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Roslingifier: Semi-Automated Storytelling for Animated Scatterplots

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Abstract—We present Roslingifier, a data-driven storytelling method for animated scatterplots. Like its namesake, Hans Rosling (1948–2017), a professor of public health and a spellbinding public speaker, Roslingifier turns a sequence of entities changing over time—such as countries and continents with their demographic data—into an engaging narrative telling the story of the data. This data-driven storytelling method with an in-person presenter is a new genre of storytelling technique and has never been studied before. In this paper, we aim to define a design space for this new genre—data presentation—and provide a semi-automated authoring tool for helping presenters create quality presentations. From an in-depth analysis of video clips of presentations using interactive visualizations, we derive three specific techniques to achieve this: natural language narratives, visual effects that highlight events, and temporal branching that changes playback time of the animation. Our implementation of the Roslingifier method is capable of identifying and clustering significant movements, automatically generating visual highlighting and a narrative for playback, and enabling the user to customize. From two user studies, we show that Roslingifier allows users to effectively create engaging data stories and the system features help both presenters and viewers find diverse insights.

Index Terms—Data-driven storytelling, narrative visualization, Hans Rosling, Gapminder, Trendalyzer.

1 Introduction

> *"...and all of the rest of the world moves up into the corner where we have long lives and small families, and we have a completely new world."* — Dr. Hans Rosling, 2006.

STANDING today at close to 14 million views, Hans Rosling's TED 2006 talk "Debunking myths about the 'third world'" [1] is perhaps the single most significant promotion of data visualization from the early aughts of the century. Rosling (1948–2017), a professor of public health at the Karolinska Institute in Stockholm, Sweden, heavily relied on data presented in his talks and writings [2] using interactive visualization, which was acquired by Google in 2007 and became a root of a Google's "motion chart." In the original TED 2006 talk, Rosling used an animated scatterplot to show the progression of various country demographics over time, handily demonstrating how our biases about the world were false. He shows the trajectories of the world's almost 200 countries jumping around on a big screen as the years advanced from the early 1900s to the present day. Despite the confusion and complexity of so many moving parts, he manages to frame the animation into a coherent and understandable story. However, while Rosling's talks are invariably informative and entertaining, anyone who has used an animated scatterplot á la TRENDALYZER [3] can attest that the experience is hardly the same.

Along with the rapid development of web-based visualization technologies, information visualization researchers have found a new opportunity of visualizations as a new medium for communication, called "data-driven storytelling" [4]–[6]. Narrative visualization [7] is one stream which enables both explorative and communicative aspects of visualization. Narrative visualization evolves into data videos [8] and DataClips [9] with increasing usage of social media and streaming platforms, attracting users' attention and providing information in a short time through the form of animated charts. Data comics [10], [11] combines aspects of comics and narrative visualization to deliver fun and engaging stories. In these techniques, the static text is used to deliver a story, or in the case of the data video, the voice from a narrator is dubbed. We find that there is no existing communicative visualization technique that fits Hans Rosling's presentation, or the new kind of presentations using animated data visualization in video-sharing and streaming platforms like YouTube. Therefore, We tentatively define a new genre of data-driven storytelling—*data presentations*—as the use of interactive visualization to support in-person presentations. The use of data visualization as the primary driver by an in-person speaker, making it a different category from data videos [8], [12]. Data presentations are widely used in diverse fields including news media and data-driven organizations in the form of weather [W1], [W2] or market reports [M1], [M2], live coverage of the referendum result [N1], or Rosling's TED talks [R1]–[R10] (see Sec. 3.2).

To support these new storytelling methods, we implement a complete pipeline system combining visual analysis, story creation, and presentation. We explore the design space of data presentations by looking at several talks by Hans Rosling and several other effective data-driven public speakers. We base our work on in-depth observational coding of several data presentations yielding a taxonomy of storytelling methods: *natural language narratives*, *visual effects*, and *temporal branching*. Our implementation of ROSLINGIFIER supports general users to semi-automate the process of data analysis and story creation, and help them to edit the output for presentation. Automatically detected trends and events in time-

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series data create a story with explaining textual narratives, and are coupled with *visual effects* and *temporal branching* to direct the viewer's attention. We also provide an interactive authoring interface for a presenter to customize the events in the story, polish the effect, and change the order and timing in a data presentation for presenting it to a stakeholder audience. Finally, we conduct an end-to-end user study to demonstrate how the ROSLINGIFIER system can help both on authoring and viewing data presentations. Our study result shows that the system is easy and intuitive for users to generate data-driven stories, and the components of the system support both presenters and viewers to find diverse insights.

The contributions of our paper include: (1) a formative study to define a design space of storytelling methods employed by effective public speakers during data presentations; (2) the implementation of the ROSLINGIFIER system, which includes automated methods and graphical interfaces for authoring data presentations from continuous time-series data; (3) comprehensive user studies evaluating the system from both authoring and viewing perspectives; and (4) a discussion of lessons learned and design implications for future research.

2 BACKGROUND

Here we review the literature on narrative visualization, including specific methods, techniques, and authoring systems.

2.1 Data-driven Storytelling Techniques

There have been many research efforts to survey and categorize existing data-driven storytelling techniques. Segel and Heer review 58 visualizations for storytelling and provide a design space of *narrative visualization* that enables both explorative and communicative aspects of visualization. Their design space consists of three dimensions: (i) genres, (ii) visual narratives, and (iii) narrative structures. Hullman and Diakopoulos [7] distinguish visual rhetorics by reviewing 51 narrative visualizations and discuss the effect of applying the rhetorics to four editorial layers in narrative visualization, which are data, visual representation, annotations, and interactivity, respectively. Hullman et al. [13] analyzes narrative sequencing of 45 narrative visualizations, arguing that narrative sequencing is of important factor that affects comprehension and memory. Stolper et al. [14] provide a survey of 45 recent narrative visualization examples. There are many factors that shape the visual narrative flow with on combinations of user input methods, story components, and visual feedback [15]. McKenna et al. [15] investigate how different visual narrative flows impact viewers' reading experience.

New storytelling and communication media are beginning to be used for narrative visualization. Data videos are motion graphics that combine pictographic representations and animation techniques into narrative visualization [8]. Amini et al. [12] systematically analyze what elements (e.g., narrative structures) constitute data videos from 50 data videos and discuss data video production approaches, such as strategies for engaging viewers. They later proposed DataClips [9], which is an interactive system for authoring data videos incorporating visualization. Data comics is an emerging new communication medium and a genre of storytelling [8] that combines aspects of comics and narrative visualization [11], [16], [17]. Bach et al. [11] propose a set of design patterns (e.g., layout) for data comics that can inform design of data comics. Wang et al. [18] conduct a study that compares effectiveness and engagement of data comics and infographics (illustrated texts), a wide-spread storytelling medium. Their experiment results indicate that data comics are more fun and engaging and better capture viewers' attention compared to infographics.

The genre of data-driven storytelling techniques most similar to *data presentations* is what Amini et al. call *data videos* [12], or what Segel and Heer recognized as the *film/video/animation* genre of their seven genres of narrative visualization [8]. We note that while data presentations are similar to data videos, and may in fact often be recorded on video (which is how many of us get to see them), the significant difference is the presence of an in-person speaker—rather than a disembodied narrator—using the visualization as a visual aid to convey a message.

Prolific examples of data presentations include Rosling's talk on common misconceptions around the so-called "Third World" [1], as well as Al Gore's presentation on CO^2 emissions in the movie *An Inconvenient Truth*. Contrast the above data presentations with videos where either subtitles or a disembodied voice—Hans Rosling has in fact recorded a few of these—narrates animated visualizations, such as in the online documentary *The Fallen of World War II* [19] or in *A Day in the Life of Mister O.* [20], an abstract short film about humanity's environmental impact on the world's oceans. The distinction is clear: in a data presentation, the speakers themselves can play a significant role in providing not just an engaging spoken narrative, but can also interact with the visualization by pointing to specific parts, highlighting important trends, and even control the visualization, such as by playing back an animation.

Sometimes the boundary between a data video and a data presentation can be blurred. For example, in the 2019 online political movie *Unbreaking America: Solving the Corruption Crisis* [T2], which very much looks like a data video, actor Jennifer Lawrence actually appears in the video with not just her voice, but also her likeness. As a result, she is able to point to, describe, and explain graph axes, data items, and insights in significant detail. Since Jennifer Lawrence is actually embedded into the same space as the visualizations themselves, we tend to think of this more as an example of a data presentation than a data video.

