fastest
15	What Will the U.S. Economy Actually Look Like in 2017?	http://time.com/money/4570031/american-economic-outlook-2017/
16	The State of America: Jobs	http://www.bbc.com/news/world-us-canada-36231675
17	An Introduction To The Balance Sheet	http://www.investopedia.com/video/play/introduction-balance-sheet/
18	Census 2016: if Australia were 100 people	https://www.youtube.com/watch?v=QBPnay87F8Y
19	Powers of Ten^{TM} (1977)	https://www.youtube.com/watch?v=0fKBhvDjuy0
20	Star Size Comparison 2	https://www.youtube.com/watch?v=GoW8Tf7hTGA
21	How Big Can a Person Get?	https://www.youtube.com/watch?v=DkzQxw16G9w
22	How Folding Paper Can Get You to the Moon	https://www.youtube.com/watch?v=AmFMJC45f1Q
23	Just How Small is an Atom?	https://www.youtube.com/watch?v=yQP4UJhNn0I
24	Is time travel possible? - Colin Stuart	https://www.youtube.com/watch?v=7H3ksmxwpWc
25	Why can't we just print money to pay off debt?	https://www.youtube.com/watch?v=EobPnLZiOo8
26	The Causes and Effects of the 2008 Financial Crisis	https://www.youtube.com/watch?v=N9YLta5Tr2A
27	What Will The Earth Look Like In 100 Years?	https://www.youtube.com/watch?v=_ipyRaGAyyk
28	How Many Nukes Would it Take to Eradicate Humanity?	https://www.youtube.com/watch?v=S1jwxZONlsE
29	What is the LOUDEST Sound Ever Heard?	https://www.youtube.com/watch?v=3W5-ZJ-TJTY
30	What's the Most Difficult Place to Get to In the World?	https://www.youtube.com/watch?v=ap4eVlcYLww
31	The JFK Assassination in 4K 360° VR	https://www.youtube.com/watch?v=whBmXPaChh4
32	This incredible animation shows how deep the ocean really is	https://www.youtube.com/watch?v=UwVNkfCov1k
33	What happens to your body when you stop exercising	https://www.youtube.com/watch?v=hQz_V9Dr8IU
34	These are the world's fastest animals	https://www.youtube.com/watch?v=9IebRS6QbAE
35	Here's how long humans could survive in space without a spacesuit	https://www.youtube.com/watch?v=_Mr8f63Vinc
36	HIV Replication 3D Medical Animation	https://www.youtube.com/watch?v=RO8MP3wMvqg
37	Universe Size Comparison 3D	https://www.youtube.com/watch?v=isppUA0MZmw
38	Why Do We Have More Boys Than Girls?	https://www.youtube.com/watch?v=3IaYhG11ckA
39	The Biggest Lies Told in History	https://www.youtube.com/watch?v=iloQeu-Yg7U
40	Toddler survives 30ft fall through bleachers	https://www.youtube.com/watch?v=61RTAyR3PvI
41	Toddler's brain damage reversed using oxygen treatment	https://www.youtube.com/watch?v=Hj_-i0nb13E
42	The Fallen of World War II	https://www.youtube.com/watch?v=DwKPFT-RioU
43	Why the Moon Landing COULDN'T Have Been Faked	https://www.youtube.com/watch?v=zhp-FTYSGe8
44	Crime Scene Reconstruction, Forensic 3D Animation	https://www.youtube.com/watch?v=Fn2cCVgZ-wk
45	JFK Assassination Magic Bullet Computer Recreation	https://www.youtube.com/watch?v=PfSXkfV_mhA
46	Tupac Shakur's Murder Perfectly Recreated	https://www.youtube.com/watch?v=ODgWWPDwddA
47	Dead Man's Tale, 3D crime scene reconstruction visual.	https://www.youtube.com/watch?v=1CSrtgYxcr4
48	The Notorious B.I.G.'s Murder Recreated Perfectly	https://www.youtube.com/watch?v=MYmOnHsooMY
49	How is DNA fingerprinting used to identify a criminal	https://www.youtube.com/watch?v=AkBUriMK9u8
50	Evidence That Lobbying Is Paying Off for Corporations	https://hbr.org/video/5053768888001/evidence-that-lobbying-is-paying-off-for-corporations
51	How Different Countries Expect Women to Show Authority	https://hbr.org/video/4824895436001/how-different-countries-expect-women-to-show-authority
52	How Non-English-Speaking Countries Stack Up on English Proficiency	https://hbr.org/video/5325501235001/how-nonenglishspeaking-countries-stack-up-on-english-proficiency
53	Lack of Information Stokes Globalization Anxiety	https://hbr.org/video/5222041925001/lack-of-information-stokes-globalization-anxiety
54	Monash University Rankings Animated Data Video	https://youtu.be/iBD4m6bliuw
55	ANZ China Beef Animated Data Video by The Datalabs Agency	https://www.youtube.com/watch?v=9iBGUhyYrHA&feature=youtu.be
56	ANZ Retail Animated Data Video by Datalabs	https://www.youtube.com/watch?v=GWOswCQnfD8&feature=youtu.be
57	Looking to 2060: A Global Vision of Long-term Growth	https://www.youtube.com/watch?v=fnIl212tBPk
58	How Far Away Can You Get From Everybody Else?	https://www.youtube.com/watch?v=3bifbg12u28
59	What is a Protein?	https://pdb101.rcsb.org/learn/videos/what-is-a-protein-video
60	How Enzymes Work	https://pdb101.rcsb.org/learn/videos/how-enzymes-work
61	Understanding percentiles in climate data	https://www.longpaddock.qld.gov.au/forage/videos/understanding-percentiles-in-climate-data/
62	How the Universe is Way Bigger Than You Think	https://www.youtube.com/watch?v=Iy7NzjCmUf0
63	Globalization	https://www.youtube.com/watch?v=3oTLyPPrZE4
64	What's the Cost of Buying a New Car vs Used Car?	https://www.youtube.com/watch?v=I4ArgsnpYCw
65	Chris Graeve - Renting vs Buying a house	https://www.youtube.com/watch?v=0fiM8x5vxcY
66	Apartment Expenses: How Much Rent Can You Afford?	https://www.youtube.com/watch?v=v_8W58LMHrs
67	How fast are you moving right now? - Tucker Hiatt	https://www.youtube.com/watch?v=wIzvfki5ozU
68	iConnect - Financial Launch Motion Graphic	https://vimeo.com/140007789
69	How big is the ocean?	https://www.youtube.com/watch?v=QUW_Zv_jJb8
70	Human Population Through Time	https://www.youtube.com/watch?v=PUwmA3Q0_OE

