

9. Just 5 Questions: Toward a Design Framework for Immersive Analytics

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Abstract. We present an initial design framework for immersive analytics based on Brehmer and Munzner's "What-Why-How" data visualisation framework. We extend their framework to take into account Who are the people or teams of people who are going to use the system, and Where is the system to be used and what are the available devices and technology. In addition, the How component is extended to cater for collaboration, multisensory presentation, interaction with an underlying computational model, degree of fidelity and organisation of the workspace around the user. By doing so we provide a framework for understanding immersive analytics research and applications as well as clarifying how immersive analytics differs from traditional data visualisation and visual analytics.

Keywords: immersive analytics, visual analytics, data visualisation, information visualisation, design framework

9.1. Introduction

This chapter is a first step toward a design framework for Immersive Analytics (IA). Such a design framework is intended to serve two important purposes. The first is to provide methodological support for the development and evaluation of IA applications. The second is to provide a way of organising, understanding, and analysing IA research. In addition, such a framework should clarify how IA

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differs from traditional data visualisation and visual analytics applications and research.

Our design framework brings together the various aspects of IA research explored in the previous chapters: use of spatial immersion, multisensory analytics, natural interaction, responsive human-in-the-loop analytics, situated analytics and collaboration. It is based upon Brehmer and Munzner's [4] well-known "*What-Why-How*" data visualisation framework. But we have extended this in three main ways.

First, to provide necessary contextual information about the intended IA applications we extend the framework with two additional questions:

- Where is the system to be used including on what kind of platform, and
- Who are the people or teams of people who are going to use the system?

Where allows us to take into account different interaction and display capabilities such as the degree of spatial immersion or world knowledge, i.e. knowledge of the physical environment, as well as the characteristics of the physical environment in which the application will be run. For instance, is the system to be used in a controlled environment like an office or in the field?

Who allows us to take into account different types of collaboration as well as user characteristics and needs. For instance, is the application to be used by a single analyst or a group of analysts, or is it designed to communicate data findings to the local community?

The second major modification is to the *How* component. We extend this by considering all sensory channels (not only vision), adding support for collaboration, including a representation of oneself and others (i. e.avatars), explicitly considering how to position views in the 3D environment around the user as well as the degree of representation fidelity.

The third modification is to broaden the *What-Why-How* framework to explicitly include the use of computer models so as to better capture all aspects of human-in-the-loop analytics. This includes machine-learning based data modelling and optimisation-based decision support in which interactive visualisation is used to understand and refine the computational model as well as to understand the original data. This adds other aspects to *What* and *How*: the kind of analytics provided, and the idioms used to build, use and understand the analytical model.

The resulting five question framework, *Where-What-Who-Why-How*, provides a rich multidimensional categorization for designing IA applications and understanding IA research. However, given the current immaturity of the field, the proposed framework should be viewed as a work in progress and will undoubtedly require refinement in light of future research.

In Section 9.2., we review previous design frameworks for data visualisation, scientific visualisation and visual analytics as well as the What-Why-How framework. We then sketch in Section 9.3. a high-level view of the major components and processes in an IA application. In Section 9.4., we present the five question design framework for IA. In Section 9.5. we show how the framework applies to six existing applications. Finally, in Section 9.6. we discuss some research questions

and issues suggested by the framework including evaluation and conclude the Chapter in Section 9.7.

9.2. Design Frameworks for Data Visualisation & Visual Analytics

Data visualisation frameworks and taxonomies fall into a number of different categories. The first category focuses on the structure of the visual representations and how the underlying data is mapped to a visual representation. Starting with Bertin [3] these frameworks detail how low-level graphical primitives, with geometric and non-geometric visual attributes (such as colour), can be combined to create sophisticated data visualisations [31, 50]. Others detail useful mappings between different kinds of data and visual representation [6, 52].

The second kind of framework focuses on the user *tasks* and the purposes for which the visualisation is being used. The sense-making loop [39] captures the high-level process by which analysts make sense of data while the knowledge generation model [42] considers the processes used for human-in-the-loop knowledge discovery. Both are widely used in visual analytics. A related model, called the problem-solving loop, has been suggested for human-in-the-loop optimisation [30].

There has also been considerable attention focussed on developing lower-level task taxonomies for data visualisation and visual analytics [1,2,17,23,44,53] or for specific kinds of data [28]. Many of these also suggest appropriate visualisation and/or interaction idioms for the tasks. A framework emphasising cognitive aspects of data visualisation has also been proposed [36].

Another category of frameworks, called *pipelines*, emphasise computer and user processes [46]. Card *et al.*'s [7] well-known data visualisation pipeline has three main steps: structuring and filtering the raw data, mapping data onto visualisation primitives, and rendering of the visualisation. The knowledge discovery pipeline [47] captures the processes for human-in-the-loop generation of a computational model for the data. It consists of data integration, cleaning, warehousing and selection, data mining, pattern (model) evaluation and rendering of the visualisation.

More recently, Brehmer and Munzner [4] introduced the *What-Why-How* design framework for data visualisation. Refined and elaborated by Munzner [34], this is widely used in the data visualisation community. It combines the task-oriented and data-oriented frameworks, capturing that the choice of visual and interaction idioms depend upon both data and task. As its name suggests, it is built around three fundamental questions:

- What is the kind of data to be visualised?
- Why is the data being visualised-what task does the user wish to perform?
- How is the data visually represented and how should interaction with that representation work? That is, what data visualisation and interaction idioms should be employed?

A number of researchers have explored some of the issues arising in data visualisation applications that move beyond the traditional desktop, e.g. interaction [27], placement of 2D views [15] and data physicalisation [20, 51]. However, to the best of our knowledge there has been no previous attempt to develop a general design framework for analytic applications in immersive environments.