2.2 Authoring Tools for Storytelling

There are many considerations to make effective storytelling ranging from highlighting for capturing viewers' attention, to design of story structures, interactions and transitions, and supplying appropriate explanations [5], [8], [15], [16]. As such, there have been many visual tools that allow efficient design of stories and narrative visualization. We see three types of approaches in the existing tool for authoring stories. The first type of authoring tools are those that help users to easily or automatically add visual components of storytelling to existing visualizations, such as labels [21]–[26]. For example, Ren et al. [25] derive design space of annotations (e.g., shapes) and present ChartAccent, which allows interactive annotations on visualization. To reduce the burden of manual creation of annotations, Hullman et al. [22] propose Contextifier, which automatically selects features and produces annotations with the features for stock visualizations. Gao et al. [23] showcase NewsViews which provides an automated pipeline for production of custom geovisualization for news. Similar to these tools, our tool also provides automated event detection and caption generation to reduce the burden of manual story curation.

In general, the process for visual analysis and for story creation is separated, so full stories are created after story pieces (e.g.,

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insights, facts) are derived from visual analysis [5]. The second type of visual tools for storytelling are those that help users seamlessly connect the separated tasks [27]–[29] by allowing users convert the analysis results into story pieces for presentation [30]. For example, Gratzl et al. [27]'s CLUE system uses the user's visual exploration history to extract and present analysis steps and annotations. Tableau Story Points and Microsoft Power BI are the existing tools for visual analysis which provide filtering, highlighting, and captioning mechanisms. Quill [31], a data-storytelling product, works on top of the visual analytics tool to automatically generate natural language narratives. However, these tools are designed for general visual analysis, and lack the specialized data presentation as well as automatic event detection features.

Finally, several visual tools have been proposed recently for creating stories for specific genres or input types [32]–[38]. For example, infographics are a popular medium for storytelling with visual elements around text messages. Designing such visual elements often involves difficult tasks in generating, repeating, and editing stages. There are visual tools proposed to help designers in each stage. For example, Kim et al. [39] and Wang et al. [34] propose a technique and system to guide users for easy creation of graphical elements with data. Methods for automating infographics design processes is another popular research topic [36]–[38]. Examples include Text-to-Viz [36] for producing infographics design based on natural language statements, and DataShot [37] for creating fact sheets based on tabular data. VisJockey allows users to play animated visualizations coupled with text segments as they read them [40]. Chen et al. [38] propose a deep-learning based automation approach which extracts components of existing timeline infographics for creating improved designs. There also exist additional tools for storytelling media that have gained popularity, such as data videos [9], [41], [42], slideshows [43], and data comics [17], [44]. Most closely related to our work is SketchStory [32], which supports not just off-line authoring of data stories, but also has a pen-based presentation mode.

While there are many tools that can be used for data-driven storytelling, to our knowledge there exists no dedicated data presentation tool equivalent to Roslingifier. Compared to prior works, our work provides the end-to-end pipeline process for the newly defined data presentation genre, by combining visual analysis, semi-automatic story creation, and presentation using animation that no single existing tool currently provides.

3 Design Space: Data Presentations

Here we present a design space for data presentations, including methods, examples, and narrative mechanisms.

3.1 Method

We started the process to derive and explore the design space of visual data presentations by reviewing existing data presentations online. We collected data presentations from online streaming services (e.g., TED, news outlets or YouTube) because, to the best of our knowledge, there is no existing technique in scientific papers. More specifically, we looked for videos presenting data-driven stories using interactive visualization where the speakers—their likeness and not just their voices—are part of the video. To seed our search, we started from the following initial categories:

- **TED talks:** The TED—Technology, Entertainment, and Design—conference and its satellite events include many data-driven visual presentations, including ten of Hans Rosling's own talks.
- **News and weather reports:** News anchors sometimes use interactive visualization to describe complex events. In particular, weather forecasts are spatiotemporal data stories conveyed by a meteorologist narrating and pointing to specific areas of interest.
- **Data-driven organizations:** Certain organizations, notably the Gapminder Foundation, publish data presentations as part of their mission, and thus constitute a rich source of inspiration.

Our search was by no means exhaustive, as we were interested in finding a representative, albeit not comprehensive, set of samples. For example, there are thousands of relevant data presentations on YouTube that would fit our general visual data presentation definition above. Thus, we did not endeavor to cast our net too widely, but rather selected a smaller set of videos that fulfilled the following criteria: (1) communicates information about data; (2) includes an interactive/animated visualization; and (3) combines the speaker's body with the visualization. Furthermore, we curated our selection to capture varied examples.

After having selected our data presentations, we used open coding [45] to understand narrative actions employed in the videos. In an initial pass, two leading authors independently coded all of the videos into actions performed by presenters in the videos, including the perceived intentions of each action. We then compared each coder's results and discussed inconsistent coding before resolving the final version. When there was a coding disagreement, a third author arbitrated the conflict. Through the discussion, we established common names for the categories and divided one category into two (e.g., distinguish *Replay* from *Rewind*.)

3.2 Data Presentations Surveyed

We selected 11 data presentations for detailed review based on the number of views, quality, and diversity from a larger set of data presentations. Since Hans Rosling was a very effective and engaging speaker who often gave data presentations, six of the videos we analyze are his (R1-R6). We also selected 5 other popular data presentation videos to include different stories, visualizations, and environments. R1-R3 are Rosling's presentations in major news media, where he presented himself on a hologram-style display. R4-R6 are TED talks, where he provides a live demo with a large screen by controlling the system on the stage. T1 shows Al Gore's CO^2 emission chart in the movie titled *An Inconvenient Truth*. T2 is a political video from an organization called *Represent Us*. N1 and W1 are news broadcasts using interactive visualizations—the EU referendum result and a weather forecast from the BBC. M1 is the stock market analysis from the CNBC.

All of Rosling's videos (R1–R6) use scatterplots, but often include other charts (e.g., line chart and map in R5 and R6). We find that a line chart is used to show the CO^2 level in T1 and various charts on a map are utilized in T2, N1, and W1, to represent spatiotemporal data.

3.3 Storytelling Techniques and Intentions

Table 1 shows our derived storytelling techniques in data presentations, including their intentions. We group these techniques into three categories: Gestures, Visual effects, and Animation playback. Here we also present an in-depth analysis of these narrative techniques used in our corpus of 11 data presentation videos. Figure 1 shows the temporal event sequence of the selected videos, and the color-coded sections indicate the categories of techniques. Additional analysis can be found in Appendix B.

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TABLE 1
Classifying storytelling techniques and intentions in data presentations.

Technique		Intention
Gestures	Pointing	Indicate an entity with hands to draw the audience's attention towards an entity.
	Tracking	Pointing and moving at an animated entity to explain changing data and emphasize trends.
	Shaping	Express the shape of data using hands to emphasize spread, ranges, and boundaries.
Visual effects	Labeling	Naming an entity or a group with a word or a phrase.
	Spotlighting	Temporarily change appearance of an entity to emphasize or draw attention to a certain point.
	Tracing	Draw paths of animated entities to emphasize trends or compare different movements.
	Accumulation	Add items to an existing visualization to emphasize change over time.
Animation playback	Pause	Stop the animation for a short time to draw attention to an event at a specific point in time.
	Slowdown	Decrease the animation speed to explain a detailed event sequence in a short time period.
	Speedup	Increase the animation speed to explain trend in a longer period, or skip where little happens.
	Rewind	Play by moving back a few frames to repeat to show the change or to deliver different message.
	Replay	Repeat the entire animation to summarize presentation.

