- Outline challenges in designing and developing for spatial computing, including highlighting specific nuances that are design challenges in AR given its overlay in the real world, and its distinction from VR

In Chapter 9, Erin Pangilinan defines data and machine learning visualization and its unique design opportunities in immersive technology. New design paradigms not conceived before with design for desktop and mobile platforms are made possible with spatial computing. She describes challenges with respect to the current ergonomic obstacles facing AR and VR, and offers resources and references to hands-on tutorials to get started creating data and machine learning visualizations in XR. Although this chapter is unable to fully cover and discuss data visualization startups with 2D dashboards analyzing user data (those like EaseVR, CognitiveVR, Retinad, etc. doing more involved analysis than simple heatmaps in Unity of XR applications), it references other aspects of embodied reality with use case examples across various B2B industry verticals visualizing data from the human body (particular to health technology—biotech not covered in Dilan Shah's discussion in Chapter 11), some of which are considered "big data" and render in real time at scale.

Chapter 10, by Unity staff Nicolas Meuleau and Arthur Juliani, describes existing AI paradigms, including reactive AI, deliberative AI, and reinforcement learning; how they are challenged by XR; and the answers they can bring. The applications involve behaviors such as animations, nonplayer characters (NPC) activities, and storytelling —behavior of the world. Meuleau focuses on behavior planning and automated animation as a part of Unity's offerings. You learn machine learning–based approaches, particularly reinforcement learning, and imitation learning methods involving player data of games in XR. Toward the end of the chapter, you learn about designing behavioral sets of demonstrations, both human provided or generated by another means (players playing games and, even more significant in AR and VR environments given a user's human body movements, gestures, we are able to use data to inform behavior of autonomous agents in simulation).

AI can be used to generate content that augments technical 3D artists in the game development pipeline as seen at Nvidia's talk at The Game Developer Conference (GDC) 2017 "Zoom, Enhance, Synthesize! Magic Upscaling and Material Synthesis using Deep Learning", Deep learning algorithms such as style transfer were used in the creation of 360 degree films by Facebook, as screened during the Tribeca Film Festival 2017. Although these are not completely covered given the limited capacity for our scope here, software engineers and designers continue to show how to enhance their XR applications and experiences through cutting-edge AI algorithms and novel ways of representing and visualizing data (user or real-world data) in a new medium. AI outside of this part can be described more in detail in the chapter on SLAM and AR cloud authored by 6D.ai cofounders, Matt Miesnieks and Professor Victor Presacariu as well as Dieter Schmalsteig's work describing in detail the overlap between XR and visualization with regard to the data pipelines in VR and AR as it relates to spatial models, object detection, 3D tracking, and rendering.

CHAPTER 9

Data and Machine Learning Visualization Design and Development in Spatial Computing

Erin Jerri Malonzo Pangilinan

Introduction

Data and machine learning visualization are transforming the future of the workplace. Framing design principles is valuable. Companies such as VR Fund–backed company, Virtualitics, which was founded by Caltech PhDs, raise large rounds of funding based on good design principles. There are also many other data visualization independent consultancies popping up across all spatial computing platforms. Many of these are within the businesses service sphere with significantly large datasets, in the B2B verticals of fintech (finance tech), health technology, and biotech.

We begin this chapter by discussing the relevance of the topic to the users experiencing data and machine learning visualization applications. We then offer a framework to consider for identifying useful purposes that make the topic unique to spatial computing versus any other platform. We outline our goals to understand, define, and set data and machine visualization design and development principles in embodied reality. Then, we discuss various challenges with data and machine learning visualization in XR, describing various examples of industry use cases for data and machine learning visualization built on top of open source data and frameworks (though some interesting work has also been done with open source frameworks and proprietary data). Toward the end of this chapter, we highlight references to tutorials for creators of data and machine learning visualizations, whether you are new or a seasoned software engineer or designer accustomed already to working on web platforms (you can easily use in A-Frame in JavaScript or other frameworks) or in native development, C# on Unity. There are a few figure examples that were created using C++ and Unreal Engine.

Understanding Data Visualization

Although whitepapers like the IEEE's "Cost-benefit Analysis of Visualization in Virtual Environments (VEs)" question the relevance and purpose of visualization in XR, asking "do we really need 3D visualization for 3D data?" Quite simply this chapter's basis assumes from the beginning that the use of VEs enables a better understanding of 3D data, given appropriate context, thoughtful design, and development.

First, we describe and define data visualization in XR and what makes it unique to other previous mediums. We look at the distinctions between interactive big data visualization versus pure infographic representation.