9.3. Architecture of IA Applications



Fig. 1: Abstract architecture of an immersive analytics application that supports collaboration in a mixed-reality environment. Boxes represent data, while arrows indicate processing steps or interaction.

As a first step in developing a design framework for IA we sketch the abstract architecture of a generic IA application.⁸ This is shown in Figure 1. Not all components would be needed in all IA applications.

At the highest level the immersive analytics process consists of a tightly coupled *presentation* and *control* loop that allows users to *discover* the answer to their question, *present* findings or simply *enjoy* exploring the data [4]. At the architecture's core is the data visualisation pipeline after Card *et al.* [7], generalised to *map* data to a multisensory representation whose elements are *positioned* in the mixed-reality environment. *Rendering* is generalised from simple visual rendering to include other modalities such as auralization, haptic presentation or data physicalisation. The user can *choose* and *transform* the raw data to create the processed data. They can *filter*, *compare* and *derive* new data from existing data, *navigate* through the multisensory presentation or *select* elements [17] as part of the analytics process [22]. The pipeline is further extended in five ways:

⁸ The architecture is idealised and does not show how data and processes might be shared in a distributed setting.

- 1. In order to cater for mixed-reality presentations and data physicalisation, the physical environment is considered to be part of the presentation. Information about the physical environment—and the location and pose of users—is gathered through sensors and is part of the integrated data representation. It is termed *system world knowledge* [33].
- 2. Furthermore, interaction is now blended [14]. Users can interact with the IA application through conventional controllers like touchscreens or with voice commands. Alternatively, gestures, physical navigation in the environment or manipulation of objects in the environment can be sensed using appropriate devices and employed for user control in addition to updating the system world knowledge.
- 3. To more fully capture the importance of analytics, the pipeline now explicitly includes models. In the case of knowledge discovery this might be a new classification model learnt from the data or an existing model fitted to the data. In decision support this might be an instance of an optimisation model instantiated with the current data. Or in scientific modelling it might be the use of simulation to predict behaviour. The model is *built* from the data and used to *generate* trends, solutions, simulations, clusters or to test hypotheses [42].
- 4. Collaboration is a fundamental component of many immersive analytics applications. Users may be co-located in the same physical environment or work together remotely in a mixed-reality environment. Collaboration may be synchronous or asynchronous. Regardless, users experience a fused multisensory presentation and can interact with the immersive analytics application and with each other either directly or through the application.
- 5. Collaboration and provenance are supported by *narratives*. These are composed of *annotated* scenes or interactions, sequences of annotated views, text, etc., that are used to *record* a history of user actions. Users can communicate with collaborators and external stakeholders by *sharing* and *guiding* other users through these narratives [17, 40].

9.4. The 5 Question Design Framework for IA

We now describe how Brehmer and Munzner's *What-Why-How* framework can be extended to provide a design framework for immersive analytics applications. Table 1 summarises the extensions. In short we need to provide more contextual information about *who* the intended users of the application are and *where* and on what platform they intend to use it, as well as by extending the kinds of idioms considered in *how* to include spatial immersion, collaboration and multisensory presentation. We now look at these in more detail.

9.4.1. Where

In traditional data visualisation and visual analytics the default, often implicit, assumption is that data visualisation is taking place on the desktop and so details

What-Why-How Framework	5 Question Framework
	Where Presentation Interaction World Knowledge Environment
What Dataset Types Tables, Networks, Fields, Geometry Dataset Availability	What Dataset Types Tables, Networks, Fields, Geometry, Function Dataset Generation
	<i>Who</i> User Collaboration
Why High-level Tasks Consume Discover, Present, Enjoy Produce Annotate, Record, Derive Medium-level Tasks Search: Lookup, Locate, Browse, Explore	Why High-level Tasks Discover, Present, Enjoy Medium-level Tasks Search: Lookup, Locate, Browse, Explore
Query: Identify, Compare, Summarize/Overview	Query: Identify, Compare, Summarize/Overview Annotate, Record, Share, Guide Derive, Build , Use
How Encode Manipulate Facet Reduce	How Encode Manipulate Facet & Position Reduce Collaborate Render Model

Table 1: The *What-Why-How* data visualisation design framework and the proposed IA design framework. Extensions and modifications are shown in **bold**.

of the output and interaction devices can be ignored. In IA applications, however, platform capabilities significantly affect the design of the most appropriate analytics tool.

Presentation: Different output devices such as desktop, HMD-based VR, AR, smartphone, smartwatch, tablet, large-wall or tangible display have quite different resolutions, viewport sizes and capabilities. This large range of sizes and capabilities mean that there is no single best visual idiom and the choice will depend upon the output device. Furthermore, new output devices introduce new challenges that go well beyond traditional GUI design. Consider, for example, that a user standing close to the left side of a wall-sized touch display will not be able to directly see and/or interact with content that is shown on the other end of the wall [21, 35].

Moreover, as discussed in Chapter 2, these output devices differ in how well the display of 3D content is supported. For instance, the use of depth on a traditional desktop display may not be effective because of the limited depth cues but quite effective when using a desktop fish tank VR display or a modern head-mounted VR display because motion perspective and binocular disparity support better depth perception.

Finally, presentation is not limited to vision. Other modalities such as sound or touch may be provided in an immersive environment. Which modalities are provided and the capabilities of the presentation devices is also part of *Where* (see Chapter 3).

Interaction: Another component of *Where* are the interaction modalities provided by the system (e.g., natural language, touch, gesture and tangible controllers). It is important that the interaction modalities are suited to the environment and the user behavior. For example, in an AR setting in which the user can freely move around, mouse or keyboard input can be cumbersome and touch, gesture, or a laser pointer [37] may be more suitable (see Chapter 4, Section 4.5.).

