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Investigating the Role and Interplay of Narrations and Animations in Data Videos

Hao Cheng[†‡1,3], Junhong Wang[†‡2,3], Yun Wang[‡3], Bongshin Lee[3], Haidong Zhang[3], and Dongmei Zhang[3]

[1]University of Maryland, College Park, [2]Fudan University, [3]Microsoft Research

Abstract

Combining data visualizations, animations, and audio narrations, data videos can increase viewer engagement and effectively communicate data stories. Due to their increasing popularity, data videos have gained growing attention from the visualization research community. However, recent research on data videos has focused on animations, lacking an understanding of narrations. In this work, we study how data videos use ***narrations and animations*** *to convey information effectively. We conduct a qualitative analysis on 426 clips with visualizations extracted from 60 data videos collected from a variety of media outlets, covering a diverse array of topics. We manually label 816 sentences with 1226 semantic labels and record the composition of 2553 animations through an open coding process. We also analyze how narrations and animations coordinate with each other by assigning links between semantic labels and animations. With 937 (76.4%) semantic labels and 2503 (98.0%) animations linked, we identify four types of narration-animation relationships in the collected clips. Drawing from the findings, we discuss study implications and future research opportunities of data videos.*

1. Introduction

As a genre of narrative visualization, data videos are gaining popularity in media outlets of domains such as journalism, marketing, and education [SH10, Sou19]. Consisting of data-driven graphics, animations, and audio narrations, data videos have proven successful in facilitating data communication and increasing viewer engagement [ARL*18, AHRL*15, ARL*17, SH10]. Different types of empirical studies have been conducted to characterize data videos through the analysis of animations. For example, researchers have collected data videos to identify animated transitions [TYT*20], animated visual narratives [SLL*21], and low-level animation design primitives [TLLS20], informing the future design and research of data videos and authoring tools.

In a data video, rich information is usually packed compactly and delivered through the coordination of narrations (verbal information) and animated graphics (visual information), both of which play an important role as indicated by the dual-coding theory [CP91]. However, there is limited fine-grained understanding about how narrations and animations are used in data videos to facilitate data presentation and storytelling. A deeper understanding of the roles of narrations and animations and their interplay in data videos can reveal designers' best practices. Such understanding may further inspire researchers to design next-generation authoring tools for data videos and take advantage of both narrations and animations. Motivated by this, we aim to take a closer look at data videos and answer the following research questions:

- **Q1**: What types of semantics are conveyed by the narrations in data videos with visualizations?
- **Q2**: How are animations applied to the graphics in data videos to present data stories?
- **Q3**: How are the two modalities of data videos, narrations and animations, coordinated to enable effective communication?

We conduct a qualitative analysis of video clips that contain data visualizations, also known as *data clips* [ARL*17]. We build a corpus of 426 data clips, covering a variety of topics. The clips are extracted from 60 data videos which are collected from high-quality sources on YouTube and last over seven hours in total.

To understand the role of narrations, we extract 816 sentences from the transcripts of the collected data clips and code the semantics of the sentences. The analysis yields a taxonomy of the contents covered in the narrations of data clips: data insights and data contexts, divided into 12 and 11 semantic types, respectively. Our coding results in 1226 semantic labels, with 679 about data insights and 547 about data contexts. Our results show the comparable importance of data insights and contexts when telling data stories, depicting an overview of the narrations in these data clips.

We then anatomize animations within the data clips and code 2553 animations to understand the role of animations. We investigate how they are applied to seven types of animated objects across different chart types. We show the distributions of three types of animation graphical effects over the objects being applied.

† This work was done during the internship at Microsoft Research Asia.
‡ These authors contributed equally. Y. Wang is the corresponding author.

Finally, we analyze the relationship between narrations and animations in data clips by manually matching them and categorize their relationship based on how they cooperate to convey information. We obtain 2728 links between 937 (76.4%) semantic labels and 2503 (98.0%) animations, with 289 (23.6%) semantic labels and 50 (2.0%) animations not being linked. By further examining these links, we find that narrations and animations of data clips can echo each other by repeating the information conveyed, complement each other by providing additional information, or indirectly link to each other by communicating data contents from different perspectives. Animations and narrations can also work independently to deliver messages. We further discuss the insights learned from our study as well as implications for future research on data videos. The data of our study is made available at https://datavideos.github.io/narration-animation-study/.

2. Related Work

2.1. Data Videos

The growing need of data presentation and communication has fostered research on storytelling in the visualization community [KM13]. Segel and Heer [SH10] referred to visualizations that are used to tell stories as narrative visualizations. They presented a taxonomy of narrative visualizations consisting of seven genres, including magazine style, slide show, video, etc. They also identified visual and non-visual tactics that facilitate data storytelling. Lee et al. [LRIC15] defined a visual data story as a series of data-story pieces ordered logically to achieve communication goals.

As one genre of narrative visualization, research on data videos typically focuses on their visual and narrative approaches based on an examination of animation designs [CDC*20]. For example, Amini et al. [AHRL*15] analyzed the types of data visualizations and attention cues to understand narrative approaches in 50 data videos, and summarized high-level narrative structures, namely establisher, initial, peak, and release. Cao et al. [CDC*20] presented four highlighting techniques and seven transition effects found in 70 data videos. Tang et al. [TYT*20] proposed a taxonomy of animated transitions in data videos. Thompson et al. [TLLS20] analyzed 52 real-world examples of data graphics to identify design primitives of animated transitions. Shi et al. [SLL*21] introduced a design space of animations in data videos characterizing how various animations facilitate narrative strategies in data videos. Compared with previous studies, we analyze at a more fine-grained level to understand data videos. By analyzing the semantics of narrations and compositions of animations and further summarizing the relationship between the narrations and animations, we aim to better understand common design practices for data videos.

2.2. Visualization-Text Interplay

Studying the narrations and animations in data videos extends the research of the relationships between visualization and text. Their relationships are being studied in more depth recently. Integrating visualizations and text has been found effective in empirical studies [ZOM19, LTC21, BLC20]. Zhi et al. [ZOM19] observed that interactive links between visualizations and text could improve participants' performance of recalling information in slideshow stories, though those links did not lead to better comprehension. Following studies [LTC21, BLC20] successfully improved visualization comprehension for users with low-level visualization literacy by virtue of gaze-driven adaptive guidance. To unleash the power of integrating visualizations and text, we need to better understand them. Recently, the visualization-text interplay in a specific type of data stories, geographic ones, has been explored [LCB21].

