

# The Stories We Tell About Data: Surveying Data-Driven Storytelling Using Visualization

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*The emerging practice of data-driven storytelling is framing data using familiar narrative mechanisms, such as slideshows, videos, and comics, to make even highly complex phenomena understandable. In this survey, we propose a taxonomy focused specifically on media types for the purpose of widening the purview of data-driven storytelling by putting more tools into the hands of designers. The classification shows that current data-driven storytelling practice does not yet leverage the full repertoire of media that can be used for storytelling, such as the spoken word, e-learning, and video games. Using our taxonomy as a generative tool, we also explore three novel storytelling mechanisms, including for live streaming, gesture-driven oral presentations, and data-driven comics.*

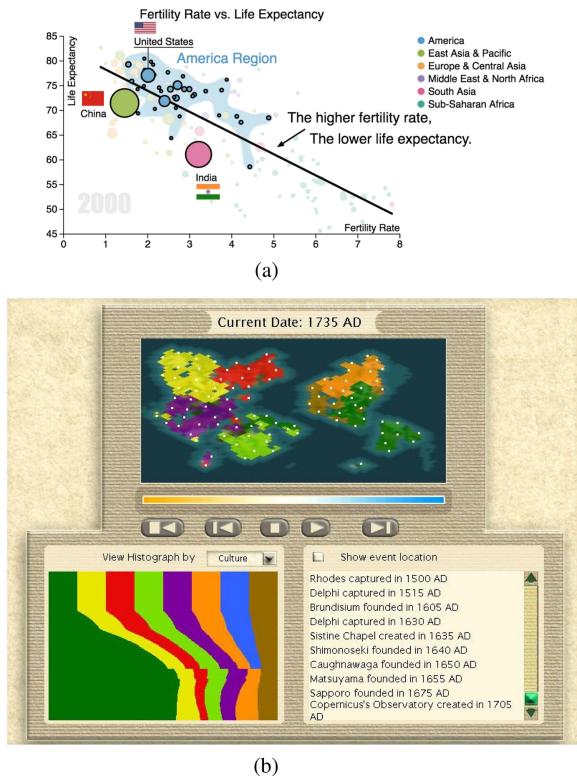
From the hunter returning from his latest foray to tell tall tales of stalking his prey, to the shaman spinning a yarn about the origins of the gods, the stars, and the moon, storytelling is one of the oldest forms of human communication, record keeping, and entertainment. Stories—sequences of events involving characters and places—are particularly well suited for this purpose because their chronological structure enables recall, entices listeners, and facilitates understanding.<sup>1</sup> For this reason, narration and storytelling retain important roles even in today's society, where these properties are particularly important in helping people get to grips with an increasingly complex world. This has recently given rise to *data-driven storytelling*<sup>2</sup> where narrative techniques are utilized for telling stories about data,<sup>3</sup> often using visual media.<sup>4</sup>

Examples of such data-driven storytelling abound (see Figure 1), and include data comics,<sup>5,6</sup> data videos,<sup>7</sup> and data-driven slideshows.<sup>8</sup> The common denominator is that they are based on story arcs evolving over time to build an argument, explain a phenomenon, or report a finding. They diverge by the form of *media*, or channels of communication, they use: sequential art, animated graphics, presentation slides, handwriting, etc.

However, while visual representations are particularly useful for storytelling, there are many additional types of media—digital and otherwise—that can be co-opted for telling stories about data. An existing framework proposed by Segel and Heer<sup>3</sup> outline seven genres of narrative visualization, but conflates the storytelling mechanism with the media being used. Furthermore, Segel and Heer also note that their sample is limited (58 items) and does not cover the full scope of possible media that can be used for storytelling,<sup>3</sup> such as video games, infotainment, and other e-learning tools. Meanwhile, much research in data-driven storytelling has used these seven genres as a starting point, which suggests that the community may be limiting itself by needlessly adhering to a framework that was intended to be generative rather than prescriptive.

What about using the spoken word for data-driven storytelling, i.e., supporting speakers talking to an audience? What about the written word (i.e., data-driven prose), such as for inclusion in a textual report? And what about other forms of human communication, such as theatre, poetry, and even dance? Much innovation remains in data-driven storytelling, but this requires going beyond existing frameworks.

To address this gap in the literature, we present a new taxonomy focused on media for data-driven storytelling with the purpose of opening the field to a wider set of future possibilities. Our work started with collecting evidence of data-driven storytelling using novel and diverse media, from the spoken word to



**FIGURE 1.** Examples of data-driven storytelling. Many possible media types are available today for data-driven storytelling. (a) Annotated chart created in ChartAccent.<sup>9</sup> (b) Data-driven story in the video game *Civilization 3* (2001).

interpretative dance and choreography. We then use these data to derive a taxonomy and classify all of these examples into a coherent framework. We use the framework to postulate some potential future media types for data-driven storytelling. Finally, by generalizing across storytelling practice for different media, we derive design guidelines for data-driven storytelling. We conclude this article with a summary and our plans for future work.

## DATA-DRIVEN STORYTELLING

Storytelling is the conveyance of a sequence of events, often involving characters and places—stories—using speech, sound, and visuals,<sup>1</sup> and has a history spanning thousands of years. A visual narrative is a story told primarily using visual media, such as illustrations, photographs, animations, video, and—now—visualization.<sup>4</sup> In particular, visualization has a specific proclivity for communication by virtue of its graphical form, yielding the notion of *communication-minded visualization*<sup>10</sup> to support collaborative analysis.