World knowledge: Another important characteristic of an immersive platform is the extent of world knowledge the system has access to (see Milgram *et al.* [33]). System world knowledge requires the platform to have sensors that allow it to sense its physical environment—objects and their position, lighting, and the position of the user—as well as an internal model of the environment which abstracts and makes sense of the raw sensor data. The range of system world knowledge in IA systems goes from traditional data visualisation on a desktop computer in which the platform is oblivious to its physical environment, to AR platforms like the Microsoft HoloLens which provide a sophisticated model of the objects in the environment.

Environment: The final component of *Where* are the characteristics of the environment in which the application is to run. These include physical aspects like the level of ambient noise or light, as well as social aspects such as whether users expect to be frequently interrupted.

However, it is important to recognise that the ability to use other sensory modalities, interaction modalities or world knowledge does not necessarily mean

that they should be used. The choice of whether to use these is part of the *How* aspect of the design framework.

9.4.2. What

The *What* component of Brehmer and Munzner's framework covers the type of the original data and pre-processing before visualisation. For an in-depth description of the data types, we refer the reader to Munzner [34] since this aspect is largely independent of whether the application is immersive or not.

We have added one new generic dataset type to the framework: *function*. In Munzner [34] only *explicit* data representations are considered. These provide a set of data samples to describe an object and use interpolation between the data samples to model continuous objects. For example, in a mesh, the object is specified using a set of vertices as well as a topology describing the interconnection of these vertices. Depending on the topology, samples at the vertices can then be interpolated appropriately across the resulting surface. However, in scientific computing applications, *implicit representations* that use an analytic description of the object, e.g., equations defining a surface, are also common. Implicit representations can be computed from terse parametric descriptions, a very simple example being spheres generated from just a radius and a position. These analytic descriptions have to be evaluated, i.e. sampled, at an adequate frequency to compute an appropriate (visual) appearance of the object. The *function* datatype captures the use of such implicit data representations.

The What-Why-How framework also considers dataset availability, i.e. whether a dataset is static or dynamic. We generalise this to consider interactive generation of data. As well as considering whether raw data is static or dynamic, dataset generation details data preprocessing and any underpinning analytics model, as well as the level of interaction supported.

Efficiency of data processing is a major concern for IA because of latency: delay in rerendering of the scene due to user interaction. Slow data processing can disrupt the user experience (and thus immersion) (also see Chapter 5). Efficiency depends upon how directly the data is mapped to its presentation, i.e., how much processing of the data is performed before it is mapped to the presentation channels. For example, multi-dimensional scaling or topological analysis methods like vector field topology require extensive processing of the data. Directness is a continuum, different methods require a different amount of data processing.

9.4.3. Who

In traditional data visualisation the diverse perceptual, cognitive and physical capabilities of the user population are rarely taken into account. A notable exception is colour blindness for which there exist colour blindness simulators and design guidelines. The default scenario also assumes a single user rather than a collaborative setting. These two aspects are considered explicitly in our framework.

User: In IA the use of non-visual presentation modalities and alternative input modes (e.g., gesture, touch and speech) results in a much wider range of user capabilities and preferences that need to be taken into account. While this means that it is now more likely that a particular user will be unable or prefer not to use some of these modalities, there is also the opportunity to improve access by providing alternative modalities. We also need to take into account cultural conventions, age, educational level and familiarity with immersive technology when developing personal analytic applications and narrative visualisations.

Collaboration: If the IA application is to be used collaboratively the tool must support this. Thus an important part of the design context is to answer the following questions. Is the tool to be used collaboratively? If so, how many people will be involved in the collaboration (a few or many hundreds)? Do they have different roles, and what does this entail? Are users collaborating locally or remotely? Are they collaborating synchronously or asynchronously? (see Chapter 8).

9.4.4. Why

Brehmer and Munzner [4] identified three high-level consume tasks of discover, present and enjoy. These respectively captured the use of data visualisation to discover new information, communicate findings and the casual use of data visualisation application for entertainment. We feel these also capture the highlevel use of IA applications. In addition, Munzner [34] identified three high-level produce tasks-annotate, record and derive. These were distinguished from the consume tasks because they add information to the data store. We think this distinction between consume tasks and produce tasks is unhelpful since, in our opinion, the three produce tasks are instead medium-level tasks that are often subcomponents of the higher-level consume tasks.

We organised the medium-level tasks around three activities:

- Traditional data visualisation: Based on Brehmer and Munzner [4], we identify three kinds of tasks: *search* which captures looking-up an item, locating an item, browsing and exploring the dataset; *query* which identifies/details a single item, compares or summarises multiple items and *derive* which produces new data items from old data items by, for instance, changing type or by using arithmetic or statistical operations. *Search* and *query* encompass the slightly lower level tasks of filter, sort, select and navigate identified by Heer and Schniderman [17].
- Model use: Based on Sacha *et al.* [42], models have two associated activities [42]: *Build* the model by, for instance, learning it from the data or instantiating a predefined model with the data, and *use* the model to produce new data such as trend lines, clusters or solutions to an optimisation problem.⁹

⁹ In the *What-Why-How* framework model use would be regarded as an example of *generating* new data. However, we feel that it is useful to distinguish between simple

- Narratives: Based on Heer and Schniderman [17] and Ragan et al. [40], we have four tasks associated with narratives: annotate visualisations to document/communicate findings, record narratives and history for provenance, review and sharing, share views, narratives and annotations for collaboration and communication, and guide users through analysis tasks or narratives.