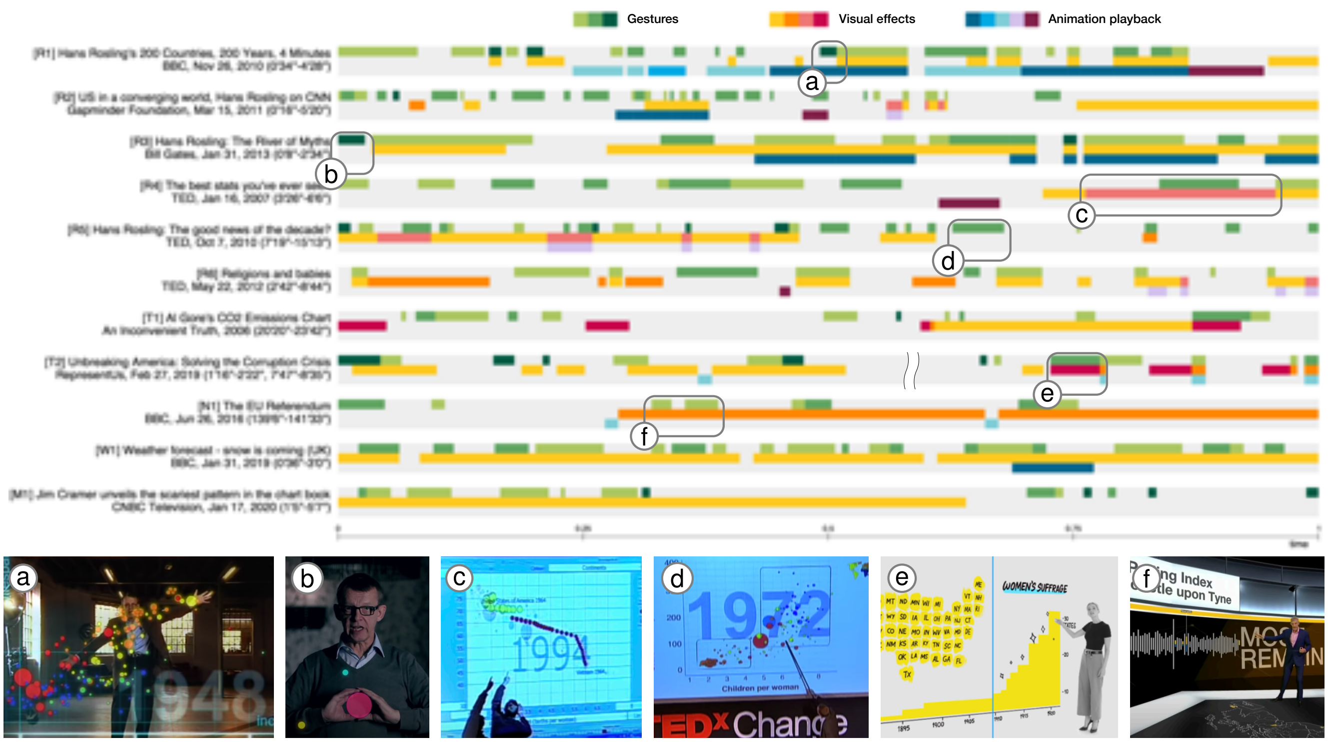

Fig. 1. Analysis of storytelling techniques in 11 data presentation videos. The highlighted time sequences in the various timelines are illustrated using insets at the bottom of the figure.

Gestures are used to indicate or point to items of interest using their hands or sometimes using a handheld pointer, and splits into three sub-categories—pointing, tracking, and shaping. *Pointing* draws the audience's attention, and is the most common technique throughout the 11 videos in Figure 1. For example, pointing is commonly used to explain the basic features on a chart, such as axes, legends, and points. Presenters also use gestures to explain the meaning of the data items on the chart. W1 and M1 are exceptions. The weather reporter in W1 does not explicitly describe the meaning of the map or isotherms. Similarly, the analyst in M1 does not explain the stock chart. In these cases, the presenters seemingly assume that their audience is already familiar with the visual representations used. *Tracking*, an action of continuously pointing at animated entities, is often used to indicate the trends or movement of data. We distinguish *pointing* and *tracking* as they have different usages and intentions. Tracking gestures usually come with the tracing visual effect on animated scatterplots (Figure 1c) or the accumulation technique on area or line charts (Figure 1e). Tracking gestures are also used to indicate the movement of a group (Figure 1d). *Shaping*, on the other hand, is used to express the geometric shape of data, such as the size, trends, boundaries, or a growing/shrinking movement. Rosling used the shaping technique to describe the size (Figure 1b) and movement of entities (Figure 1a). It is also used in T2 to explain the meaning of the axes and trend lines.

Visual effects are the techniques that modify the visual appearance in the visualization or are added in video post-production to highlight entities, trends, or insights. Visual effects consist of four sub-categories—labeling, spotlighting, tracing, and accumulation. *Labeling* is used to emphasize important items in a story. Rosling often picks a few representative countries with a big population or data anomalies. He presumably wants the audience to focus more on those countries rather than be confused by the presence of many countries. The stock analyst in M1 labels the peaks and valleys of the line chart to highlight important points. *Spotlighting*

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emphasizes an entity by temporarily changing its appearance. For example, this could be a brightness change on a black background (R2), or blinking on a beam projector (R6, R7). N1 uses the spotlighting technique (Figure 1f) to emphasize the result of a city by flashing the corresponding point. ■ *Tracing* technique (also discussed by Robertson et al. [46]) is often used on animated scatterplot to draw paths of entities over time. Figure 1c shows an example using tracing, where Rosling compares the temporal movement of two entities. ■ *Accumulation* technique emphasizes temporal changes by gradually adding new items, which is similar to the wipe in movie transitions. This technique works on the area or line chart to draw the audience's attention to the changes (Figure 1e).

Animation playback is employed to emphasize parts of an animation in different ways by changing the speed, position, or direction of the data animation to showcase specific phenomena. ■ *Pausing* is mostly used to explain the trends or reasons on an event, such as World Wars or the Spanish flu. In Figure 1 W1, the weather reporter pauses the map and emphasizes the unusual weather condition of the week. ■ *Slowdown* sometimes replaces the pause, describing an event or a reason for the event in the period. ■ *Speedup* techniques follow after a pause or a slowdown, quickly skipping the less important intervals (T2, N1). ■ *Rewinding* indicates moving back to a few time frames to repeat the interval. Rewind techniques are used to emphasize a certain event or entity or to convey different stories in the same period. ■ *Replay* also goes back to previous frames but has a different intention from that of rewind: it repeats the entire animation to summarize a specific animated segment. Rosling often replays the entire animation after explaining the overall trend (R1, R2, R4, R6). The replay technique comes at the end of the presentation (R1) to summarize the talk, or comes in the middle to give the audience time to digest the story before he moves to the next stage (R2, R4, R6). Users can mix the playback techniques based on intentions in presentations. For example, Rosling uses a series of the techniques in a novel way to better present an event in the story. In R2 (Figure 1), he showcases a combination of a pause, replay, and rewind with different playback speeds, to stress how the rest of the world different countries caught up to the U.S. with respect to income and life expectancy in multiple perspectives during 1860–2010. We call this strategy *temporal branching*, where the presenter utilizes rewinds at several time points in a given period, embedding other playback or highlighting techniques in the rewinds to deliver different aspects of an event in detail.

Note that our summary above does not include the ubiquitous narrative tool common to all data presentations: the use of a *verbal narrative* to direct the viewer's attention, explain specific phenomena, or convey a message. Since our focus here is not specifically on the use of verbal techniques, and since our implementation uses written language and not actual speech, we choose not to delve deeper into this aspect of data presentations. However, it is clear that understanding the verbal delivery of data-driven narrative involves both the *content* of the message—indicators of space, identity, magnitude, effect, causality, etc—as well as its *mode*—speed, pitch, inflection, etc. We leave such expansion of our design space for future work.

4 Creating Data-Driven Stories

Our approach in this paper is to automatically generate a data-driven story from time-series data. The approach includes detecting events in the time-series data into causal sequences that form stories, then using natural language to generate narratives, and finally using our storytelling techniques from Section 3 to enrich these narratives.

4.1 Deriving Stories from Time Series

For the purposes of our treatment, a *story* is a presentation sequence consisting of *segments* of data in a linear chronological sequence. A group of entities at a noteworthy interval in the data is called an *event*. Story generation starts with choosing events from a time-series dataset that will be presented. Taking Rosling's talks as examples, he emphasizes multiple events in his presentations by changing the playback time and highlighting them with various gestures and visual effects. In Figure 1a, Rosling emphasizes the event in 1948 where the differences between the countries were widest. Figure 1c displays the event from 1964 to 2003 and compare the trends of the USA and Vietnam after showing the global trends of the same period. Similarly in Figure 1d, he presents the event from 1960 to 1980 and groups the countries by their positions.

Events are not necessarily in a linear order; they can be overlapping or concurrent. To serialize them into a linear sequence in playback time (speaking order), we create a segment per event that comprises the story. For singleton events that have no concurrent events, this is trivial. In situations where multiple events overlap partially or completely in time, we must select a linear sequence for the resulting parallel segments. This can either be done randomly, on the basis of some interest function (e.g., the magnitude of the event), or controlled by the user. By default, we sort the parallel segments based on the starting times. Users can change the order of the segment sequences later (Sec. 5.3). Figure 2 illustrates how we can form a story from data. We use multi-dimensional time-series data that uses income on the X-axis and life expectancy on the Y-axis. Each data point represents a country. The color and size indicate the continent and population of the country. In the period of 1945–1948, we first detect a group of countries in Asia (red) that is increasing fast in life expectancy. This interval is translated into Event 1, which becomes Segment 1 with the label "Asia." At the same time, in the period 1946 to 1948, we identify Event 2 where countries in America (green) are also changing fast in life expectancy. As the Event 1 and 2 occurred in the overlapping period, these are linearized into a segment group. One period can be divided into several events (e.g., by countries or continents) depending on the data type. In this work, we create events for each continent.

Linearizing such parallel segments results in having to play out the time for one segment, and then rewind in order to start the next segment, etc. To communicate this fact to the user, we introduce intro and outro segments at the beginning and end of each group of concurrent segments. Furthermore, during playback we must convey the time being rewound when switching to another concurrent event. A segment group often represents a historical event with a global scope, e.g. World Wars or pandemic. In this case, Group 1 includes events occurring just after World War II. Intro and outro segments also summarize what happened in the period and provide reasons for the events.

