5. Immersive Human-Centered Computational Analytics

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Abstract. In this chapter we seek to elevate the role of the human in human-machine cooperative analysis through a careful consideration of immersive design principles. We consider both strategic immersion through more accessible systems as well as enhanced understanding and control through immersive interfaces that enable rapid workflows. We extend the classic sensemaking loop from visual analytics to incorporate multiple views, scenarios, people, and computational agents. We consider both sides of machine/human collaboration: allowing the human to more fluidly control the machine process; and also allowing the human to understand the results, derive insights and continue the analytic cycle. We also consider system and algorithmic implications of enabling real-time control and feedback in immersive human-centered computational analytics.

Keywords: human-in-the-loop analytics, visual analytics, data visualization

5.1. Introduction

In Chapter 4, we reviewed the basic tasks that immersive analytics systems need to support. The tasks considered in that chapter were mostly 'low-level' in the sense that each task corresponded to a single conceptual action supporting data analysis. These types of tasks were categorized in Heer and Shneiderman's task taxonomy for information visualization [24] as *data and view specification* and *view manipulation* tasks. However, we also reviewed the third category of tasks from this taxonomy on so-called *process and provenance*. These latter tasks were

K. Marriott et al. (Eds.): Immersive Analytics, LNCS 11190, pp. 139–163, 2018.
https://doi.org/10.1007/978-3-030-01388-2_5

still fairly finely grained in terms of corresponding to concrete actions but they related to "doing things" with insights gleaned from the data (e. g., *record*, *share*, *annotate*, *guide*) rather than tasks required to make these individual insights in the first place. Thus, these process and provenance tasks were required to support a full workflow around data analytics – not simply identifying particular features of data, but *making sense* of data in a more holistic way. We review these 'traditional views' of the analytics process in Section 5.2. This chapter focuses squarely on this more holistic process or workflow, also known as the *sensemaking loop* of visual analytics [44], and the various ways in which *human immersion* can play a role in this loop, and the way that that immersion can be supported by machine guidance. The sense-making loop is considered again briefly in Chapter 9 of this book along with a model for the Immersive Analytics process as part of a broader discussion of a general design framework for immersive analytics.

Also in Chapter 4, we described the opportunities for visualization researchers and designers to take advantage of the different kinds of immersion and increased user presence afforded by natural user interfaces and immersive display technologies. We described how spatial and sensory-motoric immersion can help to increase the engagement of the users in their data analysis tasks.

In this chapter, in considering more broadly the higher-level concerns of the data analytics process, the type of immersion we are seeking could be more accurately described as *Strategic Immersion*. This follows a concept from game design that—compared to other types of immersion—is more closely related to high-level problem solving, or literally, a game player's strategy for succeeding in the game [1].

Another aspect of the data analytics workflow that we begin to consider in this chapter is the integration of automatic processes, such as machine optimization and learning, into the workflow. Thus, we consider the role of a user in a larger-scale collaborative analytics process, which includes both other people and machine assistance. It is timely to consider this now because, in addition to the rapidly emerging display and interaction technologies described throughout this book, we are also in the midst of a step-change in the capability of machine learning (ML). We want to make sure that the rapid advances in deep-learning, for instance, do not close the door on interaction.

We can summarize the various considerations of this chapter as follows:

- To leverage the advantages of immersive environments for problem-solving tasks in Visual Analytics (VA) (Section 5.2.).
- We want to elevate the role of the human in human-machine cooperative analysis (over perhaps the ML or DataMining Human in the Loop perspective) (Section 5.3.).
- How do the above considerations affect algorithm/system/platform design and what are the challenges for the future? (Section 5.4.).

5.2. Analytics Process

In this section, we discuss the analytics process, including models for how people analyze data. Then we analyze which parts of this process can be augmented by immersive technologies. We also discuss how human collaborators and automatic "intelligent" processing can be integrated into the immersive analytics process. Finally, we develop an overview of the requirements for keeping an analytics system responsive enough to be used in an interactive immersive environment.

5.2.1. Example Scenario for Immersive Analytics Processes

To date, there are few compelling examples of systems that use immersion for information seeking analytical activities. An intriguing scenario proposed as a demonstration game for the Microsoft Hololens is the Fragments game (see Figure 1), which explores many aspects of immersive analytics. In the scenario, the user plays a detective that examines multiple crime scenes and gathers evidence to inform subsequent search criteria. Different 'lenses' can be used so that different aspects of the real world are highlighted – in the case of the game, x-ray lenses for seeing inside or underneath the surface of objects, infrared for exploring heat and recently manipulated objects, or audio lenses that play certain sounds triggered by examining objects in the environment.