9.4.5. How

A major modification to Brehmer and Munzner's framework is the need to generalise the *How* component. Munzner [34] divides *How* into four aspects. As shown in Table 1 we extend this classification by introducing *render*, *model* and *collaboration* aspects and adding view placement in the virtual world to *facet*.

- Encode: How data is mapped to visual and spatial variables as well as to other sensory channels in each view;
- Facet and Position: How different views are arranged and combined, and where they are placed in the immersive environment;
- **Render:** Degree of fidelity and choice of graphics rendering model;
- Manipulate: The choice of user interaction idioms for controlling data manipulation and presentation;
- Reduce: The different ways for aggregating and filtering data;
- Collaborate: Idioms for collaboration including construction of narratives and providence;
- Model: Idioms for building and using analytical models.

While we still feel this classification is useful, in immersive analytics the different aspects are not as clearly separated as they are in a desktop environment. For instance, with data physicalisation or blended situated analytics interfaces encoding and manipulation are closely linked because the same artefact is used for both data display and input.

Encode: Generating a view of the data requires the designer to map data dimensions to different *visual variables* (also called *visual channels*) in order to construct a visual idiom or metaphor. For example, one data dimension can be mapped to the height of a rectangle, another to its position in one dimension and a third to its colour, which results in a bar chart. The visual variables can be classified as spatial properties (position, size, orientation, aggregated shape—line, glyph, etc.), visual surface properties (hue, saturation, luminance, texture), and motion and blinking (motion pattern, velocity and timing, and direction) [48].

Traditional information visualisation eschews the use of the third dimension, depth. However, as discussed in Chapter 2 there are tasks (Why) for which the use of a third dimension in a view may in fact be beneficial, especially if the display platform provides head-tracked binocular presentation (Where). If depth

data transformations or computations such as subtracting two attributes to give a new attribute, and task involving true computational analytics.

is used as a visual variable then a key design decision is to choose which depth cues to use. When doing so it is important to take account of dependencies between depth cues [48].

Occlusion, the need for supporting viewer movement and/or navigation as well as challenges in precisely determining position and distances between points are potential disadvantages of using depth. Shadows, navigation grids, drop lines, transparency, use of orthogonal projection rather than linear perspective are techniques that may mitigate these disadvantages. Furthermore, the use of linked 3D and 2D representations allows both overview and fine-grained comparison and control [38]. Choosing which, if any, of these techniques to use is another design decision.

While vision will remain the most important and commonly used sensory channel for encoding data because of its high-bandwidth and low-level parallel processing, immersive environments offer the possibility to use non-visual variables to present data. There a number of good reasons for doing so. A number of studies suggest that multisensory feedback increases the feeling of spatial immersion [11, 18, 19, 41, 43] and both haptic and sound can be used to attract attention, with the advantage that sound can be used to direct attention to items which are out of view. There are also environments and users for which visual presentations are not suited. The choice of which other sensory channels to use and the choice of mapping is also part of the *encoding*-see Chapter 3.

Facet and Position: One of the most interesting research questions raised by immersive analytics is how to arrange multiple views and viewing canvases with respect to each other, with respect to the viewer, and with respect to objects in the physical environment (see Chapter 2). Only the first of these is considered in Brehmer and Munzner's framework since viewing canvases are implicitly assumed to be arranged on desktop display. Because of these other questions we prefer to call this aspect *Facet and Position* rather than simply *Facet*.

Arrangement of different viewing canvases is relatively simple in a full-screen representation on 2D output devices such as a standard monitor. If a window system is in use, visualisations can be stacked and occlude each other. Large, wallsized displays expand the workspace of the user substantially. In an immersive VR environment the user can potentially place views anywhere in a virtual 3D room. As for visual analytics, view management algorithms such as grouping views and showing exploratory workflows might benefit IA interface design [29].

The widest range of options arises with the use of AR: a canvas can be embedded into the real world, it can be projected onto a real-world surface, it can be mixed into the real world without explicit delineation or it might be printed (in 2D or 3D) to become an object in the real world. In all cases, placement (position, orientation, scaling) can be arbitrarily controlled but should relate to the task at hand (not too small, not too far away from the user etc.). Placement is constrained by the environment: you may not wish to obscure some objects and there may be a semantic meaning if a canvas is close to a particular object in the environment. As discussed in Chapter 2, currently there is no standard metaphor for arranging views in mixed reality presentations: suggestions include 2D views [15,16], embodied 3D views [5,10] or blended views in which physical objects provide the view frame [14].

Another important question is the *viewer's relationship* to the view or viewing canvases. This includes the initial placement of the user. Is the user placed inside one of the views to give an egocentric view of the data or do they have an exocentric view of the data? Is the viewpoint chosen so as to minimise occlusion? Another question is the relative size of the user and the view. In a traditional desktop setting, when scaling a bar chart only the space on the screen is considered. In mixed reality, the size of the bar chart is likely to have more impact on the viewer's understanding of its importance. A bar chart as large as the viewer might provide a different impression to one the size of a book. More generally, arrangement of viewing canvases needs to take account the physical and cognitive costs of moving and/or navigating between the different canvases, see Chapter 4.

A further consideration is the degree to which the user's *situational awareness* is manipulated. Perception of the physical environment can be altered by the mixed-reality application. It might choose to hide or simplify/abstract certain aspects of the environment in order to reduce distraction to the user or to focus attention to task-relevant objects in the environment (e.g. a server rack with only the relevant machine visible or just the relevant network port etc.).

A final consideration is how to *link* elements in these different canvases. This might by brushing or using lines to connect them, e.g. [9].