4.2 Event Detection and Narrative Generation

Roslingifier provides the recommendations that can help creators overview the data and find events that could be used to attract the audience. Creators often face a difficulty in conceptualizing

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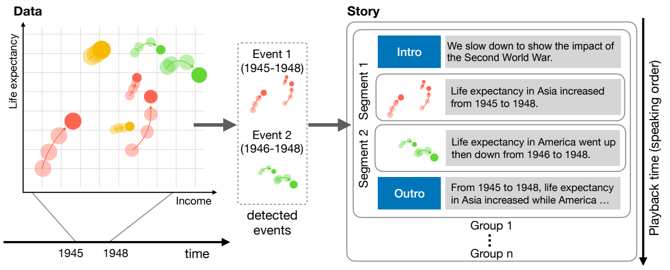

Fig. 2. Creating a story for a sequence of concurrent events. An intro and an outro introduce and summarize the segment group, respectively.

their work when they first see their data and task [47]. When this type of difficulty exists, recommendations can play an important role in guiding and inspiring creators [48]. Many approaches attempt to detect significant events from time-series data [49]–[51]. For example, Kong and Agrawala [51] decompose line charts into a set of human perceptual part—such as peaks, valleys, rising, and declining slopes—by calculating the first and second derivatives to identify curvature extrema. There are also tools based on event detection algorithms. For example, Microsoft Power BI automatically detects 17 insights from the Gapminder data on life expectancy data, which focus on showing general trends and outliers. Inspired by the work, we decide to provide event recommendations which can help creators intuitively understand unseen events in a perceptually salient way based on extrema and the size of change.

We define an event as a set of data dimension D_i (e.g., Income) of each legend g_j (e.g., Asia), a time interval denoted as t_s and t_s—the start and end time (e.g., 1945 and 1948)—and a movement pattern (e.g., rise) in the interval. Our event generation algorithm is based on calculating the size of the change for each D_i of legend g_j being tracked. If the change size continuously exceeds a threshold, the algorithm detects an event with the time interval, t_s and t_e. Depending on the movement of values in the interval, we define four events, RISE↗, DROP↘, TROUGH⤴, and PEAK⤵. Additionally, we define two more events inspired by Rosling's talks—PLATEAU→ events represent intervals with no change, and SPREAD✖ represents an interval where the difference between the values is the largest. Finally, we have user-generated events USER🔍.

We use a template-based approach to generate the natural language narratives describing each event. Here, we summarize the seven types of events and rules for narrative generation:

- ↗ RISE: The value increases in the detected interval. *Example:* The increased life expectancy in Europe after World War II. *Narrative: D* in *g* increased between t_s and t_e.
- ↘ DROP: The value decreases in the detected interval. *Example:* The decreased life expectancy in the world during the Spanish flu. *Narrative: D* in *g* decreased between t_s and t_e.
- ⤴ TROUGH: The value decreases and then increases in the detected interval. *Example:* Life expectancy in the world dropped then recovered from the impact of World War I. *Narrative: D* in *g* went down then up between t_s and t_e.
- ⤵ PEAK: The value increases and then decreases in the detected interval. *Example:* Income in Europe reached the peak in 2005 then decreased in the next year. *Narrative: D* in *g* went up then down between t_s and t_e.
- → PLATEAU: These is no change in values over a predefined number of time frames. *Example:* Income in Asia did not change from 1800 to 1820. *Narrative: D* in *g* is mostly constant between t_s and t_e.
- ✖ SPREAD: The difference between the maximum and minimum values is the largest during the time period covered for a particular data dimension. *Example:* In 1948, the difference between countries was wider than ever (Figure 1a). *Narrative:* In t_s, the difference between the items was at its widest.
- 🔍 USER: User-generated event created manually. *Narrative: D* in *g*, something happened between t_s and t_e.

Narratives for the intro get the information of a set of event segments including the time range covering all member events, from T_s to T_e. The member events with the same event type are grouped and are summarized together. For example, from 1945 to 1948, life expectancy in Asia and America increased, income in Europe went up then down. We do not provide narratives for the outro so that users can fine-tune the narrative to make a story by providing reasons or detailed analysis of events. We describe narrative editing in detail in Sec. 5.3.

4.3 Storytelling Techniques

Beyond natural language, we provide storytelling techniques to emphasize important events. In data presentation, we see Gesture is the role of the in-person presenter by indicating or pointing an entity or shaping to emphasize the data points. Therefore, we do not explicitly show a cursor or pointer to implement hand gestures. Instead, we provide two *labeling* features to indicate an individual or a group of entities. First, we automatically generate inner clusters of the legend based on the temporal proximity of the entities in the event. Clusters are labeled by summarizing the higher level of information (e.g. subcontinent of counties). We discuss details of the clustering algorithm in Appendix C. Second, we support turning on and off the labels on entities during the animation. We employ *spotlighting* and *tracing* to emphasize legends for an event. When animation is played, the bubbles are colored to stand out while others are grayed out. The traces of colored bubbles are displayed to emphasize entities' movement by drawing their traces. *Accumulation* technique is not employed for scatterplot examples because it is used to emphasize gradual changes in line charts and area charts. Sec. 5.1 describes how the system supports these features to highlight the events.

We employ the animation playback techniques to deliver the story for segment groups. We *slow down* the playback speed when playing segment groups and *speedup* for other intervals. The chronological sequence of the animation is distorted within a segment group. We use *rewinding* technique to implement this sequence. After playing the intro, the animation goes back to the starting time of the next event; this corresponds to the rewind technique. Finally, the outro is played to summarize the set of events. *Pause* and *replay* techniques are employed by the presenter interactively during presentation. The implementation of the animation playback is shown in Sec. 5.3.

5 ROSLINGIFIER

We propose the ROSLINGIFIER system to enable users to author data presentations starting from an automatically generated story that they can play and edit the presentation by interactively applying various techniques. We implement Roslingifier with Django, HTML, JavaScript, and Bootstrap. We use D3.js for the scatterplot and the line charts, and the data manipulation and the clustering is done by backend in Python 3 with the pandas library. Roslingifier consists of three visual components (Figure 3):

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Fig. 3. ROSLINGIFIER automatically generates animated data stories from temporally changing data using animated bubbles, a natural language narrative, visual effects, and temporal branching techniques.

a presentation output view (a), an event exploration view (b), and a presentation editor (c). We use socio-economic data from Gapminder.org to demonstrate the system below.

5.1 Presentation Output View

The presentation output view (Figure 3a and Figure 4) is the central component of the system, and is also used for animated presentations. This view supports changes of X and Y data and their scale (linear or logarithmic) and allow users to turn on and off the labels on the entities, change the position of the label, and check if narratives are readable. The view consists of two parts: a chart panel (Figure 4a) and a caption panel (Figure 4b). We choose a scatterplot for the chart panel to present multidimensional data in temporal animation, as Rosling did in many of his videos. Bubbles in the plot represent data points on the 2D Cartesian plane where the size and color indicate additional data dimensions, respectively. Users can change the data dimensions of X and Y axes and convert between a linear and log scale. Both Figure 4a and Figure 4 show Rosling's popular scatterplot where a bubble represents a country on the income (x-axis) and life expectancy (y-axis) coordinates, and the color and size of the bubble indicate its continent and population, respectively. The caption panel (Figure 4b) presents the narrative at the current time point, aligned with the schedule in the presentation editor (see Sec. 5.3).

The are two different modes in the view: default (Figure 3a) and highlighting (Figure 4) modes. The default mode is on when playing the interval outside event segments. All the bubbles in every legend are displayed without any labels unless the user hovers on them. The highlighting mode is activated when playing event groups. In this mode, the event indicator appears in the top-left corner (Figure 4c) to show the current event's time period. It also shows whether the animation is going forward or rewinding for presenting an event on the highlighted legend g. For example, the event indicator in Figure 4c means it is rewinding from 1917 to 1919 to focus on a legend of Asia. For each event, we first color the bubbles where the entities of the bubbles belong to the highlighted legend. Other legends are grayed out to make the legend stand out. The traces of colored bubbles (Figure 4d) are displayed to help audience track the changes.

The bubbles of the highlighted legend are clustered based on temporal proximity. We draw a convex hull to connect the bubbles in a cluster. Labels are automatically generated by summarizing the higher level information of the constituent entities (e.g., Southern Asia). When generated, cluster labels are initially placed at the center of the associated clusters. Users can later adjust the label positions by dragging. We discuss the clustering algorithm in Appendix C. Figure 4 shows an example, where bubbles for other than Asia are grayed out to present an event occurred from 1917 to 1919 in Asia. The clustering algorithm finds two clusters, one for Australia and New Zealand (top-right), and another big cluster for other than the two countries (bottom-left). The label for the bottom left cluster is generated using the subcontinents information of the countries, which are Western Asia, Southeast Asia, and Southern Asia (sorted by the number of countries). The summarized label reduces the amount of information and provides a better understanding of the bigger trends.