Furthermore, researchers have actively integrated visualizations and text for different purposes in different ways. Latif et al. proposed a framework to produce documents supporting visualization-text interaction by explicitly declaring links between visualizations and text in a markup language [LLB18] and developed an interactive interface to construct references between text and charts in data documents [LZK*21]. Metoyer et al. [MZJS18] presented a computational approach to generating bidirectional links between visualizations and text. VizFlow [SCBL21] is another tool that enables the creation of data-driven articles with text-chart links. Recently, interactive links between visualizations and text are also exploited to support the interpretation of machine learning models [HSD19] and promote the interpretation and communication of data facts [SDES19]. However, narrations are played with animations in data videos, and hence the links between them are distinct from visualization-text interplay in static data stories. Our paper serves as a first step towards a deeper understanding of their relationship in data videos.

2.3. Animations in Visualizations

Animation is the most commonly used attention cue in data videos [AHRL*15] and has been playing an important role in the area of HCI for a long time [CRP*16]. Despite their prevalence, the effects of animations in information visualization are controversial. Robertson et al. [RFF*08] found that animated trend visualizations were inferior to static alternatives. The effect of staggered animations is reported to be marginal or even negative in visual tracking tasks [CDF14]. In contrast, a large body of literature demonstrates the effectiveness of animations. Animated transitions between visualizations are found to improve graphical perception [HR07], user engagement [MRL*17], and users' ability to identify data aggregation operations [KCH19]. In addition to animated transitions, animations can also be used to improve user engagement in animated visualizations [ARL*18, WCL*16, LWZQ20a], communicate data analyses [PKHG21], and guide users' attention in data storytelling [KZLK19, WLMB*14, LWZQ20b, CRP*16]. These benefits of animations give rise to many authoring tools, declarative grammars, and automated generation techniques, such as DataClips [ARL*17], Data Animator [TLS21], InfoMotion [WGH*21], Canis [GZL*20], CAST [GLW21], Gemini [KH21], and AutoClips [SSX*21]. However, they only focus on designing and generating animations that do not associate with textual content or audio narration, and therefore are limited in the ability to create expressive data videos. We aim to understand animations from a different perspective. We consider narrations and animations as two main channels to convey information in data videos. We not only study the composition of animations in data videos, but also closely examine how narrations and animations are related in data videos.

3. Methodology

To answer our research questions, we conducted a qualitative analysis of 426 data clips. We first analyzed the semantics in narrations of data clips to understand how narrations delivered data-related contents (Q1), then examined the animations in data clips to identify how they presented graphical objects (Q2), and finally investigated how they were connected to understand their relationship and usages of telling data stories (Q3).

Data Collection. To understand designers' best practices, we first identified five reputable YouTube channels that produce high-quality videos with a high number of views: *Vox*, *The Guardian*, *Kurzgesagt – In a Nutshell*, *PolyMatter*, and *The Infographics Show*. We then manually selected data videos from these channels based on the following two inclusion criteria. (1) One data video should have audio narration in English, which can be extracted for analysis. (2) It should contain at least one data visualization (e.g., line chart, area chart, bar chart, donut chart, map).

We collected 60 *data videos* that were published between 2013 and 2021, 31 of which have been published since 2019. The total duration of the collected data videos is over seven hours. They cover various topics including politics, business, history, and science, and employ a diverse set of data visualizations with different graphic designs and animation designs. Table 1 shows the statistics of the collected data videos.

We then segmented the collected videos into video clips, such as animated graphics, real-world scenes, and cartoon characters, and extracted *data clips*, i.e., short sequences of frames that contain at least one data visualization [ARL*17, ARL*18], from the videos. When two visualizations are sequentially connected, we segmented them into two data clips. We excluded iconic representations that illustrate an abstract concept (e.g., country outlines representing countries and an animated earth image representing the "Globalization" concept). We also excluded vague visual representations that do not necessarily count as a data visualization, such as calendars, artistic representations, and numbers. When it was ambiguous to identify a data visualization, we referred to the accompanying narration. Data clips that feature more than one chart are referred to as *combined*. In the following text, when referencing a data clip, we report the source data video from which it is extracted. Figure 1 shows examples of included and excluded data visualizations in our final data clip collection. We extracted 426 data clips in total. Table 2 shows the distribution of chart types of these clips. Aligning with previous research [AHRL*15], maps, bar charts, line charts, donut charts, area charts, pictographs, and pie charts are prevalent in our corpus of data clips, covering 91.1% (388), while the other five types of charts contribute only a small portion (38, 8.9%). To conduct further analysis, we randomly selected 20% (12) of the collected data videos to form our coding standards through discussions. Then, three authors coded the remaining data videos and resolved conflicts through semi-weekly meetings.

Identifying Semantics in Narrations (Q1). To understand the contents covered in narrations, we segmented the transcript of each data clip into sentences using the sentence tokenizer of Natural Language Toolkit [BKL09], after which we had 816 distinct sentences in total (Table 2).

Table 1: *Statistics of the collected data videos.*

Channel	Videos	Duration	Data Clips
PolyMatter	15	2:35:15	110
Vox	13	1:23:23	122
Kurzgesagt	13	1:23:26	91
The Guardian	12	1:18:34	58
The Infographics Show	7	0:37:39	45
Total	60	7:18:17	426

Table 2: *Statistics of the collected data clips. Note that a sentence may be counted in more than one data clip when it is narrated across two data clips. Therefore, the total number of distinct sentences (816) does not equal to the aggregated number of sentences (840) for the data clips.*

Chart Type	Data Clips	Sentences	Avg. Duration
Map	130	252	0:00:10
Bar	102	204	0:00:09
Line	44	85	0:00:10
Donut	41	70	0:00:08
Area	34	60	0:00:08
Pictograph	22	56	0:00:11
Pie	15	26	0:00:09
Timeline	12	18	0:00:11
Treemap	10	15	0:00:08
Scatter	1	2	0:00:12
Sankey	1	1	0:00:07
Combined	14	51	0:00:20
Total	426	816	0:00:10

During the initial rounds of the coding process, we found data insights accounted for a large proportion of the semantics conveyed in data videos. Therefore, we used the well-established taxonomy of *data insights* [WSZ*20, SXS*21, SDES19] as seeds including values, proportions, differences, etc. We also found that a large number of sentences reported geotemporal values, especially when the clips involved maps. As a result, we added two types of semantic labels, namely, location and time. In addition, many sentences did not directly report data-related information, but provided context of the data stories or facilitated storytelling. Hence, we adopted and expanded semantic types summarized by Latif et al. [LCB21] to incorporate *data contexts*, including backgrounds, interpretations, questions, etc. We ended up deriving 23 types of semantic labels: 12 data insight labels and 11 data context labels. In total, we assigned 1226 semantic labels including 679 data insights and 547 data contexts.