Table A.2
Taxonomy.

Index	Time	Genre	Narrative Attributes																Narrative Tools										Visual Approaches											
			Narrative Structure				EndingType		Story Strand		Investigation		Order		Storyteller		Interactivity		Symbolic Visuals			Event Creation							Highlighting				Transition Effect							
			Chain of Facts	Chain of Hypothesis	Chain of Events	Chain of Arguments	Open	Closed	Single Strand	Multi-Strand	Investigative	Non-Investigative	Linear	Non-Linear	Restricted	Unrestricted	Interactive	Non-Interactive	2D	3D	VR	2D	3D	VR	Real Visual Cues	Voice Over	Annotations	Music	Close-Ups	Zooming (in/out)	Contrast/Affinity	Motion/Animation	Cuts	Viewer Motion	Fade(in/out)	Dissolve	wipe	Slide	Iris	Others
31	3:25	Factual Event	•					•	•			•		•	•		•				•			•	•	•	•	•			•				•					
47	2:15	Factual Event	•					•	•			•		•	•			•		•			•					•		•	•	•	•		•					
40	0:31	Factual Event			•			•	•			•		•	•			•	•	•		•	•			•				•	•		•	•						
41	0:55	Factual Event			•			•	•			•		•	•			•		•			•			•			•		•	•	•			•				
44	2:23	Factual Event			•			•	•			•		•	•			•		•			•		•	•	•	•	•		•		•	•	•					
46	3:36	Factual Event			•			•	•			•	•		•			•		•			•		•	•	•	•		•	•	•	•			•				
48	3:31	Factual Event			•			•	•			•	•		•			•		•			•		•	•	•	•		•	•	•	•			•				
1	21:24	Factual Knowledge	•				•		•		•		•		•			•	•			•				•	•	•	•	•	•	•		•				•		•
2	3:18	Factual Knowledge	•					•	•			•	•		•			•		•						•	•	•	•		•		•		•					
3	6:14	Factual Knowledge	•					•	•			•	•		•			•		•							•	•						•						
4	5:07	Factual Knowledge	•					•	•			•		•	•			•	•			•									•				•	•				
5	2:46	Factual Knowledge	•					•	•			•		•	•			•	•								•	•			•									
6	6:23	Factual Knowledge	•					•	•			•		•	•			•	•							•	•	•			•	•								
9	3:50	Factual Knowledge	•					•	•			•		•	•			•	•						•	•	•	•			•		•				•			
10	13:58	Factual Knowledge	•					•	•			•		•	•			•	•						•	•	•	•			•		•							
11	6:45	Factual Knowledge	•					•	•			•	•		•			•	•							•	•	•	•		•	•	•	•	•			•		•
14	1:44	Factual Knowledge	•					•	•			•		•	•			•	•							•	•	•			•				•	•		•		•
16	1:00	Factual Knowledge	•					•	•			•	•		•			•	•							•		•			•	•					•	•		•
17	1:10	Factual Knowledge	•					•	•			•		•	•			•	•							•		•	•	•	•							•		
19	9:00	Factual Knowledge	•					•	•			•	•		•			•							•	•	•	•	•		•		•	•	•	•				
20	6:50	Factual Knowledge	•					•	•			•	•		•			•		•							•	•		•	•			•	•					
21	15:43	Factual Knowledge	•					•	•			•		•	•			•	•						•	•	•	•			•		•							
23	5:27	Factual Knowledge	•					•	•		•			•	•			•	•	•		•	•			•		•		•	•	•	•	•	•	•				•
26	11:10	Factual Knowledge	•					•	•			•	•		•			•	•							•	•	•		•	•	•								•
29	7:40	Factual Knowledge	•					•	•			•	•		•			•	•			•			•	•	•	•			•		•	•		•	•			•
30	8:53	Factual Knowledge	•				•		•			•	•		•			•	•						•	•	•	•	•	•	•					•	•		•	•
32	3:29	Factual Knowledge	•					•	•			•	•		•			•	•						•	•		•		•	•	•								•
33	2:08	Factual Knowledge	•					•	•			•	•		•			•	•			•					•	•		•	•	•								•
34	2:22	Factual Knowledge	•					•	•			•	•		•			•	•								•	•						•						
35	1:31	Factual Knowledge	•					•	•			•	•		•			•	•			•				•		•		•	•	•								