Render: There are two fundamentally different *display methods* for rendering graphics. The object-space approach "draws" objects, usually geometry, onto the image plane using an explicit projection. The projected shape is computed and filled with the respective color values. Virtually all desktop information visualisation platforms use this approach. In immersive environments, however, it also common to use an image-space approach in which colour values of the image are obtained by computing the contribution of the objects to the corresponding image element. A common method is ray casting/tracing, where a ray is traced through virtual space and every time an object is hit, the respective contribution to the image is computed. While object-space methods are commonly used for explicitly represented objects/metaphors, image space approaches can easily be used with explicit and implicit representations (indirect ray-casting can be done per glyph [32]).

An overarching aspect to *How* in immersive analytics is the degree of *reproduction fidelity*. Even if some visual properties are not used as visual variables, they may be used to create more realistic visualisations and so increase spatial immersiveness. For example, a variety of textures might be provided even if they are not explicitly used to encode properties of the data. Different rendering methods provide differing degrees of realism, from more abstract display methods like wireframe rendering to photo-realistic output with global illumination effects like ray tracing and path tracing. More realistic rendering methods usually require more computation power and therefore their use is often limited because of this. Reproduction fidelity is also linked to the use of other sensory channels and affordances for embodied interaction. The behaviour of virtual objects can be made consistent with the physical world in various degrees, usually via a simulation running in the background. Starting from complete disregard of natural laws, realism can be increased from rigid/soft collision to simulation of physico-chemical processes like combustion, though this obviously depends on the availability of computational power and suitable models. In principle, object properties like inertia, density, momentum or charge revealed through their behavior during interaction might be used as non-visual encodings of data attributes (see Chapter 3). However, care is needed as spatial immersion will probably be negatively affected if visual and non-visual variables are not in accord. For example, it would feel incongruous if a smaller object that appeared similar to a larger object had greater inertia than the larger object.

Manipulate: User control and interaction is at the heart of immersive analytics. Two interrelated aspects distinguish many IA applications from traditional visual analytics: interaction in 3D virtual environments rather than 2D, and the use of so-called natural interaction modalities such as gesture, speech or touch rather than mouse and keyboard. Importantly, interaction methods and modalities in IA need to take into account proximity to the display and the characteristics of human attention [27].

The traditional WIMP-based desktop environment has standard idioms for low-level data manipulation tasks. However, in IA manipulation tasks related to navigate, select, arrange, change, filter, aggregate, and control are still very much the focus for research, partially because of the ever growing variety of interaction devices (see Chapter 4). LaViola *et al.* [26] report an astonishing variety of 3D UI manipulation techniques. A basic goal has been the development of interaction techniques that are natural yet allow high-levels of user efficiency, effectiveness, and comfort while diminishing the impact from inherent human and hardware limitations. Interaction attributes, such as distance to the target, target scale, precision required, domain specificity, and number of targets, affect manipulation accuracy. There is also a close relationship between the input device and manipulation metaphors, e.g., the degrees of freedom in the manipulation, e.g., whether or not two-handed input is allowed. In general, techniques using smaller and faster muscle groups (e.g., fingers) support more precise manipulation than larger muscle groups (arm and torso).

The development of more effective low-level manipulation techniques and input devices will remain a focus of research in the VR community. This will fuel research in IA into the design and evaluation of higher-level interaction idioms that take advantage of these new techniques and devices as well as advances in other input modalities such as speech.

Another important focus of IA research will be the development of interfaces that provide physically embodied interactions and affordances [12] and support responsive, fluid interactions [13] that allow users to remained immersed in their task (see Chapter 4 for more detail). **Collaborate:** Support for collaboration is an important component of many IA applications. As discussed more fully in Chapter 8 there are many facets to consider: types and roles of participants, management of private and shared views in synchronous collaboration, representation of self and remote participants, maintenance of group awareness and channels of communication in distributed synchronous collaboration, as well as communication channels and hand-over in asynchronous collaboration.

Collaboration may be with other analysts or with stakeholders. Regardless there is a need to communicate findings. Thus the choice of idioms for storytelling, i.e. the construction of narrative visualisations, and for analysis providence fall into this component of *How*. This includes mechanisms for annotation, recording and sharing as well as choice of narrative structure, rhetoric, transitions, etc.

Reduce: This aspect is unchanged from Munzner [34]. It covers idioms for reducing items and attributes by filtering or aggregation.

Model: Neither Brehmer and Munzner [4] or Munzner [34] explicitly consider idioms for building or generating results from any underlying analytics model. However, the choice of idioms for these tasks is an important component of many IA applications and is likely to significantly impact user engagement.

Creation and evaluation of a model necessitates finding information and supporting evidence, finding relations in the information, extracting meaning, schematizing that information and re-evaluation. IA systems can support such modelling by displaying relevant data/information, model output, the models themselves (if this makes sense) and the workflows used to construct them. New challenges arise around the creation, (potentially automatic) arrangement, representation, and the manipulation of models in an IA system. Such manipulation may require new interaction and visualisation idioms that allow users to refine a model by changing parameters or the model itself, to understand the appropriateness and fitness of a model, as well as to compare multiple alternative models.

Responsive algorithms with timely, clear, and easily understandable feedback are a necessity to support any modeling activity. Moreover, predictability and stability in response to user interaction is also important, as with any good user interface (see Chapter 5).

9.5. Using the Design Space Framework

In this section we look at six representative data analytics applications from the literature and analyse them in terms of the design framework we have discussed. These have been chosen to cover various aspects of IA including immersion in virtual-reality and mixed-reality, embodied interaction, responsive analytics, situated analytics and collaboration.

The first example, shown in Figure 2, is an example of a visualisation that is not designed to be immersive and one that is barely interactive: the only user



Fig. 2: Simple scatter plot and linear regression model with standard error created with R.

interaction is zooming and panning. It is intended to provide a benchmark for comparison with the following more immersive examples. It is a scatterplot, one of the most widely used visualisations for understanding multidimensional data, that has been created with R using ggplot2 [49] for display in a standard desktop environment. Linear regression has been used to fit a linear model to the data with an associated confidence interval.