This information is then used to filter both map-based geographic visualizations and lists of facts. Hypotheses can be formed and tested within the scenario and when a hypothesis is confirmed, the user moves on to deeper challenges. The scenario exemplifies many potential immersive visual analytics activities: gathering evidence, forming hypotheses, refining queries, and organizing information. It further shows how the system can facilitate both manual interaction—where the user is completely controlling the exploration based on their gaze—and automated interaction, where the system takes a combination of observations and generates a model of the results that is visualized for appropriate subsequent actions.

5.2.2. Sensemaking as the Analytics Process

There are several different models that help describe the way by which humans understand and process information. Depicted below are two models (from among many) that are commonly cited in the visual analytics literature. Specifically, in Figure 2 we have one of the earliest (1999) attempt at a visualization "reference model" by Card *et al.* [5] and then in Figure 3, the more recent (2005) and sophisticated *Sensemaking Loop* by Pirolli and Card [44]. Both of these models incorporate stages for taking in data, transforming the data into a representation convenient for interaction, and an iterative process by which we refine through successive interactions.

We have chosen to use the Pirolli-Card Sensemaking Loop (Figure 3) as a basis for this chapter in part because of its wide popularity, and in part because it breaks down the process in a more fine-grained fashion than many other models. For each of the stages, we can explore how that stage might be transformed by

Fig. 1: The Hololens Fragments game allows deeper exploration of a scene using alternate 'lenses'. *Courtesy Microsoft - used with permission.*

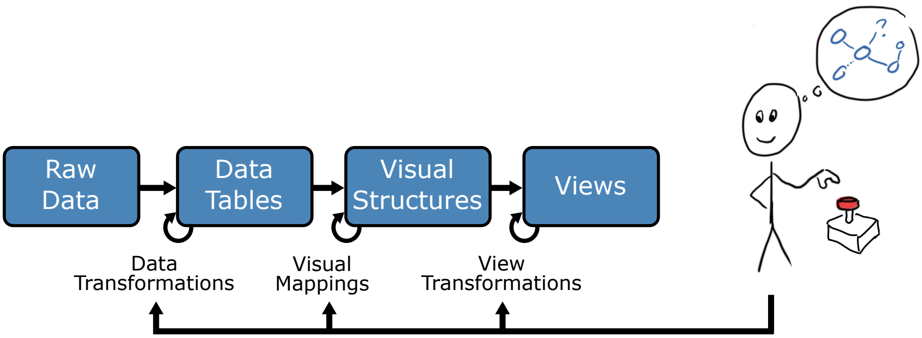

Fig. 2: The traditional reference model for visualisation, after Card *et al.* [5]

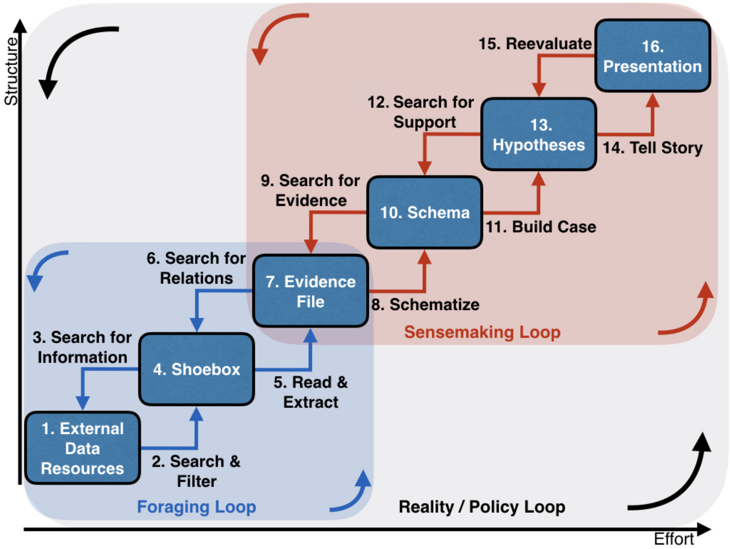

Fig. 3: Pirolli and Card's sensemaking loop (courtesy Jie Liu, 2017).

immersive capabilities. In particular, the Pirolli-Card model has a series of steps for both:

Creating a model (bottom-up) where those steps involve finding information, extracting meaning, schematizing, building a case, and subsequently communicating that information.