36	5:13	Factual Knowledge	•					•	•			•	•		•			•		•			•			•		•	•	•	•		•	•		•				
37	9:59	Factual Knowledge	•					•	•			•	•		•			•		•					•	•	•	•		•	•			•						
38	2:49	Factual Knowledge	•					•	•			•		•	•			•	•						•	•		•		•			•					•		•
39	8:18	Factual Knowledge	•					•	•			•	•		•			•	•						•	•		•		•	•	•	•		•	•		•		
42	18:30	Factual Knowledge	•					•	•			•		•	•		•		•						•	•	•	•		•	•	•			•	•				•
49	2:07	Factual Knowledge	•					•	•			•	•		•			•	•			•				•		•									•		•	•
51	1:27	Factual Knowledge	•					•	•			•		•	•			•	•							•		•			•					•		•		
52	2:16	Factual Knowledge	•					•	•			•	•		•			•	•							•		•			•							•		•
54	0:30	Factual Knowledge	•					•	•			•		•	•			•	•							•	•	•			•									•
56	1:57	Factual Knowledge	•				•		•			•		•	•			•	•							•		•			•	•						•		•
58	8:54	Factual Knowledge	•					•	•			•		•	•			•	•			•			•	•		•	•		•				•	•	•			
59	6:57	Factual Knowledge	•					•	•			•	•		•			•	•	•			•			•		•	•	•	•	•	•		•	•	•			•
60	4:51	Factual Knowledge	•					•	•			•		•	•			•	•	•			•			•		•	•	•	•	•	•	•	•	•		•		
61	5:08	Factual Knowledge	•					•	•			•	•		•			•	•			•				•			•	•	•	•	•				•	•		
62	10:27	Factual Knowledge	•					•	•			•		•	•			•	•			•			•	•		•	•	•	•		•		•	•	•			
63	8:10	Factual Knowledge	•					•	•			•		•	•			•	•				•			•		•	•		•					•	•	•	•	•
64	7:02	Factual Knowledge	•				•		•			•	•		•			•	•			•				•		•	•		•	•	•				•	•		
66	4:08	Factual Knowledge	•				•		•			•		•	•			•	•			•				•			•		•	•						•		•
67	6:09	Factual Knowledge	•				•		•		•			•	•			•	•			•				•			•	•	•		•		•	•		•		•
69	5:25	Factual Knowledge	•					•	•			•		•	•			•	•			•				•			•				•		•	•				•
70	6:24	Factual Knowledge	•				•		•			•		•	•			•	•								•	•	•		•	•								•
24	5:03	Hypothesis	•				•		•		•			•	•			•	•			•			•	•		•			•	•			•	•				•
18	2:29	Hypothesis		•				•	•			•		•	•			•	•									•			•									•
22	3:48	Hypothesis		•				•	•			•	•		•			•	•			•				•	•				•	•								•
28	6:00	Hypothesis		•				•	•		•			•	•			•	•						•	•	•	•			•		•							•
7	8:47	Persuasion	•					•	•			•	•		•			•	•			•			•	•	•	•	•	•	•	•	•			•		•	•	•
8	9:06	Persuasion	•					•	•			•	•		•			•	•			•				•		•	•	•	•	•	•	•			•	•	•	•
12	1:58	Persuasion	•					•	•			•		•	•			•	•							•		•			•				•			•		•
13	1:51	Persuasion	•				•		•			•		•	•			•	•							•		•			•	•			•					
25	10:08	Persuasion	•					•	•			•		•	•			•	•						•	•	•	•		•	•		•		•					
45	4:17	Persuasion		•				•	•			•		•	•			•		•			•		•	•				•	•		•		•	•	•			•
43	4:56	Persuasion				•		•	•			•	•		•			•							•	•		•				•	•	•				•		
50	1:39	Persuasion	•					•	•			•		•	•			•	•							•		•			•							•		
53	1:49	Persuasion	•					•	•			•		•	•			•	•							•		•			•							•		•
65	7:19	Persuasion	•				•		•			•		•	•			•	•			•				•		•	•	•	•				•	•				•
68	1:46	Persuasion	•				•		•			•	•		•			•	•						•	•	•	•	•		•						•			•
15	1:48	Prediction	•					•	•			•		•	•			•	•	•						•		•	•	•	•	•	•		•	•	•	•		•
27	3:20	Prediction		•			•		•			•		•	•			•	•			•				•	•	•	•	•	•						•	•		•
55	2:17	Prediction	•					•	•			•		•	•			•	•							•		•			•							•		
57	3:27	Prediction		•			•		•			•		•	•			•	•						•	•		•	•		•	•			•	•	•	•		