The second example, shown in Figure 3, is also based on the scatterplot. However, it is designed to be much more immersive. It is a VR application for the HTC Vive HMD that allows the analyst to use the Vive controllers to interactively create, manipulate and position one-dimensional data axes and twoand three-dimensional scatter plots and scatter plot matrices (SPLOMs) in the space around the viewer [10]. Views are naturally built from the data axes in the virtual environment using embodied direct manipulation to move the axes into the requisite position to form the view. When two visualisations are close to one another data elements in the two views are linked by lines, allowing the user to dynamically create parallel coordinate plots and similar kinds of linked multivariate data visualisations. There is no underlying analytics but users can filter data and rescale the axes. Tables 2 and 3 show a detailed comparison between the first two examples in terms of our design framework.

Our third example is another VR application, this time for network data visualisation—see Figure 4 and Table 4. It is taken from Kwon *et al.* [24, 25]. This application introduces a spherical network layout designed to immersively display network data in a VR setting. The basic graph visualisation is a node link diagram. Clustering analysis is performed before layout and position and colour is used to show the clusters. Clustering is not interactive. Edge bundling is used to aggregate edges. The main novelty in this example is in the egocentric placement of the node-link diagram. It is arranged on a spherical layout around



Fig. 3: Creating a 2D scatter plot using the ImAxes VR visualisation application [10]. Image courtesy M. Cordeil.



Fig. 4: Egocentric network data visualisation in VR from [24]. \odot 2016 IEEE. Reprinted, with permission, from [24].

Where	
Presentation	Standard monitor
Interaction	Mouse and keyboard
World knowledge	None
Environment	Controlled indoor
What	
Dataset types	Two-dimensional tabular data
Dataset generation	Static data; pre-computed linear regression + standard error; non-interactive analytics
Who	
User	Analyst; sighted
Collaboration	Single user
Why	
High-level tasks	Discover outliers, clusters, and trends
Medium-level tasks	Compare, summarize, lookup, browse
How	
Encode	Scatter plot (attributes mapped to position of points on a 2D plane), line showing regression model and polygon showing confidence interval; no use of 3D or depth cues; no use of non-visual variables
Manipulate	Standard mouse-based zooming and panning
Collaborate	Collaboration and narrative creation not supported
Facet & position	Standard 2D windowing; no situational aware- ness; exocentric view; monitor in front
Render	Explicit object-space; low reproduction fidelity
Reduce	No
Model	No interactive analytics

Table 2: Design analysis 1–Simple scatter plot with linear regression

the user, i.e., the user is surrounded by the graph. Since the visualisation shows abstract data, the visual representation is not aimed at realism and standard geometry rendering with some basic lighting is used. The paper provides no indication about collaborative scenarios. Interestingly, a user study [24] indicates that the user can perform certain tasks better with the spherical layout compared to a traditional 2D layout in the virtual environment suggesting that, at least for some tasks in VR, egocentric layouts may be preferable to more standard exocentric data visualisations.

Our next example is an interactive optimisation application for treatment planning in low-dosage rate prostrate brachytherapy [30]—see Figure 5 and Table 5. This is an example of an immersive analytics application that relies on sophisticated human-in-the-loop analytics. Optimisation is used to plan where

Where	
Presentation	HMD VR (HTC VIVE)
Interaction	VIVE controllers
World knowledge	Head and controller tracking
Environment	Controlled indoor
What	
Dataset types	Multi-dimensional tabular data
Dataset generation	Static data; no preprocessing or underlying analytics
Who	
User	Analyst; sighted, ambulatory and ability to use HMD and controllers
Collaboration	Single user
Why	
High-level tasks	Discover outliers, clusters, and trends
Medium-level tasks	Compare, summarize, lookup, browse
How	
Encode	2- or 3-D scatter plot or SPLOM (two or three attributes mapped to position of points on a 2D plane or 3D cube); standard head-tracked VR depth cues; no use of non-visual variables
Manipulate	Embodied direct manipulation for creation and placement of 2- or 3-D scatter plots and SPLOMs using controller buttons and controller tracking
Collaborate	Collaboration and narrative creation not supported
Facet & position	User-controlled placement in 3D space; no sit- uational awareness; exocentric view of visuali- sations and egocentric arrangement of visualisa- tions around user; elements in views are linked by lines when user moves two views close to one another
Render	Explicit object-space; medium reproduction fi- delity
Reduce	Filtering
Model	No interactive analytics
Table 3: Design analysi	s 2–Multidimensional VR analytics tool (ImAxes).

to place radioactive seeds in the prostrate so as to irradiate the region where the tumour is likely to be but not overdose sensitive tissue such as the urethra or rectum. The tool allows the user to create a gallery of treatment plans using interactive optimisation and then choose the preferred treatment. It has three viewing modes. In presentation mode the user can see a treatment plan on a 3D view of the prostrate with linked 2D axial, sagittal and coronal slices. Volume

Where	
Presentation	HMD VR (Oculus Rift DK2)
Interaction	Mouse, head tracking
World knowledge	Head and controller tracking
Environment	Controlled indoor
What	
Dataset types	Network data
Dataset availability	Static data, precomputation of clusters
Who	
User	Analyst. Ability to use HMD, stereo and normal
	color perception required
Collaboration	Collaboration and narrative creation not supported
Why	
High-level tasks	Discover network connectivity and structure
Medium-level tasks	Browse, explore
How	
Encode	Node-link diagram representation laid out on the surface of a sphere, colour differentiates clusters; standard VR depth cues
Manipulate	Node hovering, node highlighting (propagating
	to edges), node selection
Collaborate	Collaboration and narrative creation not supported
Facet & position	Egocentric placement of sphere around seated viewer; no situational awareness; single view
Render	Explicit object-space; medium reproduction
	fidelity-lighting
Reduce	Edge bundling
Model	No interactive analytics
Table 4: Design anal	ysis 3–Egocentric network data visualisation.