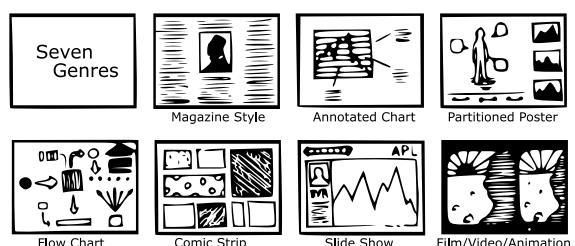
Combining the idea of communication-driven visualization with storytelling yields the notion of *data-driven storytelling*: narrative techniques for telling stories about data.<sup>3</sup>

## Narrative Visualization

Segel and Heer<sup>3</sup> were the first to propose the notion of *narrative visualization*, and used their initial survey to identify seven distinct story formats (see Figure 2) as follows.

- **Magazine style:** A data-driven image integrated in a page of text, where the text refers to and explains the image.
- **Annotated chart:** Chart adorned with descriptive text and labels for the purpose of explaining its contents.
- **Partitioned poster:** A poster consisting of multiple images, each with separate data.
- **Flowchart:** Visually ordered sequence of images and annotations designed to tell a story.
- **Comic strip:** Sequence of frames containing images and text organized in a comic layout.
- **Slideshow:** Deck of slides combining images and text to sequentially tell a story.
- **Film/video/animation:** Motion graphics that incorporate data-driven imagery and visualizations, often animated.

However, as noted by Segel and Heer, their findings are limited to a sample of 58 examples. They also do not claim that their genres are exhaustive, noting for example that their work did not include video games or e-learning tools. The seven genres have proven to be useful for categorizing research in this field; they have even played a prescriptive role, with graph comics<sup>11</sup> and data comics<sup>12</sup> arising as examples of the comic strip genre, and data videos<sup>7</sup> drawing inspiration from film/video/animation. However, there is room for expanding the framework further.



**FIGURE 2.** Narrative visualization. Seven genres of narrative visualization by Segel and Heer.<sup>3</sup>

## Visual Communication

Visual forms of communication, including icons, illustrations, schematics, photographs, and full-motion video, have long been considered to be one of the most compelling and approachable storytelling formats.<sup>4</sup> A recent development is an increased focus on live, so-called *streaming*, video, where the media is received and presented to the consumer at the same time it is delivered by the provider. This development was particularly driven by live gameplay content, where prominent gamers—called *streamers*—broadcast their game screen on services, such as Twitch.tv.

Amini et al.<sup>7</sup> identified *data videos* as motion graphics combining both sound and visuals to tell a data story. Pointing to prominent examples from the New York Times and the Guardian, their work encourages professional storytellers to use visuals to craft their narratives. Their data clips<sup>7</sup> tool enables authoring data-driven clips incorporating visualizations that can be assembled into longer data videos. More recently, Hall et al.<sup>13</sup> proposed a gesture-based method for interacting with visualizations overlaid on remote video presentations.

## Visualization for Communication

Data visualization is the use of interactive graphical representations of data to aid cognition. There are arguably two main uses of data visualization as follows.<sup>10</sup>

- › *Exploration:* Using interactive visualizations means for exploratory data analysis to gain insights and generate hypotheses.
- › *Explanation:* Presenting data and insights to an external audience using visual means.

Data-driven storytelling is a natural extension of visualization for explanation (the latter). Gershon and Page first proposed using storytelling for visualization,<sup>14</sup> and their work has since been followed up in workshops, surveys,<sup>3,15</sup> and even commercial tools. Viégas and Wattenberg remark upon the proclivity of visualization for communication by virtue of its graphical form, and encourage focusing on so-called *communication-minded visualization*<sup>10</sup> where communication enables social analysis. Finally, recent work by Brehmer and Kosara<sup>16</sup> widened the scope of data-driven storytelling to encompass a range of settings, from formal presentations in front of stakeholders audiences (“recitals”) to collaborative “jam sessions” within the team.

To reach its full potential, communication capabilities should be integrated into the visualization tools themselves; for example, Tableau incorporates both

slide stories as well as dashboards, and other tools provide similar functionality.

## MEDIA FOR STORYTELLING

Our focus in this article is on communication mechanisms—or *media*—used for conveying data-driven stories. In this article, we define “media” as the channel or the tools used to store and deliver information. While data-driven storytelling is a nascent research topic in visual communication and visualization, there has so far been no focus directed to the specific media used. To illustrate the variety of different data-driven media types in the world, we here enumerate and discuss a set of representative and innovative such examples. The purpose is to provide a basis for a taxonomy that can be used to classify the storytelling media used for the data-driven narrative. For each example, we use an informal classification scheme to describe the media in more detail. This scheme will then feed into our taxonomy in the following section.

We use the following criteria for our selection.

- › Has a *story format*, i.e., a progression (or arc) over the course of the artifact.
- › Leverages *data* to drive its narrative.
- › Uses an approach that is *novel* beyond Segel and Heer’s seven genres.<sup>3</sup>
- › Inhabits a *unique* position w.r.t other examples.