5.2 Event Exploration View

To help users explore trends and events automatically identified from data, we provide an event exploration view with two visualizations: hull traces (Figure 3b1) and line charts (Figure 3b2). Hull traces show the temporal distribution of bubbles for each legend. Figure 3b1 shows five hull traces for five legends—the world, Asia, Europe, America, and Africa—represented by different

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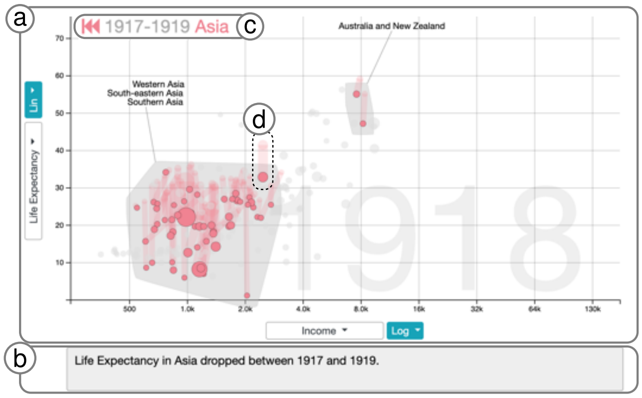

Fig. 4. The presentation output view in the highlighting mode (default mode: Figure 3a). See Sec. 5.1.

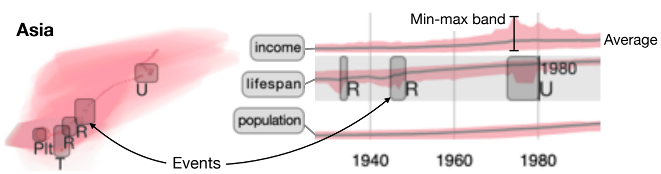

Fig. 5. Close-up on the event exploration view. Shaded rectangles show the position of events on the scatterplot and line chart.

colors. A hull trace shares the same X and Y axes with the chart panel (Figure 3b1). It consists of multiple convex hulls, each of which covers a group of bubbles at a time frame. The convex hulls are translucent to help users to determine how many layers are stacked. For example, in the hull trace of Asia (Figure 5 left), the bottom left corner is darker than other areas by stacking a more number of convex hulls. This implies that Asian countries stayed a long period of time on the bottom left corner. The centroids of the convex hulls illustrate the tendency of the direction that the convex hulls have moved over time, whether from the bottom left to the upper right, or the other way around. The centroid of the current time point is highlighted (Figure 3b3) during the animation.

Line charts (Figure 3b2) present the progression of values in X (e.g., income), Y (e.g., life expectancy), and bubble size (e.g., population) dimensions of the chart panel (Figure 4a). All line charts share the same time range for the X-axes and normalized (0–1) Y-axis. The shaded areas represent the minimum and maximum values of the data in each dimension. Figure 5 (right) shows three line charts of Asia. In the first line chart (income), the average income of the Asian countries is drawn in a line with a min-max band as a shaded area. By plotting values for the entire time range, the line charts show the changes in values and capture the trends in each data dimension. A time bar (Figure 3b4, vertical blue bar) on the line charts goes along the X-axis to indicate the progress of time during the animation.

Events are shown in the event exploration view. Gray rectangles (Figure 5) on both the hull trace and the line chart indicate the period and the type for events. Event types are labeled next to the rectangles (e.g., *P* for PEAK, *Plt* and *U* for PLATEAU and USER). A rectangle on the line chart visually emphasizes the event length, while a rectangle on the hull trace shows the approximate position on the coordinate. We discuss the event detection algorithm in Sec. 4.2. Users can draw a rectangle in the line charts to create user-driven events (i.e., USER).

5.3 Presentation Editor

The presentation editor (Figure 6) helps users manage the animation schedule that determines which frames to run in which playback time. There are two timelines at the top and bottom of the view. The top timeline shows story blocks start, duration, and entire playback time information (e.g., “00:00:00”), while the bottom one displays the data time of events (e.g., “1800”). The top timeline shows the entire running time of the presentation with a tick being a time unit (e.g., a second). The bottom timeline is non-linear to support animation playback techniques (Table 1). The blue line (g) shows time progression, which is linked to the time indicators on the event exploration view (Figure 3b3 and Figure 3b4).

Three are four types of story blocks in this view—initial segments (a), event segments (b), blank frames (c), and narratives (d). The initial segments (a) are located at the beginning of the animation to explain basic components in the chart panel (Figure 4a), such as variables assigned to the axes (e.g., income) and legends (e.g., continents). Rosling used to explain the overall data trends on the chart before the presentations began, describing the meaning of entities moving from bottom left to top right corners. We follow Rosling’s order of explanation, constructing a sequence of this segment with 4 steps: we define X and Y axes, explain the corners of the coordinates based on data trends, introduce legends by displaying one color at a time, and describe the bubble size.

After the initial segments, the presentation editor by default creates blank frames (c). At this point, if users produce a result video, it chronologically animates a series of scatter plots on the default mode (Figure 4 left) from the beginning to the end of the data (e.g., from 1800 to 2018). Each snapshot is played for a unit time (e.g., 200 milliseconds in this work). If an event is detected, it replaces the blank frames in the same period. Figure 6b shows a group of segments including PLATEAU→events in Asia and Africa. The group appears as a gray rectangle and the time range on the bottom indicates its interval, e.g., “1800–1820”. It consists of three components: the intro (I), the events, and the outro (O). Each component includes slowdown rate and data dimension information. Events are marked with a data dimension: X, Y, or S, followed by arrow icons. The intro and outro are labeled as I and O, respectively. Event segments run slower than a regular speed, and different types of events have different slowdown rates. By default, the frames of the intro and outro play 2 times slower than the unit time. We set 15 times slower frames for RISE↗, DROP↘, TROUGH, and PEAK events, 20 times for SPREAD, 2 times for PLATEAU→, and 10 times for USER events. We choose natural speed for each event type and these rates are easily editable in the presentation editor by dragging an event segment. Users can also swap the order within a group, delete events, or edit the playback time of event segments. Throughout the animation, users can (de) activate labels by clicking entities in the chart panel. The presentation editor shows the activated labels (Figure 6f). The entity labels are placed on top of the associated entities in the presentation output view (Figure 6 e1, e3-d4).

6 Use Case

We present two use cases for using Roslingifier. First, we create a story using the relation between life expectancy and income in the Gapminder data. We showcase another story using COVID-19 outbreak data [52] to demonstrate that our tool is generalizable to other datasets.

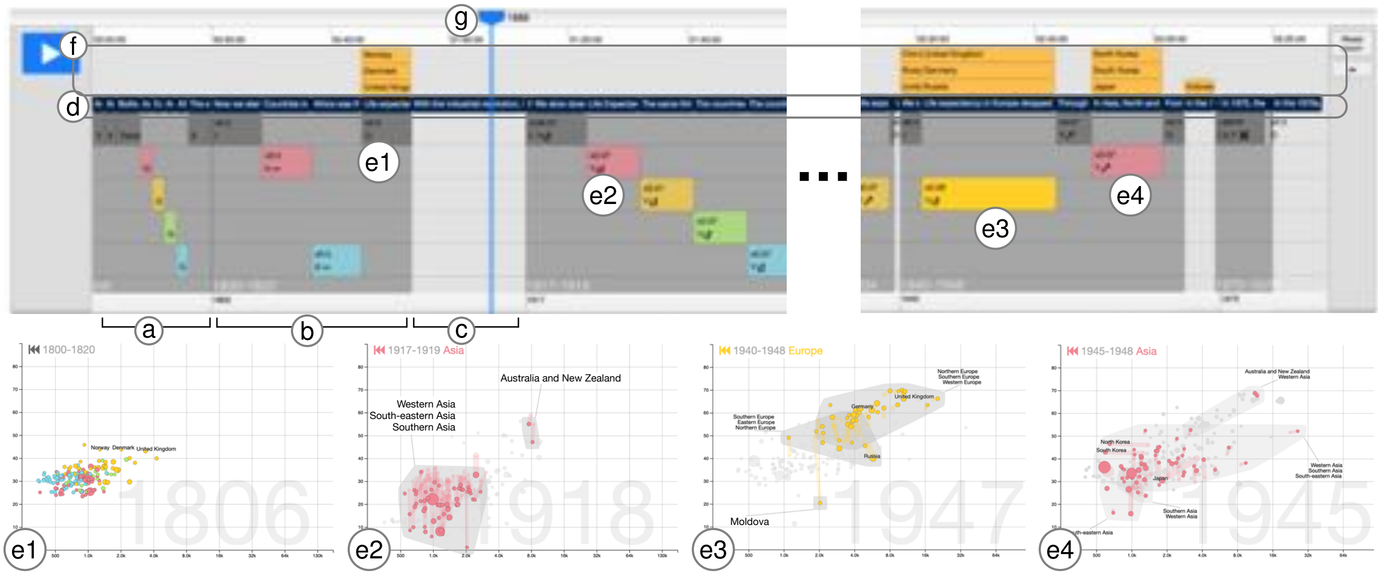

Fig. 6. The presentation editor manages the animation schedule with four types of story blocks: initial segments (a), event segments (b), blank frames (c) and narratives (d). Enabled labels are displayed in (f). The time indicator (g) shows the progression of time. e1–e4 show the chart panels for each corresponding event segment.