Fig. 5: Prostrate brachytherapy treatment planning with interactive optimisation [30].

rendering and contours, respectively, show the dosage, tumour cell density (TCD) or tumour control probability (TCP) in these 3D and 2D views. In addition summary statistics are shown in a bar chart. This example is interesting because of the idioms supporting responsive interactive optimisation. In planning mode the use can automatically generate a new treatment plan and then manually adjust the position of seeds, or re-optimise part of the plan, while in comparison mode the user can compare two treatment plans. The application runs on a standard desktop computer.

Our fifth example is an immersive visual analysis of spintronics (spin electronics) in quantum mechanics using a three-wall CAVE environment. It illustrates immersive co-located collaborative data analysis. Interactions of atoms in quantum mechanics are extremely complex. Their analysis relies on computer simulations recording electron spin, a vector with magnitude (charge density) and orientation at each sampling site. Quantum physicists are interested in how the electrons interact with magnetic fields or other electrons with spin. Figure 6 shows the display of a quantum simulation dataset of 255,772 spins in a CAVE immersive environment. Large spin magnitude variations can be queried on demand using either information-rich virtual environments [8] or SplitVectors glyphs [54, 55]. In analyzing quantum physics simulation results, physicists can extract scientific insights about their data by: a) using visualisation to understanding the large scale (global overview using the results of the entire simulation); b) interactively querying the data to identify clusters or topological structures satisfying criteria such as an equation for symmetry in order to build a qualitative understanding of pattern distributions (e.g., magnitude and orientation distribution and changes, symmetry structures, magnitude and orientation); c) visually comparing the

Where	
Presentation	Standard monitor
Interaction	Mouse and keyboard
World knowledge	None
Environment	Controlled indoor
What	
Dataset types	3D spatial and field
Dataset generation	Input data are tumour cell density (TCD), pros- trate and other organ volumes; optimisation com- putes seed placement, dosage and tumour control probability (TCP); optimisation is interactive
Who	
User	Brachytherapy treatment planner; sighted.
Collaboration	No (though plans may be reviewed and revised collaboratively)
Why	
High-level tasks	Discover treatment plan
Medium-level tasks	Use optimisation model to create plans, compare plans
How	
Encode	3D volume rendering, 2D projections with de- rived contours; 2D bar and line charts; no use of non-visual variables; standard desktop monitor depth cues
Manipulate	Mouse-controlled cutting plane manipulation and rotation of 3D view
Collaborate	Collaboration and narrative creation not supported
Facet & position	Standard 2D windowing; no situational aware- ness; exocentric view; linked 3D/2D views
Render	Explicit object-space; low reproduction fidelity
Reduce	Thumbnail view of treatment plans in gallery
Model	User computes gallery of treatment plans; can modify optimisation goal function; manipulate solution; re-optimise part of solution

Table 5: Design analysis 4–Prostrate brachytherapy treatment planning

differences between or within datasets to understand extremes, ratios, and value distributions in selected regions. The CAVE environment allows small groups of physicists to stand together to view and discuss the visualisations on the walls of the CAVE. A disadvantage is that only one user is head-tracked so the other participants' binocular presentation is distorted if they are not standing close together. Quantum physicists have commented that using a CAVE environment



Fig. 6: Immersive visual analysis of quantum physics simulation in the CAVE at NIST using the encoding methods in Zhao *et al.* [54] and Zhao and Chen [55].

lets them detect spatial pattern changes more effectively than is possible in a desktop environment.

Our final example is an AR tool for environmental monitoring [45]–see Figure 7 and Table 7. This is an example of immersive *in situ* analytics, i.e. situated analytics. The AR tool is part of a larger application that allows environmental engineers and scientists, engineers and builders working for regional authorities and private companies as well as specialists such as hydrographers to develop a shared understanding of particular environments, and to develop and discuss potential solutions to environmental issues. The complete application runs on a combination of mainframes, laptops and mobile tablet PCs.

Here we focus on the mobile tablet tool for visualising sensor data in the field. The tool allows data to be overlaid on top of the environment viewed through the tablet. The environment can be shown at different levels of abstraction, while the sensor data can be compared with simulations that have been precomputed on the mainframe. Since a small mobile device is used, only a small part of the environment is augmented. Different types of visual representations are used: visual markers for sensor positions, text boxes for sensor information, line and color plots for sensor data. Some of them are just blended into the video view, others are mapped onto the surface of the environment, e.g., a temperature visualisation based on colour mapping. The visualisations are not aimed at realism; a rather abstract representation of the data is used.

Where	
Presentation	CAVE (three-wall); stereoscopic projected dis- play
Interaction	Wand for hand-tracking, head-tracking, keyboard
World knowledge	Head and hand tracking
Environment	Controlled indoor low-light
What	
Dataset types	Raw spintronics vector data
Dataset generation	Pre-computation of data using computer simula- tion; interactive computation of topology (con- tours), symmetry, groups, and clusters
Who	······································
User	Physicists (domain experts); sighted, ambulatory and ability to use wand and keyboard
Collaboration	Co-located collaboration by small groups
Why	
High-level tasks	Discover unknown/disjoint spatial structures
Medium-level tasks	Derive, query, search
How	
Encode	3D vectors (raw, derived contours); 2D projec- tions; standard head-tracked VR depth cues;
Manipulate	Standard navigation-details-on-demand, drill down, cutting planes
Collaborate	Shared view in same physical workspace; direct communication through speech and gesture
Facet & position	Egocentric and exocentric view; egocentric place- ment of view around viewers; multiple views ar- ranged using standard windowing system
Render	Explicit world-space; medium reproduction fidelity-lighting
Reduce	Regions of interest selection; feature selection; filtering
Model	Interactive clustering, group and feature identification.