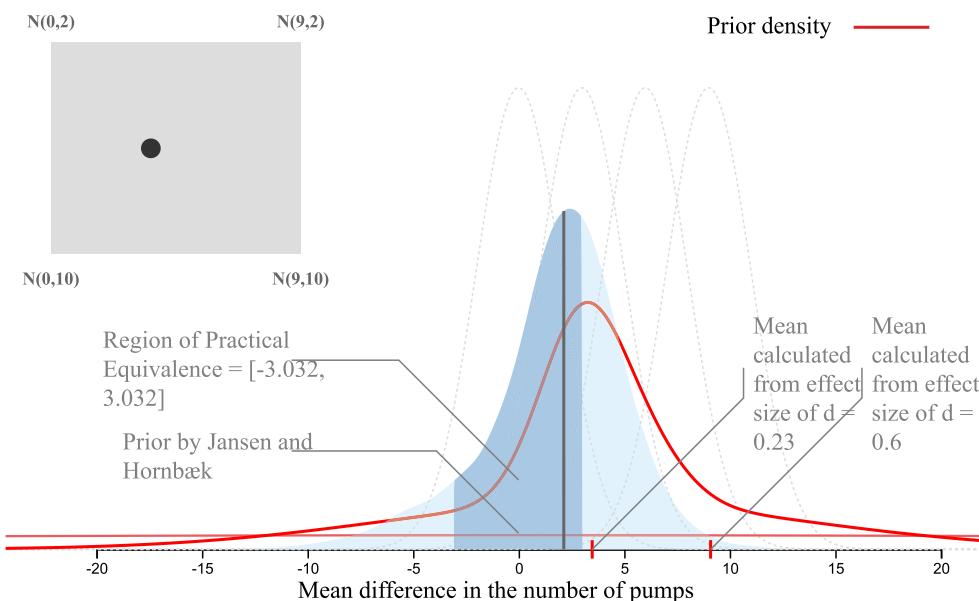
### Exhibit 1: Interactive Articles

Online journalism is changing to the point where so called *interactive articles* are becoming a new and popular form of visual communication. These data-driven narratives—or *explorable explanations*<sup>17</sup>—combine traditional journalistic storytelling with interactive components that allow a potentially large audience to engage with them. Major newspapers, such as the *New York Times*, *The Guardian*, and the *Washington Post*, have long made such interactive articles a popular part of their online presence.

While already tremendously successful in practice—ten of the *New York Times*’ forty most popular articles in 2014 were interactive articles from its *Upshot* department<sup>18</sup>—the concept of interactive articles is also beginning to take hold in the academic realm. Already in 2011, publishing giant Elsevier launched the Executable Paper Grand Challenge to find ways to improve reproducibility of research by including executable code inside an interactive article. The winner of this challenge was the Collage authoring environment, and the Elsevier journal *Computers & Graphics* even published a special issue testing the

- $y_i$  indicates the number of pumps for each participant,  $i$
- $x_i$  indicates the group (expansive or constrictive) for each participant,  $i$
- $v$  indicates the degrees of freedom
- $\mu$  indicates the mean of the t-distribution corresponding to each group
- $\sigma_y$  indicates the variance of the t-distribution corresponding to each group
- $\beta$  indicates the mean difference in the number of pumps between the two groups

Here, our primary parameter of interest is  $\beta$ , and we set a prior on this (as well as other) parameters. A prior, which is a normal distribution in this case, is determined by the following: (1) One's degree of optimism / skepticism about an effect by manipulating the location of the mean; setting the mean at zero indicates a skeptical prior, setting the mean at a value derived from prior literature indicates an optimistic prior. (2) One's strength of belief which can be manipulated by the variance of the normal distribution; setting a narrow prior indicates strong belief about the presence or absence of an effect, a wide prior indicates weak belief about the presence or absence of an effect).



Posterior probability density of the mean-difference in the number of pumps. Interact with the widget or the text sliders to see how priors affect the posterior estimates.

Our priors are a combination of skeptical (centered at 0) and optimistic (centered at a value informed by prior literature), and narrow (low variance, highly regularized) and wide (high variance, weakly regularized), based on the degree of informedness, and the strength of belief. We run our analysis using a mixture calculated from 8 different priors, which allows us to interpolate between complete skepticism to complete optimism. For the optimistic priors, we use the effect-size from the meta-analysis ( $d = \sim 0.6$ ), to calculate the mean for the Normal distribution. We show the estimates for the posterior probability distribution of  $\beta$  calculated using this mixture distribution of priors. We allow the reader to interact with the prior weights to set their own prior on the primary parameter of interest,  $\beta$  (the mean difference between the two conditions).

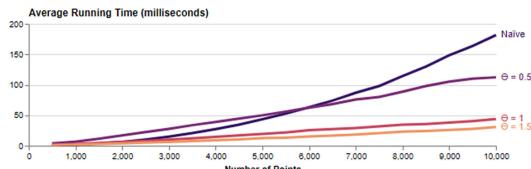
The default analysis uses a prior centered at effect sizes derived from the meta-analysis ( $d = \sim 0.23$ ). We allow interaction to explore the effect of choice of priors on the result.

**FIGURE 3.** Explorable report. Exploring multiverse analysis as proposed by Dragicevic et al.<sup>19</sup> Clicking underlined parameters in the text toggles between different animations and changes the visual representations.

environment, but unfortunately, the movement seems to have died down.

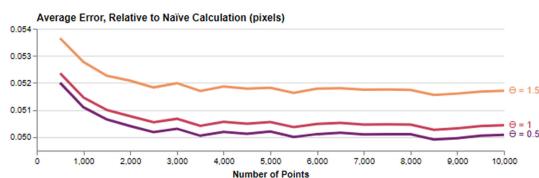
Instead of starting from the article and going to interactivity, what about starting from code and going

toward an article? As embodiments of the literate programming paradigm, where traditional source code is embedded in descriptive natural language, *computational notebooks*—which combine executable code,

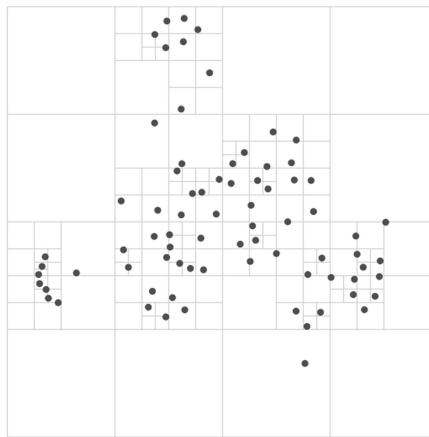


The running time results confirm that the Barnes-Hut approximation can significantly speed-up computation. As expected, the [naive approach](#) exhibits a quadratic relationship, whereas increasing the theta parameter leads to faster calculations. A low setting of [theta=0.5](#) does not fare better than the naïve approach until processing about 6,000 points. Until that point, the overhead of quadtree construction and center of mass calculation outstrips any gains in force estimation. For [theta=1](#) and [theta=1.5](#), however, we see a significant improvement in running time, with similar performance for each.