Considered the godfather of data visualization, statistician Edward Tufte writes that for centuries painters, animators, and architects have been attempting to represent data (2D and 3D) on a variety of displays (primarily in 2D space), using perspective and motion. Note that many static infographics lack motion or general understanding of perspective and thus do not qualify as "good data visualization" in spatial computing; the experience is mostly passive and does not enable rotation or other principles discussed later in this chapter. Data and machine learning visualizations enable users to see, explore, and better understand data. As said by Fernanda Viegas and Matt Wattenberg (Google's People and AI Researchers focused on data visualization) at NeuralIPS 2018, data visualizations transform data into visual encodings that help users educate, communicate, give insight, and better explore the data. Without visualization, data is just dead numbers on a page.

In his seminal book, *The Visual Display of Quantitative Information* (Graphics Press, 2001), Tufte writes that data visualization makes human understanding of large datasets more coherent. It serves a clear purpose to describe data represented in various forms; for example, as abstractions (pie charts, bar charts, etc.) and often as a term to describe 3D reconstructions of data as objects in 3D space (e.g., 3D reconstructed anatomical structures such as brain data, and flat slices of magnetic resonance imaging [MRI] files in an augmented and virtual environment). The data itself is comparative, relational, multivariate, and can allow the user to inquire specific questions or explore data generally to gain a better understanding of its qualities. Here are some of the key characteristics of interactive data visualizations in XR:

- It can plot and sort relational data through integrating descriptions to distinguish categorical data, whether it is qualitative data and can involve some statistical traits (focus on quantitative data).
- It involves information architecture that shows it as dynamic and provides interactivity to the user.

- It emphasizes aesthetics to help users understand data through good design, not just for the purpose of decoration.

Data is far less comprehensible without visualizations. As deep learning researchers put it, "data visualizations and visual analytics can be used to excel at knowledge communication and insight discovery by using encodings to transform abstract data into meaningful representations."[6]

Interactivity and animation on all platforms, desktop, mobile, and spatial computing help users make data more accessible and malleable with direct manipulation with various sets of inputs and controls.

Principles for Data and Machine Learning Visualization in Spatial Computing

Referencing the framework by deep learning researchers,[6] data and machine learning visualization creators in spatial computing should explore the five W's that will help give them a foundation to create successful applications experiences in spatial computing.

Creators should consider the design of their user experience by starting with the following: identifying their target users (Who) and where it is appropriate to use data visualization (When), the type of data visualization created (What), justify its existence as optimal in spatial computing and Why before they identify the method or (which type of visualization) that involves or does not involve machine learning before they begin selecting Where to house, process, visualize this data before selecting How (which languages to use for which platforms).

We explore more about approaches on methods and how to create the actual visualization at the end of this chapter, where we consider the holistic data-to-visualization engineering and design pipeline process.

Here is an example of those principles in practice. More specifically, the creator should consider these factors to be intentional about their visualization creation process:

Why
: *Identify the purpose, ask yourself why does this data or machine learning visualization make sense in spatial computing versus other computing.* The creator should consider the interaction of the so that the user can directly manipulate and unlock other insight to have an effective data visualization experience that would not be possible in other mediums.

Who

Specify target end users of the data or machine learning visualization spatial computing experience/application and what benefits they will gain from their experience in spatial computing (e.g., Surgeons monitoring brain data and other anatomical structure information).

We will go into detail about this as we describe data categories and how the kinds of interactions depending upon the platform of choice have evolved over time for various visualizations in Figure 9-4.

What

Select scope and size of the type of data, how large it is, and how much they desire to visualize. For specific MRI data of patients with cancerous tumors). Not all brain data is equal; for example, for larger datasets involving brain imaging, within the space of brainmapping and connectomics, researchers in Spain chose to visualize subset multidimensional data for a spatial computing visualization using Unity.[11]

Where

Select the most appropriate spatial computing platform to target either Head Mounted Display (HMD) or mobile display. Consider various prototyping tools in 2D (see in resources section at the end of this chapter) on non-spatial computing (desktop and mobile) platforms if possible. The creator should understand the complexity of data so that they know if it must be pre-processed and where it is stored and housed (on the cloud using Amazon Web Services, in the format of JSON). This may or may not involve some prototyping (sometimes this involves using 3D with in 2D tools), before loading and visualizing data fully within XR.

How

Select what method to use when you create your data or machine learning visualization. Basic visualizations do not require a ton of pre-processing, but for those that do (often ones that use Python) the whole pipeline must be considered. Select other programing languages you shall use for the platform selected to visualize the data (ex. C#, C++, JavaScript) and which Integrated Development Environment (IDE) program to use to (Unity, Unreal Engine, other game engine, your own proprietary engine to create, this book features examples predominantly from the first IDE).

Who

Some data visualizations are made for practical use that aid marketing professionals, business analysts, and executives by being able to display and interact with data, leading them to better discrete business decisions. Others might be machine learning engineers, data scientists, or software engineers who seek to find optimization techniques, explore model interpretation and can make these discoveries through spatial computing visualization exploration. They can better see layers underlying more complex multidimensional data within spatial computing than other mediums. Here visualizations serve as solutions to "the curse of dimensionality," meaning to condense multidimensional data into a more comprehensible format.