6.1 Life Expectancy vs. Income

A user is asked to give a presentation on world history to a general audience. As she knows from Rosling's videos that there are interesting story pieces on the relation between income and life expectancy, she decides to use the data in Roslingifier. In the tool, each bubble represents a country, and the size of each bubble indicates its population. The color of bubbles indicates the continents, as shown in Figure 3b1. The data includes 184 countries from 1800 to 2018.

The story generation starts with event detection. As the user sets the threshold as 3% for detecting event intervals, Roslingifier finds events that show larger differences than the threshold. Figure 3b show the detected events for the five continents. From 1800 to 1820, Roslingifier detects 3 PLATEAU→ event segments–income in Asia, life expectancy in America, and income in Africa. By using playback, she confirms that the countries gather together and do not move forward (Figure 6e1). Here she deletes the event on lifespan in America in the presentation editor to focus on the income dimension in her story, leaving two segments in the group (Figure 6b, red and light blue legends). The caption panel also reflects the deletion, presenting "*Income in Asia (Africa) is mostly constant between 1800 and 1820.*" To stress Africa as well, she removes "*(Africa)*" and adds "*Africa was the same.*" to the caption. Figure 11 (right) in Appendix D shows how the visualization changes after a user adjusts the labels and captions. Playing back the video with the captions, she thinks she can make a brief story related to the industrial revolution, when the countries in Europe move toward the upper right while other countries remain the same. In the outro, she turns on the labels of the UK and other countries in Northern Europe to emphasize the movement of those countries (Figure 6e1).

In the next segment group (Figure 6e2), she finds that all continents have a TROUGH↺, experiencing a big drop in life expectancy due to World War I and the Spanish flu epidemic and recovering during 1917–1919. She additionally sees that Roslingifier suggests to narrate these events using the rewind technique, where the chart panel shows how each continent experienced the events in detail. During a test playback, she sees many bubbles dropping and soaring simultaneously. She also notices that the clustering algorithm separates the bubbles when highlighting each continent in the chart panel. She also thinks that it is an interesting point to the audience that Australia and New Zealand form their own cluster, separated from other countries in Asia (Figure 6e2). Roslingifier emphasizes the rapid movement of the bubbles in this period with the traces of the countries. Because she believes that this segment group will engage audience, she decides to keep the group in her presentation. In fact, the story of this segment group is what Rosling also presented [R1].

Lastly, she sees in the last segment group (Figure 6e3) two Rises↗ on the life expectancy of the world (1945–1946) and Asia (1945–1948), and one Trough↺ on life expectancy in Europe from 1940 to 1948. Seeing the year information on the timeline, she notices that the detected events are related to World War II. To see what events Roslingifier finds in the time range, she plays the animation. In the animation, she observes that life expectancy in Europe (Figure 6e3) dropped significantly in 1944, and then recovered when the war ended in 1948. She also sees in the chart panel the movement of major countries—UK, Germany, and Russia. She thinks it is interesting that Moldova is located far from other European countries (Figure 6e3 bottom). While watching the events between 1945 and 1948 in Figure 6e4, she notices long traces that indicate that (1) North and South Korea experienced a huge fall in income in 1945, and (2) both life expectancy and income dropped in Japan, but soon recovered to a greater extent by 1948. Overall, she finds that the events in this group are also worth telling, so she decides to use this part for her presentation after adding labels on the countries for further emphasis. Figure 12 (right) in Appendix D shows the visualization changed by user editing.

6.2 COVID-19: Number of New Confirmed Cases

We use Roslingifier to create a story on the COVID-19 pandemic during the first three months of 2020. The data includes 170 countries with daily new case counts of 95 days. We map the X-axis to the number of days since 100 cases and Y-axis to new confirmed cases each day. Each bubble represents a country and has the same radius. The threshold is set to 4%.

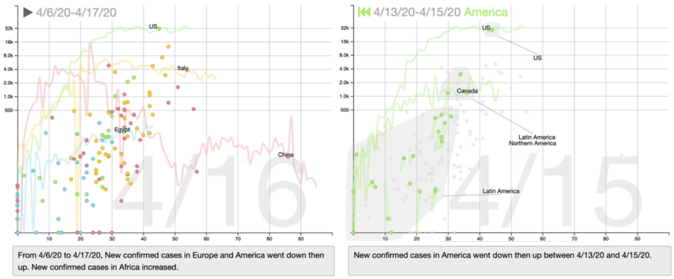

Fig. 7. Roslingifier detects a group of events (Apr 6–17, 2020) in COVID-19 dataset. Left: an intro summarizing the interval. Right: detected trough event in America (Apr 13–15). Traces highlight countries' movement for the entire time range.

Figure 7 presents an example segment group with three events from April 6 to April 17. The events are detected due to their rapid change in new confirmed cases: TROUGH↺ in Europe on April 6–16, TROUGH↺ in America on April 13–15, and RISE↗ in Africa on April 16–17. Figure 7 (left) shows the intro of the group with auto-generated narratives that summarize the interval:"*From 4/6 to 4/17, new confirmed cases in Europe and America went down then up. New confirmed cases in Africa increased.*" We then select a country in each continent to highlight their traces: US, Italy, Egypt, and China. After the intro, the story rewinds to highlight the TROUGH↺ event in America from April 13 to April 15 (Figure 7 (right)). The clustering algorithm detects three clusters. Here we can add enriched data presentations to the auto-generated narratives: "*It has the highest number of new cases each day, but the slope of the trace has become gentler after the 20th day*." "*Latin and South America in the middle (Canada, Peru, Brazil) are 10 days behind, and their slopes are less steep than that of the United States*."

In this use case, we show that Roslingifier can compose a story from other types of time-series data. Figure 13 in the appendices shows a screenshot of the system displaying the entire story for this use case.

7 User Evaluation

We conducted two user studies to evaluate Roslingifier from both the authoring (creation) as well as the audience perspective (consumption). Next we describe these user studies and their results. Note that the main goal of this work is not to simulate Rosling's style but to help users effectively create data presentations using common presentation techniques derived from skillful public speakers. Thus, we focus on evaluating how the system can help users create presentations and how public viewers understand the created data presentations rather than measuring the similarities between Rosling's and the produced styles.

7.1 User Study: Authoring

The goal of our authoring user study was to understand how Roslingifier can support general users to create a data presentation and organize the story.

7.1.1 Method

We recruited fourteen participants from a local university who are non-experts but at least have experience in creating data presentations using existing tools. As the participants entered the experiment room, we collected their written consent. We then requested them to fill out a pre-experiment questionnaire on demographic information, including age, gender, education level, and their experience using existing tools. Then we began a training session, which lasted 15–20 minutes on average. During this training, we introduced Roslingifier and demonstrated how to use the system. We then asked participants to perform all basic tasks involved in creating a story, such as adding and deleting events, changing the event order and playback time, editing narratives, moving the position of the cluster labels, and turning on and off the bubble labels. We used the child mortality and babies per woman data in the Gapminder data for this training.

The main task of the study was for participants to create a data presentation using Roslingifier with the data on the relation between life expectancy and income in the Gapminder dataset (Sec. 6.1). The participants' stated goal was to describe trend changes in life expectancy and income over 200 years of world history to a general audience. They were instructed to include any trend or event that they deemed of interest to such an audience. Because we assumed that participants often acquire background knowledge on given topics from online resources, and need to check whether presented materials are correct or not, we provided two Wikipedia pages ("Timeline of the 19th Century[1]" and "Timeline of the 20th Century[2]"), and allowed them to use the internet to search for additional information. The participants could use a maximum of 1.5 hours to create a presentation. After completing their data presentation, we asked participants to deliver the data presentation to the experimenter. By doing so, they are encouraged to give their best efforts and use many features of Roslingifier as possible. We did not analyze the presentations separately.

To complete the session, we requested participants to fill out a post-experiment questionnaire on their user experience and usefulness of the features of Roslingifier using a 7-point Likert scale (7: the strongest agreement). We also interviewed them with open-ended questions about their opinion on the system. We recorded their screen activities and logged their actions on the interface during the experiment. We recorded the screen with audio during the presentation.

7.1.2 Results

We initially recruited fifteen participants, but one of them failed to finish due to an unanticipated system failure. As a result, we analyzed data from fourteen participants. They were 25.2 years old on average (σ=1.53) and either undergraduate (8) or graduate (6) students. They spent on average 1 hour and 9 minutes (σ=26 minutes) to create presentations that were an average of 5 minutes 8 seconds long (σ=2 minutes 41 seconds). We paid 12.68 GBP per person for their participation.