To evaluate approximation error, we measure the average vector distance between the results of the naïve scheme and Barnes-Hut. In the context of a force-directed graph layout, this error represents the difference (in pixels) between node positions after applying the naïve and approximate methods.



Looking at the error results, we first see that the average error is relatively small: only ~5% of a single pixel in difference! However, we should take care in interpreting these results, as we use the *average* error per point and the *maximum* error may be substantially higher. While [theta=1](#) and [theta=1.5](#) exhibit similar running times, here we see notably higher error rates for [theta=1.5](#) versus [theta=1](#) and [theta=0.5](#).



**FIGURE 4.** Interactive article in Idyll. Jeffrey Heer’s interactive article (written in Idyll<sup>18</sup>) explaining the Barnes-Hut approximation for graph layout. As is typical for this type of artifact, the article contains multiple widgets that allow the reader to interact with the displayed model.

its output, and descriptive text and other media in a single document—is based on this premise. As a result, computational notebooks have become a *lingua franca* for presenting findings, supporting material, and breakthroughs in many STEM disciplines. For example, when gravitational waves were first observed by the LIGO–Virgo collaboration in 2015, the announcement in February 2016 was accompanied by a Jupyter notebook complete with all the collected data.<sup>a</sup> However, computational notebooks are generally rather technical and expose interactivity mostly through source code rather than widgets and controls.

*Distill*,<sup>b</sup> on the other hand, is an online academic journal for machine learning research that is based on interactive, exploratory articles. Similarly, Dragicevic et al.<sup>19</sup> proposed *explorable reports* that are designed specifically for multiverse analysis, where clickable controls in a paper allows for varying the reporting for many different statistical analyses in order to show the fragility or

robustness of the findings. Figure 3 shows an example of an example “mini-paper” implemented using this method; clicking on the blue underlined text will cycle between matching results and images.

Most recently and inspired by these efforts, Conlen and Heer<sup>18</sup> proposed *Idyll*, a domain-specific language for authoring interactive articles that is specifically targeted at journalists and designers. Using a rich standard library of components, Idyll allows even nontechnical users to quickly create compelling and highly interactive content. Figure 4 shows an example interactive article created in Idyll on the Barnes-Hut approximation for graph layouts.<sup>c</sup> In fact, Matthew Conlen, the creator of Idyll, also co-founded *Parametric Press*,<sup>d</sup> an online magazine for interactive articles built in Idyll.

**Informal classification:** Key in all of the interactive articles reviewed previously is that they are *interactive*; they allow—even invite—interaction by the reader. In some cases, this is done through low-level and technical

<sup>a</sup>[Online]. Available: <https://www.gw-openscience.org/>

<sup>b</sup>[Online]. Available: <https://distill.pub/>

<sup>c</sup>[Online]. Available: <https://jheer.github.io/barnes-hut/>

<sup>d</sup>[Online]. Available: <https://parametric.press/>



**FIGURE 5.** Data-driven presentations. Using SketchStory<sup>20</sup> to give an interactive and visual presentation on data.

means, such as changing source code in a Jupyter notebook, but in more “polished” cases intended for a more general audience, such as Distill and Idyll, the interaction is performed through standard widgets.

The other significant characteristic of interactive articles is inherent in the actual medium itself: they are based on a typical document format where the main context is textual in nature. As with previous examples of new media being introduced into society, it is clear that data-driven stories will mostly augment rather than replace existing media types. In other words, a fruitful approach to invent future storytelling media for data is to study existing ones.

## Exhibit 2: Data-Driven Performance

Some storytelling takes place in person and is enacted by one or several performers. SketchStory by Lee et al.<sup>20</sup> (see Figure 5) is close to traditional data-driven storytelling, and supports a person giving a presentation using an interactive whiteboard that responds to sketch input to generate interactive graphics. However, SketchStory is curiously alone in this area—few visualization or data science tools exist to support in-person presentations. This was also the motivation for our GestureStory concept described later.

However, there are additional ways that people have used live performance to communicate data. Figure 6(c) shows an image from a performance where dancers demonstrate how the bubble sort algorithm works.<sup>21</sup> This algorithm pushes the largest element to the right and forms a ordered sequence of numbers. For clarity, each dancer is labeled in this picture. In reality, the dancers wear uniforms with numbers on them, where each dancer stands for a different element in the array. The storyline is the movement of the elements. The data are the ordered sequence.

A similar data-driven dance performance was created by the Dance.Draw project<sup>22</sup> [see Figure 6(b)],



(a)



(b)



(c)

**FIGURE 6.** Data-driven dance. Data-driven performances enable live enactment of data. (a) Explaining computer science concepts using ballet. (b) Visualizing movement data in dance. draw.<sup>22</sup> (c) Dance demonstration of a bubble sort algorithm.<sup>21</sup>

where the movements of dancers in a physical space was conveyed using visual representations. This mechanism could also be used as a vehicle for conveying data-driven stories. Finally, the data-driven dance project<sup>e</sup> [see Figure 6(a)] has three performances designed to convey abstract data and blur the boundary between science and art: [arra]stre (data-driven dance for

<sup>e</sup>[Online]. Available: <http://www.datadrivendance.org/>

computer science theory), [data]storm (ocean storms, networks, and weather), and [pain]byte (biomedical engineering chronic pain, and dance).

*Informal classification:* In-person performances typically take place in an auditorium or studio, which supports a *large audience*. Disregarding video recordings of the performance (which would be another form of media), this does require the audience to be physically *co-located* with the performance, and to consume it in *synchronously*, in real time. This means that the performance is not stored; it is *ephemeral*. The components of the performance are human bodies in motion over the duration of the performance, and can also include text, sound, light, and visuals (typically projected in the workspace).