Identifying Composition of Animations (Q2). To understand the design of animations, we labeled the composition of animations in each data clip. For each animation, we recorded its animated objects and graphical effects using Thompson et al.'s taxonomy [TLLS20], which systematically identified animation primitives. During the coding process, we learned that animated annotations were prevalent. Further classifying annotations would reveal

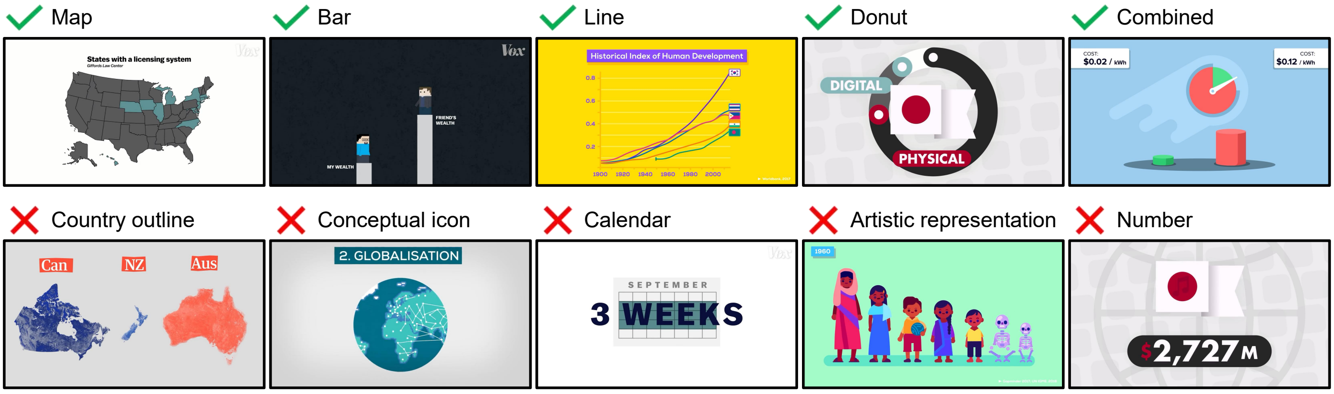

Figure 1: *Examples of data visualizations included in our data clip collection (top row) and graphics excluded from the collection (bottom row). The figures in the top row are captured from [Vox19b, Vox19a, Kur19, Pol19a, The17b], respectively. The figures in the bottom row are captured from [The18, Kur14b, Vox19b, Kur19, Pol19a], respectively.*

meaningful findings. Hence, we expanded the taxonomy by including annotation objects in Ren et al.'s taxonomy [RBB*17], which comprehensively characterized the design space of annotations in visualizations. We further found nearly all of the animations that removed objects from a scene did not convey clear and meaningful messages. Because the goal of our research is to understand how data stories are told through animations and narrations, we only recorded these animations when they had clear meanings. Similarly, scene-level transitions at the beginning or the end of data clips were also excluded. In total, we recorded 2553 animations.

Analyzing Narration-Animation Relationships (Q3). We then analyzed the relationships by linking animations with semantic labels of a sentence. An animation could be linked to a semantic label if what the animation presented was related to the meaning conveyed by the semantic label and they were proximate in time. An animation was allowed to be linked to zero or multiple semantic labels and vice versa. The coders also assigned labels to characterize how each semantic label was semantically related to the animations matched to it. In total, we obtained 2728 links between semantic labels and animations while 289 semantic labels and 50 animations ended up not being linked. We also derived four types of relationships between narrations and animations.

4. Narrations in Data Clips

In this section, we closely examine the semantics of the narrations in data clips. Table 3 gives an overview of the semantic labels assigned to the narrations and their distributions across different types of data clips. Overall, the semantic labels in narrations can be grouped into two categories, data insights and data contexts.

4.1. Data Insights

Data clips often report data insights [SDES19, WSZ*20] in their narrations, which form the basis for the stories covered in data clips, especially in donut charts, pie charts, treemaps, and pictographs. We assigned 679 data insight labels of 12 types in total.

In the narrations of data clips, **Descriptive Insights**, i.e., direct descriptions of data values are very commonly seen (457, 67.3% of data insights). Reporting **values** is the most straightforward way to describe the data shown in a chart, e.g., quantitative descriptions like *"28 straight days"* [Kur14a], and qualitative descriptions like *"that number is very low"* [Pol18a]. Data clips featuring pie charts, donut charts, and treemaps often characterize the **proportion** of a subset of data through a concrete number (e.g., *"66% of U.S. music sales"* [Pol19a]) or a rough description (e.g., *"a minority of Scots"* [The14]). **Locations** are prevalent in the narrations of data clips especially in data clips featuring maps. Locations can be referred to by names of geopolitical or geographical entities, e.g., *"California, Tennessee, Kentucky, Hawaii and Washington"* [The15] and *"Sub-Saharan Africa"* [Kur19]. **Time** is described when an event occurs or some data is generated is also often described, e.g., *"In 2012"* [Kur17] and *"30 years ago"* [The20].

By comparing the relations of data points or data items in a chart, i.e., **Relational Insights** (172, 25.3% of data insights), the narrations of data clips can highlight the significance or communicate the patterns of data items or values. **Differences** between two subsets of data is the most common relational insights, e.g., *"forty times"* [Pol19c] and *"shorter"* [Kur13]. **Ranks** reveal the positions of items when sorted according to some data values, e.g., *"rank 2nd"* [The17b]. **Trends**, often associated with line charts, describe the changes of data over time, e.g., *"begun to shrink"* [Kur17], *"a 4% increase"* [Vox17], and *"from 8% in 1975, to 76% in 2019"* [Kur19]. **Associations** characterize the correlation between two subsets of data, e.g., *"as we move up the income brackets, students score higher and higher"* [Vox19c], which are rarely reported in the narrations of data clips.