Evaluating the model (top-down) where those steps involve re-evaluation, finding supporting evidence, finding relations in the information or finding basic information itself.

Each stage can loop back down or move upwards in the chain.

5.2.3. Tasks in the Analytic Process

In Chapter 4 we described three categories of tasks that need to be supported by immersive analytics systems. Here we describe how those tasks fit into the Sensemaking Loop model.

The first two categories of tasks, *data/view specification* and *view manipulation*, describe fairly low-level operations that mostly fall within the "foraging" portion of the Pirolli and Card model. The last category, *process and provenance*, goes beyond most traditional visualization task taxonomies as it addresses typical issues that are more related to supporting the analysis process in general, and not tasks specifically related to interactive visualization. As described below, the *process and provenance* tasks are more the domain of the "sensemaking" portion of the Pirolli and Card model.

Record: Provenance research is mostly interpreted as the development of methods and tools to improve awareness of the history of changes and advances throughout the analysis process by the user of the visual analytics tool. Quite recently, Ragen *et al.* [45] published an excellent paper on the characterization of provenance in visualization and data analysis. They distinguish between various provenance types, such as provenance of data, visualization, or interaction, and present an organizational framework for clarifying the type of provenance information capture and the purpose for which it will be used. That article also surveys the most important provenance approaches like [23, 51]. Providing and analyzing history data is especially important for cases in which various analysts collaborate and work together. Simply revisiting old snapshots of an analytic session or replaying every single event that happened during such a session is usually not sufficient to reveal the same insights that an analyst might have had during the initial analysis. Thus, keeping track of the reasoning involved during a collaborative process and using this information later to review and reflect upon it can be a challenging task. For instance, analysts should have the possibility to quickly review changes performed on a visual representation and get an idea of the most interesting regions according to the user history without the need to replay every single action that was performed by previous users.

Share: Collaboration is an important aspect in practice, but still not very well researched or supported by visualization tools. "A VA system has to support discussions, dissemination of results, or interactions of several analysts at the same place and the same time (co-located) or at different places and not necessarily at the same time (distributed). Sharing views or publication of visualizations are examples of important requirements for efficient collaboration between many analysts." [30]. Isenberg *et al.* [28] provide an excellent overview of definitions, tasks and examples for collaborative visualization (also see 8). They also provide an excellent summary of ongoing challenges in this field. A recent visualization system that supports the distributed (synchronous and asynchronous) analysis of networks is OnGraX [59]. It even makes data-aware annotations available as discussed in the next item.

Annotate: Pointing to interesting elements or giving comments to individual graphical features or patterns discovered within a visualization are important for any analytical process and also for potential discussions within a collaborative setting. As a visualization is not a static image or diagram, such annotations must be stable/persistent with respect to the represented data as well as to the actual visible graphical elements. Both can and will change over the period a visual analysis is performed. An example of such a dynamic situation is the analysis of a social network where network nodes might appear/disappear, and the layout may change due to a reconfiguration by the analyst (e. g., by using another layout algorithm). In consequence, annotations should be viewable in their historical context. Thus, it should be possible for analysts to review old visualization states where the annotation took place (cf. the provenance and history discussion above). As an example, the OnGraX network visualization system [59] makes it possible to link textual annotations and chat messages to specific network elements. Those annotations are permanently tracked and stored in a database.

Guide: Analytics processes are typically non-linear, i. e., the representation of workflows is challenging. Guiding the user through workflows for shared activities would be clearly beneficial, for instance. The first approach to a more detailed characterization schema for guidance in visual analytics has been recently proposed by Ceneda *et al.* [8]. Another related conceptual approach for guidance was proposed by Streit *et al.* [53], but there the authors only focus on previously defined workflow-driven approaches for concrete biomedical use cases. Besides the previously mentioned works, there is only a little work done to understand or define the process of user guidance in general, and there are also only a few practical realizations. Guidance provided by the VA system can be based on several inputs (individually used or all together), such as the input data itself, interaction when using the VA system, user/domain knowledge, or it may even be based on emotion tracking or similar sources [9]. The exact way in which a system supports guidance and to what extent (more proposing or more decisive) can be varied too.

5.2.4. The Analytics Process in an Immersive Environment

We now discuss the potential for integrating the analytic process with immersive environments. In particular, we examine specific components of the sensemaking process that could be enhanced by immersive technologies.