### Exhibit 3: Storytelling in Augmented Reality

Augmented reality is making significant inroads in society as technology becomes availability and new ideas to leverage the technology are introduced. Aspects of technology has in fact already been used in a limited capacity in broadcasting for a long time, particularly in sports, where it can be most accurately named “composite” graphics. Figure 7(a) shows a typical example of informative graphics inlaid on an American football field on a live broadcast.

The practice has also recently been employed in weather reporting. In fact, weather reporting has a long history of using image composition to combine the reporter’s image with a virtual background through chromakeying. Augmented reality allows for more advanced effects. Figure 7(b) shows an image inspired by the “immersive hurricane” footage from the Weather Channel, where the impact of hurricane florence on North Carolina in September 2018 was shown in a live broadcast.

*Informal classification:* Clearly, augmented reality has much potential for storytelling. When experienced by a person using an AR headset, the audience is a single person, whereas the broadcasting examples discussed here are clearly intended for a broad audience. Similarly, interaction depends on whether it is experienced in person—in which case the person can navigate freely in the real world and interact with virtual objects—or viewed as composite graphics on a screen, where the interaction is limited to playback.

### Exhibit 4: Data-Driven Storytelling in Video Games

While Segel and Heer<sup>3</sup> explicitly noted that they chose not to include video games in their survey, games



(a)



(b)

**FIGURE 7.** Composite graphics and augmented reality in broadcasts. Live TV broadcasts are increasingly becoming useful media for data-driven storytelling using visualization. (Images generated by MidJourney v5.) (a) Graphics displayed on the pitch for a football game. (b) Immersive augmented reality hurricane experience on the Weather Channel.

have long been instances where visualization is often integrated.<sup>23</sup> As it turns out, they have also been used for data-driven storytelling. Figure 1(b) depicts an image from the replay session that is shown at the end of a completed game session, i.e., after one of the players (human or computer) has achieved one of the victory conditions: conquering all opponents, winning the space race, taking over most of the land, or scoring a diplomatic or cultural victory. The replay shows a history of how each civilization was founded, expanded across the world, and was eventually defeated. While the interaction is limited, playback controls allows the user to go back and forward in the history. Similar session playback tools—often called *theater mode*—can be found in *Halo 3* and *Call of Duty: Black Ops*.

*Informal classification:* The audience for most theater modes is *individual* players who want to study their own and other players’ performance. However, many theater modes typically also allow the player to cut and paste clips together, eventually producing a resulting *video* to share with others. The resulting video will have the same features as a data video (see the previous). A playback session typically uses a map view, so the bandwidth requirement is lower than

full-motion video, thus reducing the cognitive load. One feature of most theater modes is that they make it easy to navigate in 2-D or 3-D in the scene, thus changing the viewpoint. While the action itself cannot be changed (since it represents events that already happened), this interaction is powerful in that it can, for example, allow a player to put themselves in the shoes of another player to see what an encounter looked like from their viewpoint.

## TAXONOMY OF DATA-DRIVEN STORYTELLING MEDIA

The goal of this survey is to identify, study, and classify media that have traditionally been used for storytelling. This will help expand narrative visualization to encompass the entire scope of storytelling in society. This, in turn, would generate new ideas for how to best use such media for data-driven storytelling.

### Methodology

Informed by Segel and Heer,<sup>3</sup> we first gathered *candidate examples* from the literature by searching IEEE Xplore, the ACM Digital Library, and Google Scholar for papers matching the search terms “data-driven storytelling” and “narrative visualization.” We then applied the *inclusion criteria* (story, data, novelty, and uniqueness) from the previous section to select a set of representative examples. Both authors were involved in this process and both had to agree to include each paper. Given our methodology, while we do not claim that our corpus is exhaustive, we think that it is diverse and representative.

Based on our survey of the existing evidence of a wide variety of media for data-driven storytelling, we derived multiple *candidate dimensions* for classifying the different methods. We then selected five dimensions based on their ability to discriminate between storytelling media that are qualitatively different. In summary, we ended up with the following dimensions.

- › *Audience cardinality (A)*: Who is the intended recipient for the story? *Motivation*: Different media are suitable for different audiences; for example, a private conversation works best for a small set of people.
- › *Space and time (S/T)*: What is the temporal and spatial delivery mechanism for the story? *Motivation*: The distribution of storytellers and audiences in space and time for this media type; for example, a live Zoom call is remote and synchronous.

- › *Media components (MC)*: What are the visual and sound building blocks employed? *Motivation*: The nature of the media type (e.g., animations, text, charts, etc).
- › *Data components (DC)*: How is the data conveyed to the viewer? *Motivation*: The nature of the data representation for the media type (e.g., temporal, spatial, or statistical graphics).
- › *Viewing sequence (SQ)*: How is the media viewed by the viewer? *Motivation*: The control effected by the viewer; for example, a recorded video has playback controls, whereas a live performance is not interactive.

The selected examples have been classified into the taxonomy and can be viewed in Table 1. Some of our discarded candidate dimensions include the story purpose, data bandwidth, interactivity, and persistence. These were discarded either because they added no clear discriminatory power to the taxonomy, or did not seem consistent with its focus on media types.

### Audience Cardinality (A)

In our notion of the audience of the data-driven story, we also include the storytellers: whether it is one or several people who are creating or viewing the narrative, respectively. A group performance, such as the bubble sort dance in the abovementioned example, would be an example of many storytellers (the dancers) conveying data to many recipients (the audience in the studio).

Note that this dimension refers to when the data-driven story is *consumed* and not when it is *created*. For example, several people may be involved in creating an illustrated report with visualizations, but it would still be classified as a one-to-one audience cardinality because a single report is read by a single reader at a time.

Audience has the following values.