We developed our new taxonomy adhering to a systematic methodology of applying both open and close coding of the data videos. This methodology was performed to avoid subjectivity and to produce the most robust taxonomy possible. To highlight the expressive power of the taxonomy, five case study data videos were examined.

We do not claim that the design space of the taxonomy is exhaustive. In contrast, we continue to seek data videos that do not fall into our genres, structures, and narrative tools. This would allow us to create new classifications that would allow us to further expand and develop our taxonomy. For example, if data videos exist with goals other than the ones we presented, this would result in the creation of new genres.

In future work, we will continue to apply our taxonomy to a wide range of videos, from which we can identify more features and modify our design space. We believe the taxonomy of data videos can be a cornerstone for further research. In addition, we will examine the effectiveness of 2D, 3D, and VR technologies applied in data videos, in order to determine their suitability for supporting narrative visualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

See Tables A.1 and A.2.

Appendix B. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.visinf.2019.12.002.

References

Abercrombie, N., 1996. Television and Society.

Allen, R., 1989. Bursting bubbles:" Soap opera" audiences and the limits of genre. In: Remote Control: Television, Audiences and Cultural Power. Routledge, London, pp. 44–55.

Amini, F., Henry Riche, N., Lee, B., Hurter, C., Irani, P., 2015. Understanding data videos: looking at narrative visualization through the cinematography lens. In: Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems. ACM, pp. 1459–1468.

Amini, F., Riche, N.H., Lee, B., Leboe-McGowan, J., Irani, P., 2018. Hooked on data videos: assessing the effect of animation and pictographs on viewer engagement. In: Proceedings of the 2018 International Conference on Advanced Visual Interfaces. ACM, p. 21.