The first half of Pirolli and Card's sensemaking process is about foraging for information. We can envision using attributes of both Augmented Reality (AR) and Virtual Reality (VR) technologies to help find and access appropriate information on an as-needed basis. In an AR setting, we can associate information sources with objects in the real world by taking advantage of their spatial context (see Chapter 7). In an application on a factory floor, for example, simply looking at a particular machine could provide usage and maintenance statistics associated with that machine. Traffic patterns throughout the factory could be shown by patterns superimposed on the floor. In a VR setting, we can use models in a fashion similar to icons to represent data sources, but those models could have additional semantic meaning associated with them–so that a model of an engine might serve as a gateway for information about emissions, maintenance, power output, etc. This type of semantic association could entail both advantages and disadvantages for the sensemaking process: on the positive side, it could help remind people what is available; but, on the negative side, more abstract measures and data might be difficult to associate with concrete representations.

The second half of the sensemaking process is about synthesizing information–organizing collected information, formulating hypotheses and arranging supporting and contradictory evidence. It has been shown that space (a physical interaction space or relatively large display space) can play an important role in this process and assist in task completion by allowing greater space for organization [2, 60]. Analysts can use the space to organize and structure not only collected information but also their analytical workflow and thought processes.

As a simple example of combining these two portions of the sensemaking process, an immersive environment can serve as a huge canvas where information can be accessed relative to the user. Furthermore, as a user moves around the space, information can be organized using spatial position and relative proximity between data representations to imply a relationship between them. Another potential advantage of immersion is the possibility to provide a physical instantiation of the 'memory palace' mnemonic device so that parts of a complex model can be compartmentalized to different spatial locations–virtual in the case of VR or physical in the case of AR.

5.2.5. Support for Analytics Steps in Immersive Environments

Next, we discuss how well specific types of interactions in the various steps of the sensemaking process may be supported by immersive environments. In the following, **bold numbers** refer to the individual steps in Pirolli and Card's Sensemaking Loop model in Figure 3.

The sensemaking loop contains a variety of different search processes (see steps **2,3,6,9,12**). These could be supported through easier visual access to large amounts of information, e. g., by rotating the head. As long as the cost of navigation is small, say due to a one-to-one mapping between user and viewpoint, accessing large amounts of information through physical navigation is beneficial [2]. Yet, if navigation becomes challenging, e. g., in large-scale environments or due to the use of more complex interaction schemes for navigation, the cost of navigation can become a bottleneck. Given strong spatial memory, we can re-find information more easily when it has been associated with a spatial position. Furthermore, automated search can reveal information 'in-context' by highlighting the results while preserving their spatial positions, reinforcing spatial memory. There are still obstacles in using immersive environments for search. One notable example is that current resolutions in both VR and AR are extremely limited in comparison to the real world. Experiments with foveated displays may assist, but especially when working with textual data, we need large, high-resolution displays for effective interaction.

For schematizing (steps **8,10**), it is possible to use the immersive environment to bridge the gap between data embedded in the real world and abstract data, for example, by augmenting a real-world scene with an abstract data display. This can help to create stronger associations, that further support visual search. This can also support aspects of distributed cognition, enabling analysts to readily offload cognitive activities into the environment.

Sensemaking tasks that are focused on data manipulation (steps **8,11,10,13**) rather than data retrieval may be harder to accomplish in immersive environments as detailed interaction (especially with textual information) may pose more usability challenges (at least with current technologies). Whereas, interacting with large amounts of information may be made easier by exploiting greater degrees of freedom. Pointing and selecting data objects in immersive environments is often not as efficient as on the desktop. Thus, the trade-off between input modalities is different in immersive environments. Speech, gesture, and other input modalities might counterbalance the shortcomings of interactions in other modalities. Some interactions are easier because they are naturally supported

(e. g., panning head). Others might become more difficult (e. g., selection), and require the use of gestures or voice (see Chapter 4).

The presentation of analysis results at the end of the sensemaking loop (step **16**) can be augmented through immersive environments, including overlaying results on the real world. However, a potential downside is that the potential for deception might be even stronger than in more abstract representations since abstraction might require more verification of the substance of the arguments. Early experiments with augmented presentation techniques in which gestures and speech trigger 3D visual animations are promising in helping to convey complex concepts. One current difficulty is in the complexity of authoring such experiences. Another difficulty is in viewing them. Do viewers need for themselves to be in a virtual environment? How do differing viewpoints affect the presentation?