- › *One-to-one (1:1)*: one storyteller and one recipient (such as a private conversation).
- › *One-to-many (1:N)*: one storyteller and many recipients (such as a presenter talking to a group).
- › *Many-to-one (N:1)*: many storytellers and one recipient (such as staff briefing a commander).
- › *Many-to-many (N:N)*: many storytellers and many recipients (such as a dance troupe giving a performance to an audience).

**TABLE 1.** Media types for data-driven storytelling. Classification of our representative (diverse and unique) sample of different media used for data-driven storytelling. Examples in italics are categories.

Example	Audience Cardinality				Space & Time (S&T)				Media Components (MC)						Data Components (DC)					Viewing Sequence (SQ)							
	T1	T1N	N1	NN	Color	Distr	Sync	Async	Audio	Music	Image	Video	Graph	Anim	Text	Tab	Map	Stat	Event	Time	Graph	Textvis	None	Playback	Navig	Basic	Full
Comp. notebooks	☒	☒	☐	☐	☒	☒	☒	☒	☐	☐	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☐	☐	☒	☒
- Jupyter notebooks	☒	☒	☐	☐	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☐	☒	☒	☒
- Observable	☒	☒	☐	☐	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☐	☒	☒	☒
<i>Interactive articles</i>	☒	☒	☐	☐	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒
- Idyll/Parametric Press	☒	☒	☐	☐	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒
- Explorable reports	☒	☒	☐	☐	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒
<i>AR data-driven stories</i>	☒	☒	☐	☐	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒
- AR weather reports	☒	☒	☐	☐	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒
- Immersive hurricane	☒	☒	☐	☐	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒
- AR instructions/train	☒	☒	☐	☐	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒
<i>Data comics</i>	☒	☒	☐	☐	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒
- DataComicsJS (Zhao)	☒	☒	☐	☐	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒
- Graph comics (Bach)	☒	☒	☐	☐	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒
- Sketcholution (Zhao)	☒	☒	☐	☐	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒
<i>Data videos</i>	☒	☒	☐	☐	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒
- Data Clips (Amini)	☒	☒	☐	☐	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒
<i>Annotated charts</i>	☒	☒	☐	☐	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒
- Ellipsis (Satyanarayan)	☒	☒	☐	☐	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒
- ChartAccent (Ren)	☒	☒	☐	☐	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒
- VisJockey (Kwon)	☒	☒	☐	☐	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒
<i>Data-driven performance</i>	☒	☒	☐	☐	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒
- Dance.draw (Latulipe)	☒	☒	☐	☐	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒
- Sorting Dance (Zoltan)	☒	☒	☐	☐	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒
- Arrestre (ballet)	☒	☒	☐	☐	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒
- SketchStory (Lee)	☒	☒	☐	☐	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒
- Augmented chironomia	☒	☒	☐	☐	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒
<i>Slide show</i>	☒	☒	☐	☐	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒
- Tableau Story Points	☒	☒	☐	☐	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒
- StoryFacets	☒	☒	☐	☐	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒
<i>Video games</i>	☒	☒	☐	☐	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒
- Civilization 3 replay	☒	☒	☐	☐	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒
- CoD:BO replay theater	☒	☒	☐	☐	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒
<i>Infographics</i>	☒	☒	☐	☐	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒	☒

## Space and Time (S/T)

The space–time matrix has long been used to characterize forms of groupware based on the spatial and temporal relations of the human users. It is a useful property because both space and time have a significant impact on the delivery and storage mechanism for the data-driven story.

Space and time has the following two values, one for each dimension.

- › **Space:** relative physical locations of storyteller and recipient.
  - *Co-located (coloc):* the storyteller and the recipient are in the same physical space (such as a presenter giving an in-person talk).
  - *Distributed (distr):* the storyteller and the recipient are not in the same physical space (such as a presenter giving a remote talk over Zoom).
- › **Time:** temporal locations of storyteller and recipient.
  - *Synchronous (sync):* the storyteller is delivering the story to the recipient in real time (such as a presenter giving a live talk).
  - *Distributed (distr):* the storyteller is delivering the story in a form that the will be consumed by the recipient at a later time (such as playing back a recorded talk).

## Media Components

The nature of the media captures the composition of the media being used for data-driven storytelling. Since we are typically talking about composite media types, the MC is a set variable for one or several of the following.

- › *Audio (aud):* audio (such as speech recordings, ambient noise, or sampled sound effects).
- › *Music (mus):* ordered sound forming music.
- › *Photographs (pho):* pixmap images.
- › *Live video (vid):* animated pixmap images.
- › *Static graphics (gra):* static vector graphics.
- › *Animation (ani):* animated graphics.
- › *Text (txt):* textual representations.

## Data Components

The core purpose of a data-driven storytelling artifact is to convey data from the storyteller to the viewer. The form that this takes is captured in the DC dimension. It is a set variable of the following values.

- › *Table (tab):* data table representation.
- › *Map (map):* geographic maps.
- › *Statistical graphics (stat):* statistical graphics, such as barcharts, scatterplots, and linecharts.
- › *Discrete event visualization (event):* event timelines.

- › **Continuous time visualization (time)**: time-series data.
- › **Graph visualization (graph)**: network visualizations (such as node-link or adjacency matrix representations).
- › **Text visualization (txtvis)**: text visualizations (such as word clouds or visual concordances).

## Viewing Sequence

The level of interactivity associated with a storytelling artifact governs its level of engagement, cognitive load, and adaptiveness. This variable takes one of the following values.

- › **No interaction (point)**: the artifact cannot be interacted with; it will play from start to finish.
- › **Playback control (playback)**: the viewer can stop and rewind or at least restart the narrative.
- › **Navigation (nav)**: the artifact allows the user to zoom and pan around in the representation.
- › **Basic control (basic)**: the artifact allows the user to click and focus on part of the representation to highlight or trigger other effects.
- › **Full control (control)**: the artifact provides full filtering, linking, and transformation control.