Amini, F., Riche, N.H., Lee, B., Monroy-Hernandez, A., Irani, P., 2017. Authoring data-driven videos with dataclips. IEEE Trans. Vis. Comput. Graphics 23 (1), 501–510.

Baber, C., Andrews, D., Duffy, T., McMaster, R., 2011. Sensemaking as Narrative: Visualization for Collaboration. VAW2011, University London College, pp. 7–8.

Bach, B., Stefaner, M., Boy, J., Drucker, S., Bartram, L., Wood, J., Ciuccarelli, P., Engelhardt, Y., Koeppen, U., Tversky, B., 2018. Narrative design patterns for data-driven storytelling. In: Data-Driven Storytelling. AK Peters/CRC Press, pp. 125–152.

Bastiras, J., Thomas, B.H., 2017. Combining virtual reality and narrative visualisation to persuade. In: Big Data Visual Analytics (BDVA), 2017 International Symposium on. IEEE, pp. 1–8.

Beaver, F.E., 1983. Dictionary of Film Terms. McGraw-Hill.

Borkin, M.A., Vo, A.A., Bylinskii, Z., Isola, P., Sunkavalli, S., Oliva, A., Pfister, H., 2013. What makes a visualization memorable? IEEE Trans. Vis. Comput. Graphics 19 (12), 2306–2315.

Brehmer, M., Lee, B., Bach, B., Riche, N.H., Munzner, T., 2017. Timelines revisited: A design space and considerations for expressive storytelling. IEEE Trans. Vis. Comput. Graphics 23 (9), 2151–2164.

Broder, A., 2002. A taxonomy of web search. In: ACM Sigir Forum, Vol. 36. ACM, pp. 3–10.

Bryan, C., Ma, K.-L., Woodring, J., 2017. Temporal summary images: An approach to narrative visualization via interactive annotation generation and placement. IEEE Trans. Vis. Comput. Graphics 23 (1), 511–520.

Bulterman, D.C., Hardman, L., 2005. Structured multimedia authoring. ACM Trans. Multimedia Comput. Commun. Appl. (TOMM) 1 (1), 89–109.

Cao, R., Walsh, J., Cunningham, A., Thomas, B.H., 2017. Examining the affordances for multi-dimensional data videos. In: Big Data Visual Analytics (BDVA), 2017 International Symposium on. IEEE.

Card, S.K., Mackinlay, J., 1997. The structure of the information visualization design space. In: Information Visualization. Proceedings., IEEE Symposium on. IEEE, pp. 92–99.

Chandler, D., 1997. An Introduction to Genre Theory. The Media and Communications Studies Site.

Chevalier, F., Riche, N.H., Plaisant, C., Chalbi, A., Hurter, C., 2016. Animations 25 years later: new roles and opportunities. In: Proceedings of the International Working Conference on Advanced Visual Interfaces. ACM, pp. 280–287.

Chi, E.H.-h., 2000. A taxonomy of visualization techniques using the data state reference model. In: In: Information Visualization. InfoVis 2000. IEEE Symposium on. IEEE, pp. 69–75.

Claes, S., Vande Moere, A., 2017. The impact of a narrative design strategy for information visualization on a public display. In: Proceedings of the 2017 Conference on Designing Interactive Systems. ACM, pp. 833–838.

Cohn, N., 2013. Visual narrative structure. Cogn. Sci. 37 (3), 413–452.

Fairclough, N., 1995. Media Discourse. Edward Arnold, London.

Figueiras, A., 2014. Narrative visualization: a case study of how to incorporate narrative elements in existing visualizations. In: Information Visualisation (IV), 2014 18th International Conference on. IEEE, pp. 46–52.

Friendly, M., 2008. A brief history of data visualization. In: Handbook of Data Visualization. Springer, pp. 15–56.

Gershon, N., Page, W., 2001. What storytelling can do for information visualization. Commun. ACM 44 (8), 31–37.

Glaser, B., Strauss, A., 2009. The Discovery of Grounded Theory: Strategies for Qualitative Research. Transaction Publishers.

Heer, J., Robertson, G., 2007. Animated transitions in statistical data graphics. IEEE Trans. Vis. Comput. Graphics 13 (6), 1240–1247.

Herman, D., 2011. Basic Elements of Narrative. John Wiley & Sons.