Sensemaking Step	**IA Support**	**Comments**
1. External Data Sources	−	not well suported
2. Search & Filter	∼	filtering not well supported
3. Search for Information	+	visual search
4. Shoebox	+	large display space
5. Read & Extract	+	access to much information
6. Search for Relations	+	visual search
7. Evidence File	+	large display space
8. Schematize	+	easy to organize with more space
9. Search for Evidence	+	visual search
10. Schema	+	distributed cognition
11. Build Case	−	interaction-heavy
12. Search for Support	+	visual search
13. Hypotheses	−	interaction-heavy
14. Tell Story	−	storytelling not well supported
15. Reevaluate	∼	comparisons easier
16. Presentation	+	immersive displays

Table 1: Summary of support of sensemaking activities through immersive analytics systems. '+' indidates good, '∼' partial, and '−' little or no support.

In Table 1 we list all steps in the sensemaking process and defined how well they are supported by current immersive systems. Steps that rely mostly on visual perception or scanning (e. g., steps **3,6,9,12,15,16**) and/or can benefit from large interactive display spaces to organize information (e. g., steps **4,5,7,8,9**) are already reasonably well supported by immersive systems. On the other hand, steps that are interaction-heavy, potentially require substantial amounts of text to be entered, or require the user to externalize complex thoughts "through" the system (e. g., steps **1,11,13,14**) are less well supported. This highlights the potential need for complementary methods to support such steps.

Moreover, the fact that some steps are better supported than others also poses the question of whether immersion is needed for all parts of an analysis process? Given that current systems do not support all sensemaking steps well, we believe that it is prudent to support easy, rapid and seamless switching in and out of immersion. An illustrative example is that an analyst may want to switch out of an immersive system to write up a page of a report about the insights gained from the current immersive session in a word processor and then go back into the immersive system to hunt for additional insights. Similarly for switching out of the immersive system to ask a colleague to bounce ideas around for the exact formulation of a hypothesis. Or someone who has to engage with a long, complex text document and (due to individual preferences) wants to read it on a tablet in a more comfortable setting. All these scenarios point out that the transition into and out of, or between different forms of, immersive analytics systems needs to be well supported, too.

Overall, some parts become easier, some parts are harder in immersive environments. Thus, there is no clear win-win situation, but there are many trade-offs that pose challenges to user interface and system designers. Interestingly, the difficulties identified here match, at least to some degree, the challenges that occur in other types of visual analytics systems. This highlights again major avenues for future work.

Below we discuss a new lens on the Pirolli-Card model, which incorporates automatic processes into the sensemaking process. In general, collaboration is an essential component of data analytics, and we discuss this in the following section.

5.3. Collaboration between Humans and Automated Processes

In this section, we discuss how immersive analytics systems can assist with sensemaking at larger scales. In particular, we target situations where multiple people are working together and are assisted by multiple automatic processes. The (potentially infinite) space available in immersive environments provides an appropriate "canvas" for all intermediate results in such a collaboration.

At this point, we consider an extended sensemaking loop, where multiple people interact with an evolving (intermediate) set of computationally generated/refined and human-mediated analysis results and insights. Much of the work discussed in the Chapter 8, such as maintaining awareness, applies to both human and machine actors. Here we discuss only aspects that are central to immersive analytics.

A tenet of successful collaborations is that the actions of any single actor (be they humans or algorithms) should never destroy other actors' work (without their consent). This means that multiple, potentially parallel, analyses and/or scenarios need to co-exist and the system needs to support them and their management [61]. Moreover, it should be possible to merge advances of work on a given analysis/scenario into other analyses/scenarios to avoid re-doing of work.

While source-code control systems are a traditional way to handle branching and merging of text documents, the visual nature of immersive analytics makes it necessary to explore graphical user interfaces for branching and merging. Here it is important to point out that structured code documents are fundamentally different from free-flowing text or graphical content and that source-code control systems are not necessarily the best way to handle such content. A recent exploration in this direction presented a graphical user interface for parallel work in the domain of generative design [58] and these ideas seem directly applicable to immersive analytics.

One of the primary reasons for sensemaking tools is to help people deal with more information than can comfortably be managed by an individual. Thus, it seems intuitive (and is also supported by research [2,19]) that larger displays can enhance people's sensemaking abilities.