## APPLICATIONS

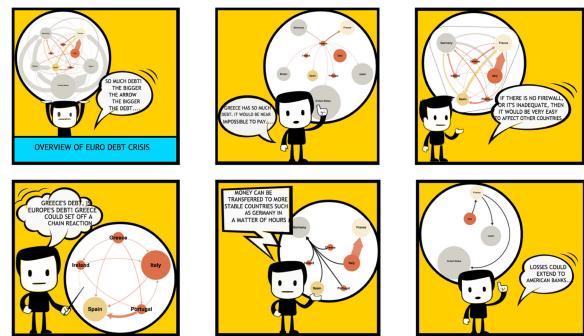
Given our taxonomy, we here explore a few designs for data-driven storytelling.

### Sequential Art for Data: Data Comics

Data comics is an approach to show how *sequential art*—also known as comics—can be used as a novel method for storytelling. Several researchers have studied this phenomenon, including Bach et al.'s,<sup>5</sup> Zhao et al.'s,<sup>6</sup> Bach et al.'s,<sup>11</sup> Zhao et al.'s,<sup>12</sup> Zhao et al.'s,<sup>24</sup> and Kim et al.'s work.<sup>25</sup> We here discuss the first system for building data comics called **DATAComicsJS**, originally proposed in 2014<sup>6</sup> (also the origin of the “data comics” term).

The **DATAComicsJS** authoring system allows the user to build narratives using comic layouts that contain both images, text, figures, and live visualizations. Comic features, such as motion lines, captions, thought and speech bubbles, build on the universal language of comics. The prototype is a Chrome extension and enables the user to create a data comic by clipping images, data, and visualizations in the web browser, and then combining them into comic strips.

Figure 8 is an example of a data comic produced using our prototype implementation by clipping sources and images from the web. More specifically, the designer starts by collecting the data visualizations



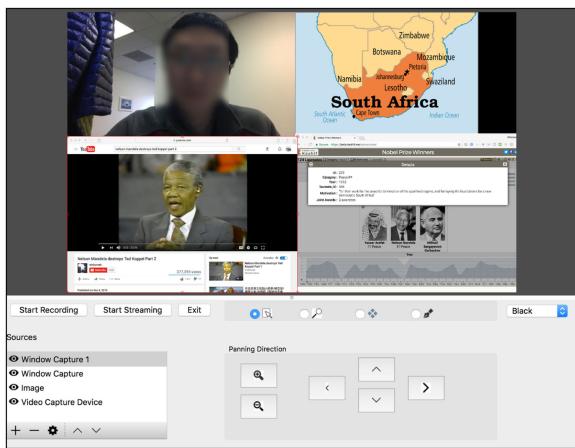
**FIGURE 8.** Data comics. Data-driven sequential art describing the 2014 European debt crisis.

and other material. The designer then crops subgraphs and splits them across panels to allow the reader to focus on one part at a time (rather than the entire thing at once).

In terms of our taxonomy, data comics are designed for entertainment, information, and education. The author cardinality (A) is one-to-many, since that a comic is typically designed to be viewed on a computer or personal device, and thus it has a distributed and asynchronous space and time (S/T) value. Comics are generally not interactive, but they do support navigation. The MC include static graphics, and text, whereas the DC include virtually any static visualization element. Comics are permanent in that they can be stored and transmitted easily.

### Live-Streaming Data Analysis: DataTV

**DATAtv**<sup>26</sup> is a prototype system for authoring live-streaming data videos using a single, integrated desktop interface. The approach is based on the idea of using live-streamed or recorded video for data-driven storytelling. The prototype (see Figure 9) supports three separate modes for 1) production, 2) recording, and 3) editing, in a highly streamlined and optimized workflow that allows a single content creator to control the entire process, even during live streaming. The tool incorporates multimedia sources, such as live webcams, live audio recordings, web browsers, image viewers, and full-motion video. In particular, it supports live recording of any selected window on the user's desktop. This could be used to stream an interactive visualization, a web browser, or a specific application window. Furthermore, the tool incorporates advanced video functionality, such as chroma-keying (making parts of a stream transparent, such as for blue or green screens), picture-in-picture, hand-drawn annotations (for highlighting important parts of a stream), viewport control (zooming and panning), and



**FIGURE 9.** Streaming as a medium for data-driven storytelling. Webcam and Keshif visualization being recorded for the Nobel Prize Winner data video. A data video can be made with the user as the presenter.

advanced source composition operations (transitions, stretching, and fitting).

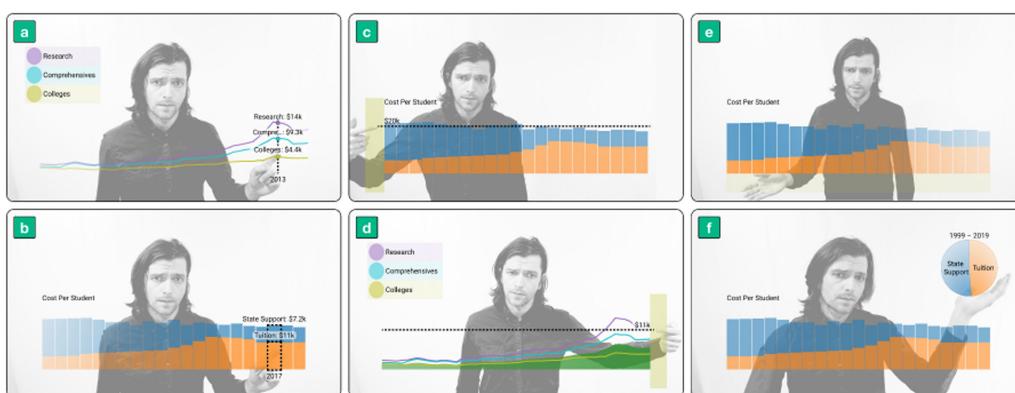
In terms of our taxonomy, DataTV is designed for both entertainment, information, and education. The author cardinality (A) is one-to-many, since a live streaming is typically designed to be viewed on a computer or personal device, and thus it has a distributed and synchronous space and time (S/T) value. Live streaming generally does not support interaction (unless the streamer provides a chat channel for viewers to give feedback), so the SQ is playback only. The MC include audio, live video, static graphics, and text, whereas the DC include virtually any static visualization. Live streaming is generated once, and the interaction cannot be replicated.