Table 6: Design analysis 5–Immersive visual analysis of quantum physics simulation in a CAVE

The AR tool is designed to support distributed collaboration. This is between users on-site as well as between on-site and off-site users. A shared view service and voice communication supports synchronous collaboration while geo-referenced annotations support construction of narratives for asynchronous collaboration.

This last example highlights the importance of considering the working environment and platform when developing immersive analytics applications



Fig. 7: Environmental monitoring in the field with AR [45]. Reprinted by permission from Springer Nature: Personal and Ubiquitous Computing [45], COPY-RIGHT 2012.

as mobile hardware like tablets typically have limited computational power and relatively small display size. Furthermore, because of the remote location and possibly hostile weather conditions, network connectivity and equipment robustness as well as the ability to use the equipment while wearing gloves were important design considerations.

9.6. Research Questions and Issues

This chapter suggests a number of research directions. The most obvious is to refine the design framework as we learn from future successful (and unsuccessful) IA applications. As part of this we need to develop evidence-based design rules and a portfolio of idioms to help designers answer the various aspects of *How*. We particularly need guidelines and successful idioms for interaction, workspace arrangement and collaboration in mixed-reality environments, design of multimodal presentations, and integration of different kinds of analytics into responsive interactive analysis tools.

A second fundamental research question is how do we *evaluate* and *validate* the design of an IA application. Immersive analytics brings together the virtual reality, data visualisation and visual analytics communities. Each field has developed its own evaluation methods, all of which are relevant to immersive analytics. All fields heavily rely on controlled user studies to evaluate task performance (speed, errors and accuracy) as well as user preferences. Virtual reality researchers have developed methods to evaluate spatial and social presence (the degree of spatial and social immersion) (see Chapter 1) and investigate how immersive technologies affect this. Data visualisation and visual analytics consider scalability and expressiveness of visual representations and scalability and responsiveness of

algorithms. Both make use of ethnographic methods such as contextual inquiry to better understand the application domain. Visual analytics, in particular, employs in-the-wild studies, smaller focussed studies using domain experts and participative use-driven evaluation. For immersive analytics to succeed, we believe that researchers will need to demonstrate through such in-the-wild studies that the adoption of immersive analytics solutions can increase productivity, improve team collaboration and reduce costs in real-world applications. What is missing are ways to measure user engagement, emotional response and psychological immersion. Furthermore, while some data visualisation researchers have investigated memorability and learnability (accessibility, naturalness, discoverability and affordances) this is uncommon. Development of standard measures and techniques for measuring all of these different aspects is an important research direction.

Where	
Presentation	Mobile tablet
Interaction	Touch screen
World knowledge	Positions and object types from GPS, user track- ing, geo-referenced data
Environment	Uncontrolled outdoors
What	
Dataset types	Spatially embedded sensor data; plans, maps & 3D data
Dataset generation	Sensor data is dynamic; statistical analysis, sim- ulation data pre-computed
Who	
User	On-site environmental scientist, engineers etc; Ambulatory, sighted.
Collaboration	Synchronous and asynchronous distributed col- laboration
Why	
High-level tasks	Discover patterns in environmental data; discover and evaluate solutions to environmental issues
Medium-level tasks	Search, compare, annotate, share, guide
How	
Encode	Digital overlays of $1/2/3D$ data visualisations on the environment
Manipulate	Typical navigation idioms
Collaborate	Voice communication, position and view sharing, graphics, text and voice annotation
Facet & position	Geo-referenced overlays as well as standard window manager
Render	Explicit object-space
Reduce	Filtering, aggregation
Model	Not applicable in AR tool as simulations may take many hours and are run off-line

Table 7: Design Analysis 6: AR Environmental Monitoring Tool

A third class of research questions relate to broader ergonomic, health and societal concerns. We know that virtual reality environments can lead to motionsickness and fatigue. What are the possible health risks of long term use of mixed mode and virtual reality environments? Do we need to develop guidelines for ethical design of user studies so as to mitigate these risks? What are appropriate ergonomic standards for the workplace? How do people outside a virtual world communicate or interrupt someone who is in a virtual world? E.g., imagine you are wearing your HMD performing some data exploration in a virtual world and your colleague wants to notify you that you have a guest. What are the societal benefits and disadvantages of immersive telepresence and remote working/home office scenarios? We have already seen concerns about mixed-reality HMDs being used to record events without permission. What level of real-time analysis of the objects and people in your environment with results displayed in your head-mounted mixed reality display is permissible?

9.7. Conclusion

We have presented an design framework for immersive analytics based around five questions, *Where-What-Who-Why-How*, that extends Brehmer and Munzner's well known *What-Why-How* design framework for data visualisation. It extends the framework by considering the context in which the analysis is taking part: *Where* takes into account the capabilities of the immersive analytics platform and the type of physical environment, while *Who* takes into account the number of users and their characteristics and needs. The *How* component is also more complex in immersive analytics because it may include the use of non-visual representations, collaboration, 3D arrangement of views in the user's environment and the use of analytics for data modelling and decision support.

We believe the design framework provides a good basis for designing IA applications as well as suggesting directions for further research. However, given the current immaturity of the field, the proposed framework should be viewed as a work in progress and further development of the design framework is also, we believe, an important topic for future immersive analytics research.

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