On the other end of the spectrum, some visualizations often are miscategorized as data visualizations and actually fall into the spectrum of presentation and infographic design and are seen as "beautiful" artistic experimental pieces; they are perceived as created for the purpose of being purely decorative, or more for aesthetic value and appreciation than they are for practical use. We go into detail about this as we describe data categories in Figure 9-4 later in this chapter.

Why Data and Machine Learning Visualization Works in Spatial Computing

We delve into this topic deeper as we describe the evolution of data visualization design, how its purpose has improved and evolved with the introduction of spatial computing as medium its purpose, various categorizations of data and effective interaction designs.

The Evolution of Data Visualization Design with the Emergence of XR

Tufte goes on to say in his later book *Beautiful Evidence* that data visualizations provide producer and consumers of the creation to display evidence. He further explains that the basis of visualization design comes from underlying fundamental principles of analytical design, which are agnostic to "language or culture or century or technology of information display." Tufte elaborates:

> Powerpoint is like being trapped in the style of early Egyptian flatland cartoons rather than using the more effective tools of Renaissance visual representation.
>
> The principles of analytical thinking—and not from local customs, intellectual fashions, consumer convenience, marketing, or what the technologies of display happen to make available.[13]

Although this is true, some of the data visualization design best practices (which are primarily designed for paper, desktop, and mobile mediums) can be seen as obsolete and do not all directly apply in the medium of the XR spectrum because they account for designing primarily for only a 2D space with flat user interface (UI), even with 3D data, or a single window or screen. This limits the user and does not allow the user and producer to fully understand the data discoveries that can be unlocked with the potential of emerging technologies. These technologies can enhance analytical thinking, given the emergence of computational search and artificial intelligence (AI) displaying multidimensional data that can be more easily explored with new technologies.

Tufte, like many other data scientists and academics have criticized "bad" 3D data visualization such as 3D pie charts and instead offer more simple approaches to data visualization, stating that 3D geospatial data with a simple map on 2D paper suffices. They dismiss the use of any 3D visualization altogether, but this is misguided and backward. With the introduction of AR and VR, the UI of 3D geospatial maps has evolved much since the time that Tufte had created the paper 3D map. New conceptions of data are now encoded into the actual application experiences that improve the user's interaction with their data. For example, in WebVR, maps tend to look more like a game in which users can move in the z-plane, as depicted in Figure 9-1. Data visualizations can be "gamified" into mobile VR platforms (see Figure 9-2) on ARKit and MapBox.

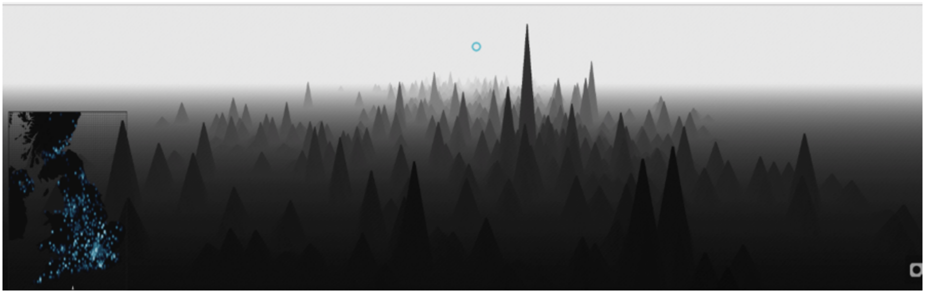

Figure 9-1. A plot of the number of times people indicated that they disliked British television host Piers Morgan in a specific region, made in the webXR framework, A-Frame, which is viewable on a VR headset[1]

This uses an old version of A-Frame (0.2.0). Some code might not achieve the desired results. If possible, upgrade to the latest version of A-Frame (which as of this writing is 0.9.0). All major browsers (Chrome, Firefox, Oculus Browser, Edge etc.) will begin support of the WebXR specification in 2019. The old webVR API will be deprecated.