Maintaining awareness of the activities of others in the system (both human and automated) is a challenge. With multiple actors, it becomes necessary to keep track of who did and modified what, i. e., maintaining provenance of data and annotations about the data need to be supported

An interesting facet of the challenge to maintain awareness is that changes by other actors can impact an individual's sensemaking activities. In the foraging loop, either another individual or the computer can augment the search for information based on the currently gathered information. When new information is thus retrieved, this information can be added at the appropriate level of abstraction. For example, new raw data could be added to the shoebox, new relational data could be inserted into the evidence file, or a strong correlation could be added as a potential hypothesis. The system can use visual cues such as spatial organization or representation to help distinguish such new information from previously examined information. As more of the models are built, the system could automatically flag information that supports or contradicts any given conclusion–again using spatial or visual representation to help distinguish the material.

As we scale a system to deal with more people and more automated processes, the challenge of maintaining awareness of the activities of others increases. While this is not unique to immersive environments, we can use certain aspects of immersive environments to help manage that scale. In particular, we can move from overviews of the data to focal areas while maintaining context. We can use visual attributes in different ways to show who (or what) has contributed new information or what information may have changed since last viewed.

Just as we change the level of detail at which we might observe the information, we can choose to have private views of the information in addition to a shared view. In this way, we can locally modify information without destroying the work of others. This poses yet more challenges with respect to version control of the information, rolling the system back to previous organizations and models of the data.

5.3.1. Human-in-the-loop Analytics

Immersive analytics seeks to broaden the bandwidth of communication between machine and human through more complete engagement of human sensorial perception (in the machine-to-human direction) and more fluid interaction (in the human-to-machine direction). We have discussed in previous sections and chapters the challenges involved in designing improved multisensory displays and more natural and expressive interaction devices and techniques. However, even assuming these challenges can be met to create a higher-bandwidth communication channel between machine and human, there remain a number of technical challenges in order to create completely immersive data analytics experiences. In particular, we focus in this section on the algorithmic and system architecture requirements that must be met to:

1. open algorithms to the possibility of human-in-the-loop control;
2. ensure responsiveness of algorithms in the face of the dynamic changes to parameters or the underlying data.

These challenges can arise in scenarios such as:

- large quantities of data, i. e. *scalability*;
- data changing in real-time, e. g., from *streaming data* feeds;
- prediction and optimization that can deal with uncertainty;
- synchronizing and scheduling long-running processes.

These challenges are not unique to immersive analytics scenarios and progress has been made in these areas in a number of fields, such as data mining. However, it is arguable that the focus on user-engagement in immersive analytics systems and the potential for this higher-bandwidth communication channel, make these requirements for interactive data analysis systems more pressing than ever. Thus, this section provides a survey of the state-of-the-art in the area of design patterns and issues involved in engineering algorithms to be responsive.

Immersive Algorithms (Live feedback and control) The research field of Human-Computer Interaction has long recognized the importance of minimizing delay. For example, in 1968 Miller described this not only as an "operational need" (the computer has to respond to a command before the plane crashes into the mountain) but also as a "psychological need" [38]. Card *et al.* later quantified the desirable limits on delay in an information visualization system [6], identifying three distinct time constants that a system must meet:

Perceptual processing - 0.1 second was the time they considered acceptable for a screen refresh.

Immediate response - 1 second was nominated as the time a human takes to acknowledge (not necessarily answer) a question. This was therefore suggested as a reasonable upper limit on the time an automated agent in an information visualization system might reasonably take to respond.

Unit task - 10 seconds was considered a reasonable time limit on completing a basic task or operation in the system.

These three basic time constants have become "rules-of-thumb" for user interface design [40, Chapter 5] and lore around acceptable latency for asynchronous interfaces, for example in web design [41]. However, advances in technology have arguably made some of these time limits seem generous. For example, predictive interfaces such as autocomplete (originally conceived as an accessibility feature for keyboards [15]) are now an integral part of both web and desktop search and routinely offer results to queries in significantly less than a second.

Similarly, advances in display and interaction hardware have shown that users of multitouch displays not only perceive but can be adversely affected by latencies of significantly less than 0.1 seconds [39]. In VR, latencies of more than about 20 milliseconds, from tracking of head-position movement to re-rendering the view, not only ruin immersion but can make users ill [7].