Summary Insights describe patterns like extrema, categorizations, distributions, and outliers, which can provide a quick overview of the underlying data. Overall, summary insights are not very common (50, 7.4% of data insights) in the narrations of data clips, except **extrema**, i.e., maximum and minimum, which describe the range of data, e.g., *"the world's highest GDP of around 18.5 trillion dollars"* [The17a] and *"the largest chunk"* [Vox20c]. **Categorizations** list all or the major the categories of an attribute in the data, e.g., *"first, LPs, EPs and 8-tracks, then cassettes, CDs,*

Table 3: *Examples and statistics of different semantic labels in the narrations of data clips.*

Semantic Type	Example	Map	Bar	Line	Donut	Area	Pictograph	Pie	Timeline	Treemap	Scatter	Sankey	Combined	**Total**
Data Insights	-	**187**	**150**	**60**	**70**	**37**	**62**	**27**	**15**	**15**	**2**	**0**	**54**	**679**
Descriptive Insights	-	**167**	**65**	**19**	**57**	**14**	**47**	**23**	**15**	**12**	**1**	**0**	**37**	**457**
Value	*A 747 would need 28 straight days to fly to the moon, [...]*	30	22	2	6	2	20	1	3	1	1	-	14	**102**
Proportion	*In 2015, for example, 66% of U.S. music sales were digital.*	9	17	7	33	1	10	15	3	9	-	-	4	**108**
Location	*[...] nearly 80% comes from California, Tennessee, Kentucky, Hawaii and Washington.*	106	12	2	12	8	8	4	4	1	-	-	13	**170**
Time	*In 2012, Google made about $14 billion US dollars while employing 58,000 people.*	22	14	8	6	3	9	3	5	1	-	-	6	**77**
Relational Insights	-	**11**	**64**	**34**	**10**	**20**	**14**	**1**	**0**	**2**	**1**	**0**	**15**	**172**
Difference	*A Mercury year is shorter than the Mercury day, [...]*	7	36	5	9	10	8	1	-	2	-	-	10	**88**
Rank	*They also rank 2nd in total nuclear power generation at 419 billion kWh [...]*	1	6	-	1	1	-	-	-	-	-	-	1	**10**
Trend	*But, since 1973, the generation of new jobs in the US has begun to shrink.*	3	20	28	-	8	4	-	-	-	1	-	4	**68**
Association	*And as we move up the income brackets, students score higher and higher.*	-	2	1	-	1	2	-	-	-	-	-	-	**6**
Summary Insights	-	**9**	**21**	**7**	**3**	**3**	**1**	**3**	**0**	**1**	**0**	**0**	**2**	**50**
Extremum	*The USA has the world's highest GDP of around 18.5 trillion dollars.*	5	19	7	3	3	1	3	-	1	-	-	1	**43**
Categorization	*If we break it down by format, first, LPs, EPs and 8-tracks, then cassettes, CDs, [...]*	3	1	-	-	-	-	-	-	-	-	-	1	**5**
Distribution	*This lactose intolerance is not spread evenly around the world, though.*	1	-	-	-	-	-	-	-	-	-	-	-	**1**
Outlier	*[...] this period was somewhat artificially high, [...], it looks more like an anomaly, [...]*	-	1	-	-	-	-	-	-	-	-	-	-	**1**
Data Contexts	-	**218**	**122**	**50**	**33**	**41**	**19**	**10**	**16**	**4**	**1**	**1**	**32**	**547**
Informative Contexts	-	**193**	**96**	**44**	**29**	**36**	**13**	**9**	**16**	**4**	**1**	**1**	**25**	**467**
Vis. introduction	*This graph shows local jail inmates in the United States.*	7	17	3	-	1	1	1	-	-	-	-	1	**31**
Dataset description	*As of polls taken in 2014, vegans now make up roughly 2.5% of the population.*	-	2	1	3	2	1	-	-	1	-	-	-	**10**
Background	*In January, Senator Elizabeth Warren proposed something called a "wealth tax."*	119	26	10	9	13	5	3	13	1	1	1	15	**216**
Domain knowledge	*[About 25% is dark matter; and 70% is dark energy.] Both of which are invisible.*	16	1	1	-	7	-	-	-	1	-	-	1	**27**
Interpretation	*Such growth would be a huge challenge for any society.*	26	39	24	13	9	6	5	2	1	-	-	6	**131**
Quote	*But researchers say this shows that licensing works.*	-	1	1	-	-	-	-	-	-	-	-	-	**2**
Judgment	*Regardless, it's not an easy feat.*	21	8	4	4	2	-	-	1	-	-	-	1	**41**
Conclusion	*[...] the Electoral College gives certain people more power to pick the president.*	4	2	-	-	2	-	-	-	-	-	-	1	**9**
Structural Contexts	-	**25**	**26**	**6**	**4**	**5**	**6**	**1**	**0**	**0**	**0**	**0**	**7**	**80**
Question	*What does this show?*	11	10	3	-	2	1	1	-	-	-	-	1	**29**
Transition	*But there's another type of additional property that has had a big impact.*	11	8	2	3	2	5	-	-	-	-	-	4	**35**
Attention guidance	*If you look at its design, it's not hard to figure out what it was built to do.*	3	8	1	1	1	-	-	-	-	-	-	2	**16**

and later, digital" [Pol18b]. **Distributions**, e.g., *"not spread evenly around the world"* [Kur20b], characterize how data is distributed to summarize patterns in the data. **Outliers** refer to data points or data objects that are significantly different from others, e.g., *"it looks more like an anomaly"* [Pol18b].

4.2. Data Contexts

The narrations of data clips also provide necessary contexts to facilitate storytelling. We refer to those semantics as data contexts, which make the stories in data clips more natural and easier to understand. In data clips containing area charts, bar charts, line charts, maps, timelines, and combined charts, the occurrences of data contexts are balanced with those of data contexts, while in other types of data clips, data contexts are less commonly provided. We assigned 547 data context labels of 11 types to the narrations of the collected data clips.