Overall, the participants positively assess Roslingifier as shown in Figure 8. Specifically, they thought that Roslingifier provides an intuitive user interface (5.36), and is easy to learn (6.0) and use (5.5) They also felt that Roslingifier helps them effectively find (6.5) and highlight (6.07) the insights. There are several features that help participants find insights, including event detection, automatic grouping, min-max band in the line charts, and traces of countries. One participant, C14, also highly evaluated the automation because they helped save effort: "*Automatic clustering and drawing traces save a lot of effort in creating a story compared to when doing it manually.*" C3 also stated that "*This system makes the process of extracting events from data easy and simple, [...] The min-max band in the line charts effectively show the general trends and outliers.*"

1. https://en.wikipedia.org/wiki/Timeline_of_the_19th_century
2. https://en.wikipedia.org/wiki/Timeline_of_the_20th_century

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We also find that participants tend to actively use detected insights as a source for highlighting, such as clustering results; "*Clustering the countries with similar movement and labeling them (Central Asia) tells a clear story and provides what to search.*" (C6) Our findings indicate that Roslingifier's design allows participants to enjoy (6.21) their work: "*[Roslingifier] is fun to use as I can directly see the changes on the chart by selecting interesting periods.*" (C9) C4 expressed a similar sentiment: "*I like watching the changing history of the world in Roslingifier [...] I would recommend this to my friend who majors in history, as she would use this tool all day.*" C2 expressed that she really enjoyed using Roslingifier, and even formulated her own conclusion after using Roslingifier: "*Despite numerous wars, the entire world moves upward in the end. I felt that there is hope for humanity.*"

Participants frequently used highlighting features to improve audience comprehension, and they tended to respond positively, as shown in Figure 8. They thought country (6.21) and cluster (5.36) labeling were useful to highlight the major countries of events or victorious and defeated countries of the wars, which are the main actors or results of historical events. For example, C9 labeled four middle east countries in the 1970s in the presentation, to highlight a sharp increase of income during the oil crisis. Country tracing (6.57) received the highest score. A participant, C6, who focused on outlier countries, stated that "*Country traces are very helpful for emphasizing bubbles with different movements [...] I believe that the highlighted part can also attract users in the presentation.*" Slowdown (5.86) and rewind (4.93) were not as frequently used based on participants' intention. Rewind techniques, for example, allow participants to help the audience better understand details on the events by repeating explanation of periods. Some participants tended to use rewinding multiple times for a period with highlighting techniques to develop engaging storylines. C1, for example, first explains World War I from a global perspective, then used the rewind four times to deliver a common pattern of the continents during the war. Then she used rewinds again to contrast movement patterns of the continents during World War II. C1 stated: "*The rewind technique emphasizes a very interesting point that in World War I, the life expectancy of all continent dropped, but in World War II, each continent showed different movements.*" Some participants never used the rewind operation, suggesting that they felt rewinding was not aligned with their story. For example, C5 and C12 desired to focus on describing events on world wars in a global perspective using all continents, so they thought it was not necessary to explain individual continents' events. "*As World Wars affect across the world, I think the impact of the wars in a global perspective should be the main point of my presentation. [...] I did not find a place for using rewind in my presentation.*" (C5)

We provide additional quantitative analysis in Appendix F, including the use of time on the system/web, the types of searched keywords, and the number of system-generated and user-generated events that they used while creating the presentation. We also provided clustering results of individual comments in Appendix G.

7.2 User Study: Audience Viewing

We conducted another user study to assess how the data presentations created with Roslingifier are interesting and insightful. We in particular investigated which system features were useful for viewers.

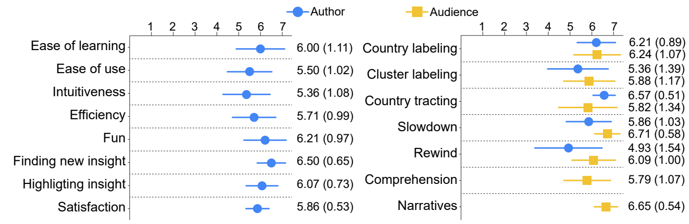

Fig. 8. Summary of post-experiment ratings for authors and audiences (Sec. 7.1.2 and Sec. 7.2.2); the dots and whiskers represent the means and standard deviation on the both side on a 7-point Likert scale.

7.2.1 Method

For this study, we created a 3.5-minute long data presentation video (Sec. 6.1; submitted as a supplementary material) by recording the result in the presentation output view in Roslingifier. No additional external video/image editing tools were used in the video production. We did not use the outputs from Sec. 7.1 because the participants in Sec. 7.1 were not experts and their presentations tend to focus on one narrow story sometimes include false claims. We recruited participants from Prolific, a crowdsourced platform, to collect qualitative feedback on our data presentation video. After participants reached the experiment website and electronically signed our consent form, they were asked to provide demographic information. Then we requested them to read a tutorial, watch a video, and answer a simple question based on the contents of the video; the latter served as an attention trial to filter random clickers. Once they passed this attention trial, they were directed to the experiment page with our data presentation video, which was the main task in the study.

On the data presentation page, we asked participants to watch the video, and to leave at least three comments on (1) what made them think a segment interesting (e.g., visual effect) as well as (2) any insights that they gained from the video. We provided an annotation interface where participants could specify a start and an end time of a target video segment for every comment (Appendix H). We provided them with incentives based on the quality and number of their comments. After the study, we asked them to rate their comprehension level, the visual effects, video playback, and narratives used in the video with 7-point Likert scale (7: the strongest agreement).

7.2.2 Results

Overall, 36 participants (20 males) successfully completed the study and we paid 3.03 GBP/participant on average for their participation. They were 29.4 years old (σ=8.5) on average, spent 19.3 minutes on average for the entire session, and made 6.61 comments per person (238 comments in total). The participants in general provided positive ratings for techniques as follows: comprehension (5.79/7.0), country labeling (6.24/7.0), cluster labeling (5.88/7.0), traces of countries (5.82/7.0), slowdown (6.71/7.0), rewind (6.09/7.0), and narratives (6.65/7.0).

Figure 9 shows the distribution of participants' comments over the runtime of the video. First, we found 14 comments that recognize the explanation on the axes and trends in the initial segments, as shown in (a): "*Plotting the descriptions of each corner physically on the plot really clarifies the meaning of the axes*" as P1 stated. Second, the number of comments at (b) had 41 comments, where participants mentioned that the trace strongly attracts them in the segment, stressing the big life expectancy drop after World War I: "*The trace of bubbles here clearly exemplifies*

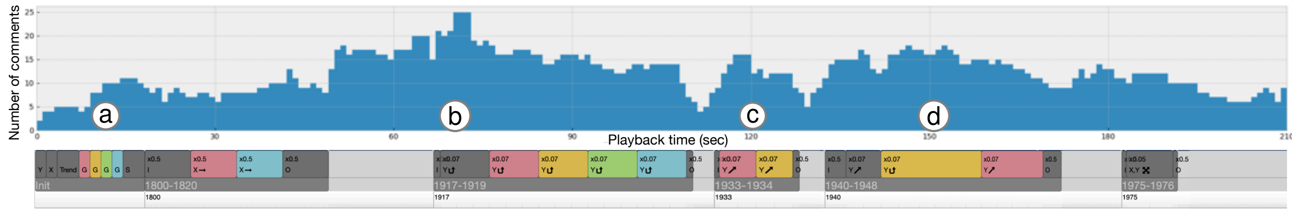

Fig. 9. The number of comments based on playback time and events in the video. See Sec. 7.2.

how horrific the mortality rate was globally [...]" The participants gave 5.82 points to the tracing technique.

Participants frequently mentioned labels throughout the video, but we found the labels on clusters in (c) to particularly capture audience attention (35 comments): "*The sudden increase in life expectancy in Kazakhstan and other Central Asian countries makes me curious to find out what was causing this sudden increase,*" P41 stated. The cluster labels received 5.88 points. We observe 30 comments at (d), where a few countries have significantly different movements from others. The participants also reported that the auto-generated labels on countries are useful in understanding the narratives; "*Country labeling is useful to tell a narrative about the outliers.*" They gave 6.24 points to the labels on individual entities.

Animation playback techniques received 21 comments, but participants gave higher score on them (slowdown: 6.71, rewind: 6.09). We attributed the high scores to the role of techniques—*divide and conquer stories* [8], which reduce the risks of overloading audience with information. Overall, participants thought the video is easy to understand (5.79 points) with interesting narratives (6.65 points). We also found that some participants expected more detailed stories on specific countries; e.g., "*I would like to have a little bit more info about Kazakhstan and why life expectancy rose so much.*" In Appendix I, we provide clustering results of individual comments with respect to their contents.