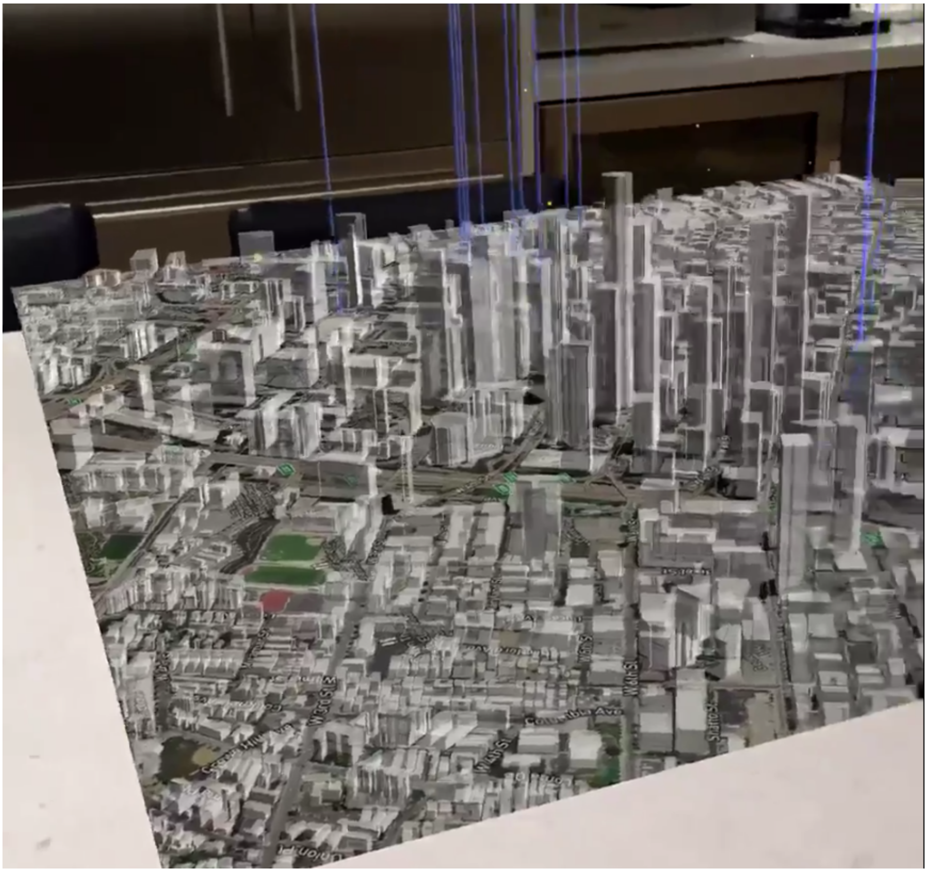

Figure 9-2. Data visualization mapping FourSquare check-ins using ARKit and MapBox by technologist Aaron Ng

Furthermore, AR and VR input enable new interaction paradigms that were not possible before in 2D space, which redefines human–computer interaction (HCI) as user interface via controllers, begin to directly load, and directly manipulate data with more sophisticated voice (via natural language processing [NLP] evolutions) and touch controls (haptics as they also continue to develop).

Much has been written about data visualization restricted to a 2D plane or 3D data that has been trapped in a 2D medium (which is very constraining for digging deeper into insights for those working in the fields of biotech and health technology, with data ranging from human anatomy in medical imaging microscopy, DNA molecular visualization, and protein visualizations) in 2D abstract data in a 3D space.

In his book, *Fundamentals of Data Visualization* (O'Reilly Media, 2018), University of Texas professor and trained biologist, Claus O. Wilke, emphasises *position* in XR as part of his discussion of data visualization. He talks about the importance of various elements (color and line) and so on. The focus for this chapter is on *positionality*, given XR's ability to place data as objects on the z-axis rotation.

2D and 3D Data Represented in XR

There are different types of data shown in data visualization within desktop, mobile, and spatial computing platforms. The categorical data shown in Figure 9-4 ranges from static to dynamic on various platforms. The types of data that are represented often in XR include the following:

- Abstractions of 2D data seen in 3D within XR (often seen as bar charts and line charts)
- 3D data from 2D data (anatomical structures such as brain fMRI imaging that is reconstructed several times over to look 3D and fit into 2D space)
- 3D data represented in 3D space, within XR (DNA molecular visualizations seen in XR)

After you select the type of data you are working with, you can visualize that data.

Some data makes less sense to visualize than other data. For example, Tufte references 3D pie charts as backward. Wilke continues this and specifically points toward effective data visualizations in XR that are all about the *context*.

Wilke says, "...it makes sense to use 3D visualizations when we want to show actual 3D objects and/or data mapped onto them."

2D Data Visualizations versus 3D Data Visualization in Spatial Computing

Although Tufte has been widely quoted against the incorrect usage of 3D data visualization (namely abstract data out of context like pie charts, which he believes add no substantial difference than a 2D visualization) and fancy animations, other scholars like Wilke show that there is some value in 3D data visualization and in spatial computing because they understand its ability to engage the user with their data in ways that are not constrained in a 2D screen. 3D data visualization by itself, without appropriate thought for the type of content and how it is represented, does not suffice. Interaction for the sake of interaction would make some sort of artistic piece, but it would not necessarily make an experience of data visualization and not necessarily involve data. There must be careful consideration into the design choices in XR. The recommendation to avoid it altogether, however, is short sighted. If we avoided 3D