Informative contexts supply information that helps the audience to better understand the content of chart videos and are prevalent in the collected data clips (467, 85.4% of data contexts). **Visualization introduction** can help the audience understand the visualizations in data clips, e.g., *"This graph shows local jail inmates in the United States."* [Vox19e] The sources of the underlying data or how the data is preprocessed is often offered in **dataset descriptions**, e.g., *"polls taken in 2014"* [The17c]. **Background** information can help the audience better understand what is behind the data, e.g., *"In January, Senator Elizabeth Warren proposed something called a 'wealth tax.' "* [Vox19a] Such information is often provided in data clips of maps to accompany descriptive insights like locations. **Domain knowledge** is similar to background information, but it is more domain specific, e.g., *"Both of which are invisible."* [Kur15] provides the domain knowledge of dark matter and darn energy. **Interpretations** of data can make the reported data more approachable to the audience, e.g., describing the projected large population of Sub-Saharan Africa as *"a huge challenge for any society"* [Kur19] to highlight the significance or potential impacts of the reported data. **Quotoes** from researchers or critics exhibit their opinions about the reported data, e.g., *"But researchers say this shows that licensing works."* [Vox19b] In contrast to quotes, **judgments**, are the opinions of the video creators, e.g., *"Regardless, it's not an easy feat."* [Pol19d] **Conclusions** often appear at the end of data clips and provide key takeaways, e.g., *"What doesn't, is that the Electoral College gives certain people more power to pick the president."* [Vox20a]

Structural contexts serve structuring purposes and help make the narrative more coherent. They are less commonly provided (80, 14.6% of data contexts) compared with informative contexts. **Questions** stimulate the audience to think about the data reported in chart videos, e.g., *"What does this show?"* [The20] **Transitions** in the narrations of data clips switch the focus of a story to another topic. For example, *"But there's another type of additional property that has had a big impact."* [The20] **Attention guidance** directs the audience's focus to specific aspects of a chart or the story being told, e.g., *"If you look at its design, it's not hard to figure out what it was built to do."* [Vox20b]

5. Animations in Data Clips

In this section, we look into how animations in data clips are composed. In particular, we are interested in two aspects of the 2553 animations recorded in the collected data clips, animated objects and graphical effects.

5.1. Animated Objects

Data clips exploit animations on diverse objects. In total, we identified seven types of animated objects including five types covered in Thompson et al.'s taxonomy (glyphs, groups, axes and legends, annotations, and cameras) [TLLS20] and two types that do not belong to their taxonomy (charts and backgrounds). **Glyphs** refer to the marks that encode data in a visualization, e.g., the arc that gradually shrinks in Figure 2(c). An animation can also be added to a **group** of glyphs in a visualization, such as the groups of bars shown in Figure 2(d). **Axes and legends** are often animated when a visualization in a data clip is being presented. **Annotations** include various forms of visual elements in data clips, such as text (e.g., textual labels in Figure 2(a)), shapes, higlights, images, and their combinations [RBB*17]. **Cameras** are a type of special animated object which controls how a scene is shown. For example, Figure 2(e) illustrates an animation that changes the zoom level of the camera. **Charts** in data clips can also be the animated objects. This category covers either an entire chart or the major part of a chart (e.g., its plotting area). For example, the multi-series area chart shown in Figure 2(f) is split into two area charts smoothly. **Backgrounds** are often used to increase the visibility of visual elements in data clips. Even though they are not a component of charts, they can be animated in data clips as well, as shown in Figure 2(b).

The top half of Table 4 shows the distribution of animated objects in different types of data clips. It can be seen that annotations are the most prevalent type of animated objects (1431, 56.1%). This is probably because annotations include various forms of visual elements and are applicable to various chart types. We further examine the animated annotations by labeling them using Ren et al.'s taxonomy [RBB*17] and find that text is the most common type of animated annotation (760, 53.1%). Different from annotations, some types of objects tend to be animated more in certain types of data clips. For example, data clips featuring maps extensively make use of camera animations (e.g., zoom in, zoom out) because those animations are a natural way to steer the focus of viewers on maps. In addition, axes and legends, especially axes, are more often animated on bar charts and line charts than on other types of visualizations because most of other types of visualizations in our dataset do not have an axis or a legend.

Table 4: *Distribution of animated objects in different types of data clips (top) and distribution of graphical effects for different types of animated objects in data clips (bottom).*

		Glyph	Group	Axis &Leg.	Annotation	Camera	Chart	Background
	Total	**436**	**209**	**166**	**1431**	**148**	**145**	**18**
Chart Type	Map	67	39	4	396	86	31	1
	Bar	106	95	91	341	27	17	3
	Line	47	16	38	147	7	9	1
	Donut	40	1	4	119	1	30	-
	Area	42	15	16	112	8	6	6
	Pictograph	44	5	2	84	7	18	6
	Pie	7	8	-	55	-	16	1
	Timeline	11	5	2	43	5	6	-
	Treemap	23	8	-	41	1	-	-
	Scatter	-	1	3	1	-	-	-
	Sankey	-	-	-	-	2	-	-
	Combined	49	16	6	92	4	12	-
Graphical Effect Type	Presence	302	144	145	1233	-	96	15
	Attribute	133	59	21	194	-	46	3
	Configuration	1	6	-	4	148	3	-

5.2. Graphical Effects

Animations in data clips appear in different forms, dictated by their graphical effects ranging from a plain appear effect to a much more sophisticated effect. Overall, the graphical effects in data clips can be classified into three categories defined in Thompson et al.'s taxonomy [TLLS20]. **Visual presence** represents graphical effects that controls the appearance and disappearance of visual elements. For example, in the animations illustrated in Figure 2(a), a textual label directly appears beside a line while in Figure 2(b), a background pushes into the scene from outside to make room for a pictograph. Animations of **visual attributes** determine the length, position, shape, color, size, transparency etc. of visible elements in data clips. For example, the length of the black arc in Figure 2(c) slowly shrinks counterclockwise; in Figure 2(d), the transparency of multiple bars in the stacked bar chart gradually increases. **Configuration** refers to animations that change the parameters of the invisible "camera" in front of a scene or the organization and layout of some visual elements. The zoom in effect displayed in Figure 2(e) belongs to this category because it enlarges a specific area in a scene to highlight the area. The animation shown in Figure 2(f) is another example of configuration in that the organization of the