7.3 Usefulness for Authors vs. Audiences

There are many features in Roslingifier which authors can use for their data presentations. However, there may be a disconnect between the features authors and audiences deem important and useful. To find out if there is any such gap, we asked the usefulness levels from both authors and audiences. Figure 8 (right) shows the survey results. We see that the authors put a higher value on the visual effects, such as country labeling and country tracing, as these effects play an explicit role in presenting entities of the narratives. But they did not focus on the usefulness of rewind, assuming that audiences do not need repeated but detailed explanation in narratives. C12 stated that "*I wanted to increase the year as the animation progresses, so the idea of going back and repeating the same period was a little confusing to me.*"

Audiences, on the contrary, tended to appreciate animation playback techniques (slowdown and rewind) more than authors. We think these results show that audiences prefer techniques that could allow additional time to review and digest given narratives with detailed explanations, leading to audiences' better understanding and engagement with the story. Said P11, "*Separately showing how each continent/group of countries were affected by the Second World War was a good way to help break all the information down and keep the visual easy to digest.*"

8 Limitations and Discussion

In this work, we designed a semi-automatic storytelling system that incorporates automated methods and data presentation techniques derived from professional data presenters. Although the evaluation results show the effectiveness of the system and approach, we believe there are additional considerations that could further improve the technique used in this work. In this section, we present the limitations of the system, the lessons learned from this work, and the design implications for future data presentation systems.

Using Advanced Event Detection Algorithms: To support users in quickly finding events that can be tailored to their own stories, we incorporated an event detection algorithm and allowed users to have seven types of events. While the detection algorithm helps authors create effective stories, as described in Sec. 7.1.2, there may be other approaches that can be further considered.

First, we used an event detection algorithm that is not tied to and optimized for a specific domain. We chose this direction because we think it could widen the spectrum of the generated stories without limiting the authors' perspectives on data, which is also used in other existing tools, such as Microsoft BI. We also considered that demonstrating the effectiveness of complex event detection algorithms is beyond the scope of this work due to differences in the datasets and background knowledge of users by domains. From the authoring user study, we observed that users utilize various types of events in different types of stories with their interests and views on the events (Figure 14(c) in Appendix F). Different from our approach, we think it is beneficial for a system to be able to provide more advanced or domain-specific algorithms to capture more complex patterns in the datasets, such as periodical events or asynchronous correlations over time. For example, a participant in the user study asked about an algorithm that could detect entities with similar movements over time (e.g., finding all genocide events from detecting life expectancy value drops). If such algorithm can be used, we conjecture that authors could obtain more detailed results from the algorithms, which would give rise to in-depth storytelling in data presentations. At the same time, we were concerned about the possibility that very few or no analysis results can be returned without arduous parameter turning for some datasets or users may not understand or explain why such results are returned from the algorithms. A future study could measure the impact of different types of event detection algorithms on story generation, how authors use the algorithms, and what types of stories are generated from the events.

Impact of Clustering in Story Generation: In this work, we tested a set of clustering algorithms and found that different clustering algorithms generate slightly different results. For example, in our test, we found that the mean shift algorithm [53] creates two clusters in Figure 4, while the affinity propagation algorithm [54] creates six clusters for the same event. In this case, there is a high chance that authors using the affinity propagation algorithm could build a more fine-grained story with a higher number of clusters in Asia compared with those using the mean shift algorithm. Additionally, we observed that the clustering results are highly dependent on the parameter settings, which implies that ease of use should also be considered in incorporating clustering algorithms. Although we found that the mean shift algorithm is easy to understand and is effective in supporting users, as shown in the user study results, it is possible that users may not be satisfied with the clustering results. For example, users may find that the results are not fully aligned with their intentions or they may not be confident with the returned clustering results (e.g., uncertainty in algorithm accuracy). One possible approach for resolving this issue is to present clustering results of multiple clustering algorithms with various configurations so that users can explore and choose the most explainable ones in alignment with their stories or the most accurate ones. A future system may adopt the approach so that users can preview and compare the stories generated from various clustering algorithms, as proposed in Clustervision [55]. In addition, the system even allows users to define their own clusters, so that the clusters can be tightly aligned with their intention in the stories, as suggested by a participant in the user study (Sec. 7.1).

Simulating and Evaluating Rosling's Presentation Style: In this work, the system provides a set of storytelling techniques derived from several public speakers to assist users in building presentations. We chose this approach because we believe that it could boost the creators' imagination and allow diverse presentation styles. Alternatively, a system may support users in simulating a specific presentation style, which is also a valuable research direction and could be an effective extension of this work. To achieve style simulation, a future study could first investigate and characterize diverse presentation styles in many aspects and formulate a design space that not only includes comprehensive storytelling techniques (e.g., voice tone, speed, facial and body expressions), but also presentation contexts, goals, personal preferences, and environments. For example, the presentation style and gestures in weather reports are different from those used in referendum results. Even Rosling himself used different styles of gestures depending on the environment (e.g., hologram display versus TED talks). Once a design space is defined with various styles and gestures through investigation and characterization, a system can be implemented to guide or help users simulate a specific presentation style. For example, a style simulation system can provide specific instructions at a certain point, such as "follow the node with a finger" or "shape a rectangle with your hands to highlight the range." To evaluate the style simulation system, we can consider measuring the similarity of the original and simulated styles and assessing the effectiveness of the created presentations in conveying the story.

Beyond Scatterplots: This paper primarily focuses on time-series data in the form of scatterplots to create data presentations. However, there are many different types of time-series data used in data presentation. Hans Rosling himself also interchangeably used maps and line charts with scatterplots in his presentation to convey a variety of information. We believe that the data presentations using complex data types, such as maps, graphs or multi-dimensional data require a new design space. Each data type could include various types of event supported by different sets of gestures, visual effects and animation playback techniques, presumably including zooming in/out, clustering by attributes, etc. The design space of each data type should be carefully investigated through a similar process we used in this work. In addition, one can investigate the transition methods used in data presentation: gestures and visual effects when switching various data types, or different playback speed used in the transition.

Additional Features: While our creators tended to think the system was easy to learn and use, they requested several new functions that they would prefer to have. Examples include keyboard shortcuts undo functions which would allow more efficiency in the creation process. There are also other features that can potentially improve the system, such as supporting different levels of events, filtering events by their types, and providing an intuitive user interface to indicate the start and end of visual effects. The system shows segments and plays the segments once unless a user drags the time indicator, which results in inconvenience in structuring stories, as reported by a few participants in the user study. We believe the system can give users more freedom and fine-grained control in structuring stories by allowing the stacking of multiple segments for a concurrent event (e.g., showing Asia and Europe together) or repeating the same segment with a different narrative. We summarize the comments about system improvement in Appendix G. Although we have so far not implemented these features, Roslingifier's is open sourced[3] so that anyone can improve, extend, and use the system.

9 Conclusion

We design Roslingifier, a semi-automatic storytelling system based on techniques derived from an analysis of data presentation videos. Roslingifier provides three views to support users quick prototyping of data presentation with auto-detected events and enabled storytelling techniques, such as gesture, visual effects, and animation playback. Our experimental results and expert feedback indicate that Roslingifier supports users in effectively creating data presentations that attract audiences using highlighted events and narratives. The contribution of our work lies in the formative study on the data-presentation genre, and the implementation of an end-to-end system. Our imminent future work includes investigating automated data presentations for specialized data types beyond scatterplots, as well as exploring how human presenters incorporate their knowledge, insight, and experience into data presentations produced by our tool.

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APPENDIX A
REVIEWED DATA PRESENTATION VIDEOS

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[R2] Gapminder Foundation. US in a converging world, Hans Rosling on CNN (Fareed Zakaria GPS). Mar 15, 2011. https://youtu.be/WjVHvC9EeB4

[R3] Bill Gates. Hans Rosling: The River of Myths. Jan 31, 2013. https://youtu.be/lYpX4l2UeZg

[R4] TED. The best stats you've ever seen. Jan 16, 2007. https://youtu.be/hVimVzgtD6w

[R5] TED. Hans Rosling: The good news of the decade? Oct 7, 2010. https://youtu.be/OT9poH_D2Iw

[R6] TED. Religions and babies | Hans Rosling. May 22, 2012. https://youtu.be/ezVk1ahRF78

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[T1] YouTube Movies. An Inconvenient Truth. 2006. https://youtu.be/x-VjNZBbjD4

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[N1] ElectionsUK. The EU Referendum - FULL Results - BBC. Jun 26, 2016. https://youtu.be/1TmUP1StPf0

[N2] CNN. John King: Trump enjoying a significant uptick in his political standing. Feb 6, 2020. https://youtu.be/Is4uSbnfRWM

[W1] Mark 1333. Weather Events 2019 - Weather forecast - snow is coming (UK) - BBC News. Jan 31, 2019. https://youtu.be/74sMio3c8Xo

[W2] UK Weather Forcast Channel. UK Weather Forecast HD: WORLD GLOBAL WEATHER FORECAST. Jan 3, 2018. https://youtu.be/o1QMZcdN8Kw

[M1] CNBC Television. Jim Cramer unveils the scariest pattern in the chart book. Jan 17, 2020. https://youtu.be/zQIZJQmnoV0

[M2] CNBC Television. Cornerstone Macro technician charts today's market carnage. Feb 24, 2020. https://youtu.be/WKbnovqyIsg

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