Hook, J.D., 2018. Facts, interactivity and videotape: Exploring the design space of data in interactive video storytelling. In: Proceedings of the ACM TVX International Conference on Interactive Experiences for Television and Online Video. Association for Computing Machinery(ACM).

Hullman, J., Diakopoulos, N., 2011a. Visualization rhetoric: Framing effects in narrative visualization. IEEE Trans. Vis. Comput. Graphics 17 (12), 2231–2240.

Hullman, J., Diakopoulos, N., 2011b. Visualization rhetoric: Framing effects in narrative visualization. IEEE Trans. Vis. Comput. Graphics 17 (12), 2231–2240.

Hullman, J., Drucker, S., Riche, N.H., Lee, B., Fisher, D., Adar, E., 2013. A deeper understanding of sequence in narrative visualization. IEEE Trans. Vis. Comput. Graphics 19 (12), 2406–2415.

Kelliher, A., Slaney, M., 2012. Tell me a story. IEEE MultiMedia 19 (1), 4.

Kosara, R., 2017. An argument structure for data stories. In: Proceedings of the Eurographics/IEEE VGTC Conference on Visualization: Short Papers. EuroVis '17, Eurographics Association, Goslar Germany, Germany, pp. 31–35. http://dx.doi.org/10.2312/eurovisshort.20171129.

Liang, J., Huang, M.L., 2010. Highlighting in information visualization: a survey. In: Information Visualisation (IV), 2010 14th International Conference. IEEE, pp. 79–85.

Marcengo, A., Rapp, A., 2014. Visualization of human behavior data: the quantified self. In: Innovative Approaches of Data Visualization and Visual Analytics, Vol. 1. IGI Global, Hershey, PA, pp. 236–265.

Marriott, K., Schreiber, F., Dwyer, T., Klein, K., Riche, N.H., Itoh, T., Stuerzlinger, W., Thomas, B.H., 2018. Immersive Analytics, Vol. 11190. Springer.

Mayer, R.E., Heiser, J., Lonn, S., 2001. Cognitive constraints on multimedia learning: When presenting more material results in less understanding.. J. Edu. Psychol. 93 (1), 187.

Mitra, S., McEligot, A.J., 2018. Can multimedia tools promote big data learning and knowledge in a diverse undergraduate student population?

Neale, S., 1990. Genre, London: British film institute (solely concerned with film); an extract can be found in Tony Bennett, Susan Boyd-Bowman, Colin Mercer & Janet Woollacott (Eds). In: 1981: Popular Television and Film. British Film Institute, London, p. 48.

Ojo, A., Heravi, B., 2017. Patterns in award winning data storytelling: Story types, enabling tools and competences. Digit. J. 1–26.

Orehovec, B., Alley, M., 2003. Revisiting the Reading Workshop: Management, Mini-lessons, and Strategies: a Complete Guide to Organizing and Managing an Effective Reading Workshop that Builds Independent, Strategic Readers. Scholastic Inc..

Qu, Z., Hullman, J., 2018. Keeping multiple views consistent: Constraints, validations, and exceptions in visualization authoring. IEEE Trans. Vis. Comput. Graphics 24 (1), 468–477.

Rayner, P., Wall, P., 2008. As Media Studies: The Essential Introduction for AQA. Routledge.

Richards, L., 2014. Handling Qualitative Data: A Practical Guide. Sage.

Satyanarayan, A., Heer, J., 2014. Authoring narrative visualizations with ellipsis. In: Computer Graphics Forum, Vol. 33. (3), Wiley Online Library, pp. 361–370.

Segel, E., Heer, J., 2010. Narrative visualization: Telling stories with data. IEEE Trans. Vis. Comput. Graphics 16 (6), 1139–1148.

Stam, R., 2000. Film Theory: An Anthology. Blackwell Publishing.

Thudt, A., Perin, C., Willett, W., Carpendale, S., 2017. Subjectivity in personal storytelling with visualization. Inf. Des. J. 23 (1), 48–64.

Wang, Y., Chen, Z., Li, Q., Ma, X., Luo, Q., Qu, H., 2016. Animated narrative visualization for video clickstream data. In: SIGGRAPH Asia 2016 Symposium on Visualization. ACM, p. 11.

Yu, L., Lu, A., Ribarsky, W., Chen, W., 2010. Automatic animation for time-varying data visualization. In: Computer Graphics Forum, Vol. 29. Wiley Online Library, pp. 2271–2280.