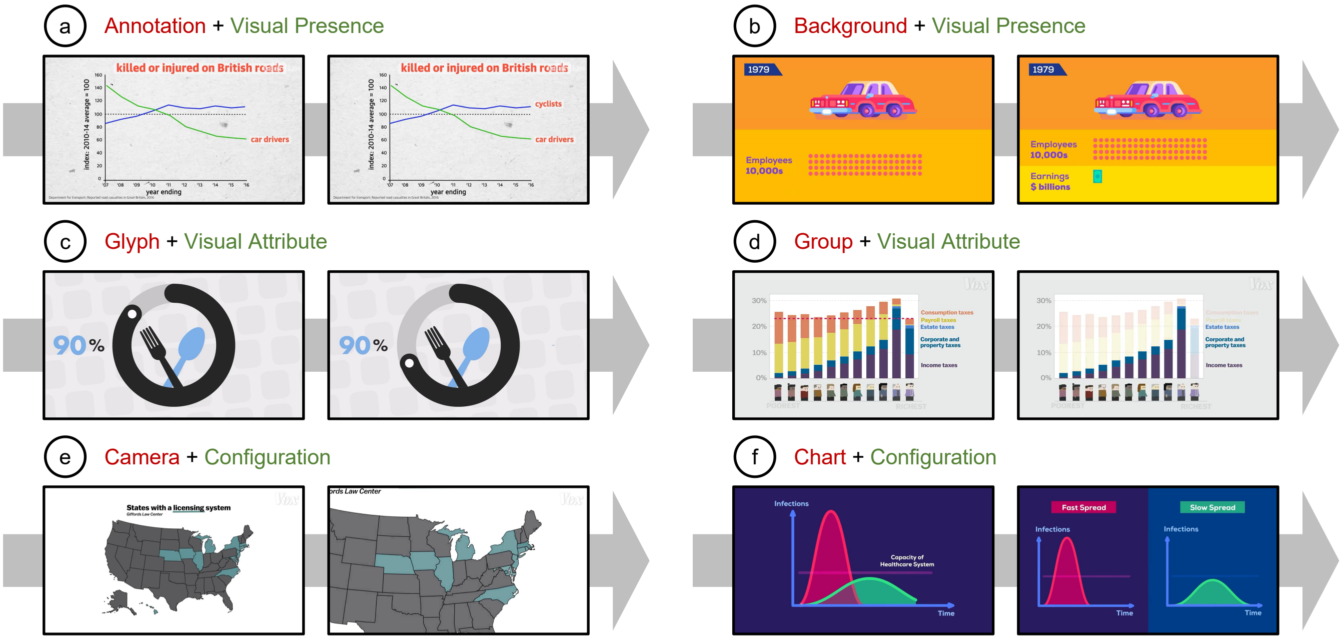

Figure 2: *Examples of animations in data clips. (a) A textual label appears beside a line in the line chart [The19a]. (b) A yellow background enters the scene from the bottom [Kur17]. (c) The length of the black arc shrinks counterclockwise [Pol19d]. (d) Groups of bars in the stacked bar chart become transparent [Vox19d]. (e) The "camera" zooms in on the northeastern part of the map [Vox19b]. (f) The area chart shown in the left figure is disassembled into two area charts [Kur20a].*

multi-series area charts is changed, which transforms it into two separate area charts.

The bottom half of Table 4 presents the frequency of each type of graphical effects for each type of animated objects. Overall, visual presence effects (1935, 75.8%) are most often used for almost all animated object types, except for cameras which by definition are not compatible with visual presence effects. This is probably because most animated objects do not exist on the scene at the beginning of their associated data clips and are revealed separately so that viewers will not be overloaded with a visually dense scene. The most prevalent combination of animated objects and graphical effects is visual presence of annotations (1233, 48.3%) due in part to the prevalence of animated annotations as shown in the top half of Table 4. We also observe correlations between graphical effects and their corresponding animated objects to some extent. Over 85% of annotations, axes and legends are animated with visual presence effects. Compared to them, the visual attributes of glyphs, groups, and charts are moderately more likely to be changed by animations, e.g., Figure 2 (c) and (d).

6. Communication with Narrations and Animations

In this section, we examine how data clips deliver their content through narrations and animations. Overall, we find that narrations and animations can work together or function independently. In the data clips that we analyzed, most semantic labels (937, 76.4%) and animations (2503, 98.0%) are linked, which results in 2728 narration-animation pairs. A small portion of semantic labels in narrations (289, 23.6%) and animations (50, 2.0%) cannot be linked, which are referred to as independent narrations and independent animations, respectively.

6.1. Animated Objects Across Semantics

Each narration-animation pair consists of a semantic label of the narration and potentially more than one animation that are related to the meaning captured by the semantic label. We first closely examine the composition of animations that are matched to different semantic types. In other words, we are interested in how the animations are composed in data clips to work with narrations.

Table 5 shows the frequency of animated objects in the matched animations for each type of semantic labels. Annotations are most frequently animated for almost all semantic types. Specifically, animations on annotations are used slightly more heavily for data contexts (574, 56.9%) than data insights (930, 54.1%). When we further examine into those animated annotations using Ren et al.'s taxonomy [RBB*17], we find that while text is the most important type of annotations for both data insights and contexts, data contexts use a higher percentage of images (200, 32.7%) as annotations than data insights (193, 20.8%) because many data contexts, especially backgrounds, rely on animated images (such as cartoon figures and icons) to make the intended messages more intuitive.

For most types of semantic labels, animations on glyphs are also often used to accompany both data insights and data contexts since the data clips in our dataset are data-driven. Overall, animations of glyphs are more important for data insights (360, 20.9%) than for data contexts (112, 11.1%) because most data insights are directly related to the glyphs in their data clips while data contexts are not.

Table 5: *Distribution of animated objects for different types of semantic labels in narration-animation pairs.*

Semantic Type	Glyph	Group	Axis & Leg.	Annotation	Camera	Chart	Background
Data Insights	**360**	**132**	**106**	**930**	**87**	**94**	**10**
Value	75	22	9	149	8	8	7
Proportion	74	18	9	198	5	42	-
Location	49	16	-	168	47	14	-
Time	11	1	15	39	1	5	-
Difference	70	33	18	170	14	13	1
Rank	5	5	1	17	-	1	-
Trend	53	14	35	121	4	10	2
Association	4	1	1	7	1	-	-
Extrema	17	16	13	55	7	1	-
Categorization	1	6	5	5	-	-	-
Distribution	1	-	-	-	-	-	-
Outlier	-	-	-	1	-	-	-
Data Contexts	**112**	**99**	**69**	**574**	**87**	**62**	**6**
Vis. introduction	7	17	24	27	10	10	-
Dataset description	2	1	1	5	1	1	-
Background	49	36	11	318	35	27	3
Domain knowledge	12	4	3	58	15	2	3
Interpretation	26	19	8	101	8	13	-
Quote	-	-	-	1	1	-	-
Judgment	1	5	5	21	3	-	-
Conclusion	4	2	4	4	2	2	-
Question	5	7	4	13	3	1	-
Transition	1	2	3	6	4	5	-
Attention guidance	5	6	6	20	5	1	-

In contrast to the prevalence of animations on annotations and glyphs for different types of semantic labels, other types of objects are used differently across semantic types. For example, animations on axes & legends are often used when trends are reported, primarily because trends are often associated with line charts which have axes & legends. Such animations are also used when visualizations are introduced in data clips because visualizations including their axes & legends need to be revealed when they are introduced. Animations of cameras are often associated with locations and backgrounds, especially background information for locations, because such animations can facilitate viewers' understanding by guiding their focus on visualizations, mostly maps in this case.