## Supporting Oral Tradition: GestureStory

Body language has long been a part of storytelling, but it is only recently that modern technology has enabled people to use their gestures and entire bodies to control digital devices. What if we could use data-driven storytelling to support a speaker talking to an audience, simply by using the speaker's body language and gestures as input to control the audio-visual material (slides and data visualizations) used to support the presentation? Inspired by Lee et al.'s work on SketchStory,<sup>20</sup> where pen input drives the narrative, as well as Hall et al.'s gesture interaction for video presentations,<sup>13</sup> we call this idea GestureStory. Unlike the earlier two applications in this section, this one is fictional; however, Figure 10 showing Hall's system can serve as illustration for the design.

A GestureStory tool would enable the presenter or even the audience to control the visual components of a presentation consisting of data visualizations using their gestures and voices. Similar to Hall's work,<sup>13</sup> the application would presumably use a camera to track body movements and posture. We also envision using a microphone to recognize spoken commands. These inputs be used to control interactive operations, such as panning, zooming, moving, and annotating. The visual components can be made to follow the gesture controls while textual annotations can be added by transcribing the presenter's speech.

In terms of our taxonomy, a gesture story tool is designed for entertainment, information, and education. The author cardinality is one-to-many, since a presentation is typically designed to be viewed in the same location as the presenter while being presented, and thus it has a distributed and synchronous space and time (S/T) value. The benefit of a live presentation



**FIGURE 10.** Gestures for data-driven storytelling. Examples from a data-driven storytelling system by Hall et al.<sup>13</sup> for video presentations where gestures control interactive visualizations.

is that the audience can interact with the presenter by asking questions, so this media supports at least basic interaction control. The MC include audio, static graphics, animation, and text, whereas the DC include most static visualization elements. Gesture stories are generated with the author's improvisations, and thus cannot be replicated easily. We classify it as part of our "data-driven performance" category.

## IMPLICATIONS FOR DESIGN

We have successfully labeled some thirty new and representative examples using our taxonomy (see Table 1). The examples cover movies, documentaries, web articles with data visualization, infographics, comics, social media, visualization tools, games, dance, and sketching tools, which are a large part of the major categories for storytelling.

Our taxonomy is an extension that builds on the foundation that Segel and Heer<sup>3</sup> laid in 2010. While this foundation has proven instrumental in the guiding the development of data-driven storytelling, their model is limited in scope and conflates the delivery mechanism with the media used for the message. We believe our taxonomy provides a more comprehensive view of media for data-driven storytelling while still building on their foundational work. Using our taxonomy, designers will be able to widen the horizon of data-driven storytelling. By providing a taxonomy with detailed dimensions, we explored the possible values for each dimension. By expanding the list of dimensions and dimensions values, we can also keep tracking of the emerging media types. In particular, the terms and dimensions in our taxonomy provides a standardized vocabulary to use when discussing data-driven storytelling. This enables researchers and practitioners alike to classify their own work so that existing and new media can be systematically organized with a common ground.

However, the true value of a taxonomy, such as ours is in generating new ideas by identifying gaps in the literature. By grouping and labeling the dimensions of existing media, our taxonomy can help researchers identify new areas to explore in the future. For example, this new design space can be generated by exploring previously untested combinations of dimensions. We have done so in the previous section: the DataComicsJS authoring system as well as the DataTV and GestureStory applications are all based on our taxonomy.

A common theme for many of the novel storytelling methods such as Distill, Idyll, and even some data comics is *interactivity*. This clearly goes in hand with the old adage attributed to Confucius that "*I hear and*

*I forget/I see and I remember/I do and I understand.*" In other words, learning is best scaffolded by interactivity that allows the learner to change parameters and study its effects. A concrete example is Omar Shehata's Parametric Press article "Unraveling the JPEG,"<sup>4</sup> which provides many interactive tools for exploring the surprising depths of the JPEG image format. It is clear that the future of data-driven storytelling will include interactive media.

A particular such interactive medium is video games. We have already surveyed some examples of data-driven storytelling in games (or created through the use of games in what is known as *Machinima*), and we think that there is significant potential for this in the future. In particular, games for education and/or games in augmented reality may be particularly fertile grounds for adoption data-driven storytelling. This points to an obvious limitation to our survey: that we do not go far enough. Our survey corpus is diverse and unique, but that is no guarantee that it is exhaustive or even complete. We think data-driven storytelling should be a constant work in progress, just like storytelling in general, and we look forward to seeing new and experimental innovations in the future.

Let us close on Marshall McLuhan's famous note that "*the medium is the message.*"<sup>27</sup> It is clear that the medium used to convey a story will also affect the message and content of that story. This is not only true because the medium we choose affects the audience that will be able to consume it, but also that the unique aspects of the medium gives specific capabilities to the storyteller. We look forward to seeing how the data-driven storytelling community will explore such novel media in the future.

## CONCLUSION

We have proposed a taxonomy of media for data-driven storytelling for the purpose of widening the discourse on which storytelling techniques can be used for telling stories about data. Our work began with a survey of the wide range of evidence of such novel data-driven stories, resulting in us identifying several representative dimensions to categorize these media types. We then defined our taxonomy and used it to classify a large collection of novel data stories. Based on these ideas, we propose several novel applications for data-driven storytelling, and then close this article with some takeaways for designers looking to expand their repertoire in this domain.

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<sup>4</sup>[Online]. Available: <https://parametric.press/issue-01/unraveling-the-jpeg/>

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