6.2. Narration-Animation Interplay

To further inspect how narrations and animations are connected semantically in narration-animation pairs, we also analyzed their relationship based on how much information is delivered by narrations and animations, which led us to four types of narration-animation relationships. More complicated relationships may exist by mixing these basic relationships. There does not exist a clear line between each type of relationships because narration-animation relationships are complicated and our goal is to inform future research of data videos. Figure 3 shows four examples for these narration-animation relationships.

Animations can be a faithful representation of the meanings conveyed by the accompanying narration, i.e., they **echo** each other. For example, the proportion reported by the narration presented in Figure 3(a) is reflected by the animations matched to it. For most types of semantic labels, echoes are the most common relationship between narrations and animations probably because designing narrations and animations in this way will make data clips easier to follow. This type of narration-animation relationship is especially common for descriptive insights because such insights are often simple and can be easily expressed in animations. For data contexts, animations that echo them typically take advantage of the expressiveness of textual annotations.

The narration in data clips can deliver more information than its connected animations, i.e., **additional information in narrations**. For example, in Figure 3(b), consider the semantic label "difference" of the sentence (actually that is the only semantic label of the sentence) which captures the difference in revenue between AWS and McDonald's; the accompanying animation presents a McDonald's logo in the scene but does not reveal the difference, and such information can only be learnt from the narration. A reason behind this type of narration-animation relationship is that not all information narrated can be easily shown through animations for certain visualizations. Such relationship can also be observed for some complicated semantics such as informative contexts.

Additional information may also be provided by animations, i.e., **additional information in animations**. For example, in the data clip shown by Figure 3(c), the narration only roughly describes the trend of Africa's childhood mortality, while the animations that are matched to the trend present concrete numbers so that viewers can learn that Africa's childhood mortality rate drops from 32% in 1950 to 7.5% in 2017. In this case, the information expressed by animations is not explicitly mentioned in the accompanying narration, such as the specific values and the time interval. This type of narration-animation relationship is often observed for relational and summary insights, such as trends in the aforementioned example. Animations for those insights tend to serve as the evidence of the narration and make the data clip more convincing by providing detailed data and information.

Animations do not always directly convey the meanings of the accompanying narration; instead, they may be an **indirect representation** of the narration. For example, consider the difference reported by the narration in the data clip shown by Figure 3(d); the animations show the number of nuclear power plants in the United States, Russia, China, and India, successively. Even though the difference is not directly shown, it is implied by the numbers displayed through the animations. It indicates that the narration and animation channels sometimes convey information in different ways. In this example, the narration reports a data insight from a higher level while the animations provide lower level data values to support the narration. Similar situations also happen for informative contexts when data clips present data to support arguments in the narration.

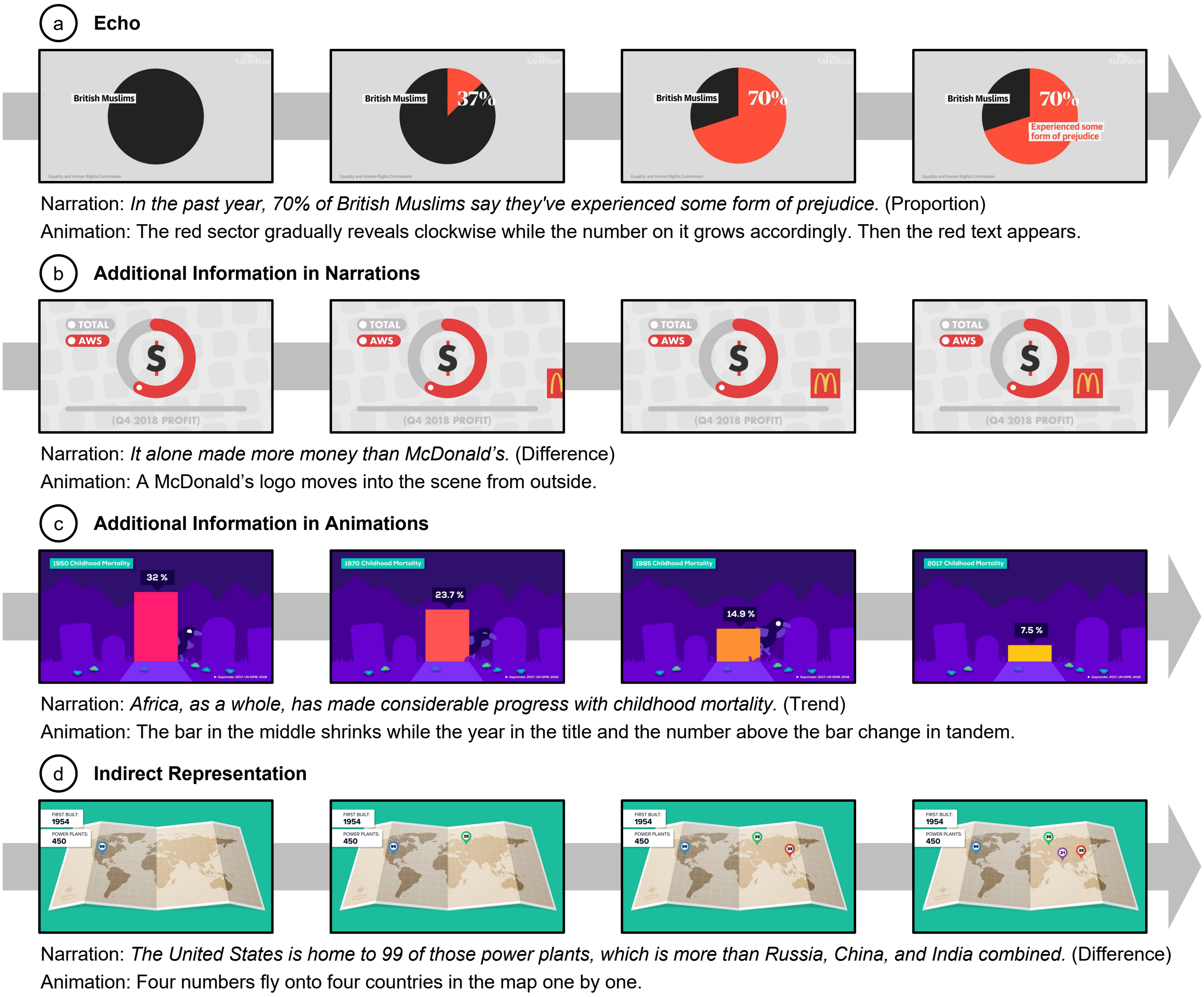

Figure 3: *Examples of narration-animation relationships in data clips. Figures are captured from (a) [The19b], (b) [Pol19b], (c) [Kur19], and (d) [The17b], respectively. For each example, the semantic labels to consider are appended to the narration in brackets.*

6.3. Independent Narrations and Animations

After pairing the narrations and animations, there is a set of semantic labels in narrations and animations that cannot be linked, which we call independent narrations and animations.

A considerable portion (175, 32.0%) of data contexts are independent compared with data insights (114, 16.8%). For example, judgments (28, 68.3%) and transitions (21, 60.0%) typically are not matched to any animations. Data insights or contexts are often independent in the following two cases. (1) Sometimes the meaning conveyed by the narration does not correspond to any visual elements in the associated data clip and cannot be easily illustrated by animations. (2) In addition to that, some independent data insights and contexts are already evident from the associated visualizations or the leftovers of previous animations, and therefore adding animations for such data insights and contexts is not necessary.

Similarly, there are three typical situations where independent animations are used in data clips. (1) A data clip may pause its narration temporarily and only present animations in order to stimulate viewers to think. In a data clip of a line chart [The20], two descending lines about interest rates are shown without narration to lead the audience to think about the *"ultra low interest rates"* which will be introduced later in that data clip. (2) Independent animations are used to provide less important information that does not need to be explicitly narrated, such as data sources and visualization legends. (3) The last situation relates to the aesthetic role of animations. Such animations are purely used to embellish a data clip, e.g., a rotating dashed line around a donut chart.

7. Discussion

7.1. Design Practices of Data Videos

The common design practices we observe from the data videos may inspire hypotheses of follow-up studies, such as empirical studies from different angles and lab studies with video designers. It may also serve as a reference for future data video authors and researchers of video authoring tools.

Provide simple data facts and sufficient context. While existing studies on data insights and data facts emphasize advanced statistics such as distributions and associations [SDES19, WSZ*20], we find the most commonly reported data insights are descriptive insights (457, 67.3%) including values, proportions, locations, and times. We also find a large proportion (547, 44.6%) of the semantic labels in the narrations of data clips are data contexts. Similar to Latif et al.'s findings [LCB21], backgrounds and interpretations account for a significant proportion of data contexts. It indicates the importance of providing context in data storytelling not only for data-driven articles, but also for animated visualizations in data videos. Since the narrations in our dataset are used to accompany data visualizations and may describe more about data, data contexts might play an even more important role in other clips of data videos. Hence, future data video authors should avoid reporting only data insights, but instead, provide enough contexts for viewers to follow and understand data stories.

Match narrations and animations. In data clips, various graphical effects are applied to different types of objects. Those animations make data clips more vibrant and visually appealing. We find annotations are most frequently animated compared with other types of objects. For both data insights and data contexts, text and images are two important types of annotations that facilitate the delivery of messages. In our dataset, most semantic labels in narrations and most animations are matched together. Only a small fraction of them are independent. By illustrating animations that can be matched to the narration, the message delivered by data videos may be easier for viewers to understand. Even though repeating the same information in both narrations and animations seems natural, narrations and animations do not always echo with each other. Distributing the information that is intended to be delivered into different modalities may make data videos more approachable and appealing at the same time.

7.2. Study Implications for Future Research

Existing research on data videos tends to focus on animations while largely ignoring narrations. Without a proper understanding of the narrations in data videos, current authoring tools and generation algorithms [ARL*17, SSX*21] are mostly designed to only illustrate data insights and provide limited support for incorporating narrations. However, data videos created in this way are very different from the videos we have analyzed which intersperse data contexts with data insights in their narrations and link animations to narrations in different ways. Future research may explore more advanced authoring paradigms and generation algorithms to produce data videos that align with the common design practices we found.

Authoring tools of data videos can utilize common practices of data video designers to improve their user experience. For example, Section 5.1 shows that some objects are more likely to be animated on certain types of visualizations. Authoring tools can take advantage of the knowledge to recommend potential objects to animate based on visualization types. Similarly, the relationship between animation effects and animated objects found in Section 5.2 can also be used to recommend animation effects in an authoring tool. For example, since most annotations are animated with visual presence effects, when a user selects an annotation to apply animations, the tool can ideally suggest a visual presence effect to the user.

Our results show that most narrations and animations of data clips are usually linked, and in most cases, echo with each other. This could inform future research of automatic generation techniques [WWS*21]. Future research can start with generating animations from text descriptions. For example, animated annotations, ranging from simple text snippets to more complicated graphics, are often used to accompany the narration of data insights and data contexts. To generate animated annotations, generation algorithms need to understand the data insight or data context in the associated text descriptions, decide which form of annotations to use, and select the best graphical effects. Generating fully-fledged data clips from narration scripts would be harder. Users' input can be introduced to enable a mixed-initiative authoring experience.

7.3. Limitations

Even though we tried to make sure the collected data videos were as diverse as possible, the number of data videos in our collection is still limited, and our findings may not generalize to any data video. Besides, we examine both narrations and animations in small units. How they work at a higher level is also important, such as how a sequence of data insights and data contexts are organized and how a set of animations are arranged. We leave these questions to future research. Different types of interplay between narration and animation cues in data clips are also worth further investigation. Kim et al. [KSA21] found that readers' takeaways on charts depended on how the caption of a chart was related to the chart. Based on their findings, we hypothesize integrating narration and animations in different ways may affect viewers' perception of the messages communicated by data videos. Future empirical studies are thus needed to examine users' perception of different types of data videos.

8. Conclusion

We have presented a qualitative analysis of data videos from a low-level perspective of narrations and animations. We extracted 426 data clips from 60 data videos, from which we identified 1226 semantic labels in 816 sentences and 2553 animations. We have observed patterns of narrations and animations in data clips. Two important types of content are covered by the narrations of data clips, i.e., data insights and data contexts. Different types of graphical effects are applied to various objects, which constitutes diverse animations in data clips. We have also investigated the relationships between narrations and animations in data clips: they can work with each other in different ways or function independently. The study reveals common design practices of data videos which may inspire future data video authors and the broader research community.

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