This section describes what conditions analytics algorithms have to fulfill to allow for immersive analytics. A potential metaphor is that immersive analytics means human and machine co-processing. We survey classes of data analysis and data production algorithms and name necessary requirements as well as enhancing properties for data analytics. Furthermore, we give examples of algorithms that are close to fulfilling the minimal requirements of immersive analytics. Typical requirements are:

(1) Immediate, or seemingly immediate, feedback in the sense that there is no human impression of latency. This includes situations where the human triggers the rerun of an analysis of a larger subset of the data or reruns a simulation that may necessarily take time, but where the human still needs feedback indicating the status of the computation.
(2) Possibilities for the human to control, steer or interfere with the algorithm.
(3) Allowance for human reasoning about the algorithmic results, e. g., allow for human co-processing. This requires mechanisms for the human to look behind the curtain, i. e. any black box method must allow for human inspection on request if the human questions the computer.

While a complete fulfillment of these requirements provides an open challenge, in many cases there are algorithmic developments in recent years heading in the right direction. Some examples by field:

Data Mining: There already exist data mining algorithms that support streaming results. As an example, there is work on data stream clustering, for example, Silva *et al.* [50]. However, taking the human back into the loop is an open challenge.

Clustering: Other classes of clustering algorithms allow users to manually steer the clustering process. Such algorithms use strategies like semi-supervised clustering where must-link and cannot-link constraints are added by the user as in BoostCluster [32]. Another class of such algorithms are subspace search and grouping of similar subspaces that incorporate the user into the clustering, see [54].

Optimization: Optimization and operations research are discovering the importance of human-in-the-loop operation, recognizing that not every optimization problem can be completely modeled and then solved in isolation [37]. In multi-objective optimization, strategies like exploring Pareto frontiers allow for human co-processing [55]. Goodwin *et al.* [22] explore requirements for visual profiling of Constraint Programming solvers. Liu *et al.* [31] explore the relationship between interactive optimization and visual analytics, proposing a "problem-solving loop" for optimization, analogous to the sensemaking loop.
Text Analytics: Interactive topic modeling enables users to view and refine analyses of large document collections [11]. Some existing systems allow the user to define relations between documents spatially to the machine so algorithms can take this into account to incrementally update topic models, for example [20].
Dimension Reduction: With respect to dimension reduction techniques, there are ideas like probing [52] allowing human analysts to gain an understanding of the projections using interaction, or direct manipulation of the projection output to explore projection parameter spaces [17].
Scientific Simulation: For flow simulations, there are some methods that allow the interactive study of particle traces including interactive seeding of additional particles [48]. In similar scientific contexts, some feature detection systems allow for interactive feature definition [16]. While this has been explored for point-based feature detection, this may also be beneficial for particle-based feature extraction [47]. Even topological data analysis algorithms have important parameters with respect to simplification and interactive presentation, as well as further inspection [25]. Here, immersive interaction opens the way for a deeper human understanding of structural data properties.
Information Theory: There are also ideas to use information theory to find unusual data, e. g., by measuring entropy [29]. However, methods that allow the human to indicate which part of the data has highly informative content are missing to date.

Some general questions have not been addressed appropriately, for example, how can an algorithm explain to the human how its conclusions are reached?

5.4. Challenges

From the extended sensemaking loop we identify some aspects that can be improved through immersive design principles. In the following we identify some examples for existing paths through–and potential for new extensions of–the sensemaking loop.

5.4.1. The Role of Alternatives

Good analysis practice considers alternative explanations for any given observation, often in the form of more or less explicit hypotheses. Another form of alternatives occurs in the visual analytics process through different views of the same data, including comparisons and multi-scale views. Yet, such alternatives are not just a part of the process to arrive at insights, they can also play a central role to enable collaborative work between humans while also integrating algorithmic assistance.

Consider a group working asynchronously together. To avoid the potential for destruction of each other's work, it is necessary that any visual analytics system can support parallel, independent alternative views and interactions. If multiple people work independently on the same content, such as a dashboard, it is appropriate for the system to support such parallel work, e. g., by keeping people aware of other changes. But as network connections cannot always be taken as granted, the support for post hoc integration of changes (aka post hoc merging), is also highly beneficial.

Full support for asynchronous work also enables more seamless integration of machine assistance. A notable issue here is that machine processes can take indeterminate amounts of time to finish. Having (multiple) humans wait on a machine is not appropriate for modern workflows, especially if the results provided by the algorithmic assistance are not part of the core thread of work, such as speculative machine optimization building on human-derived results. This can be addressed by supporting alternatives and thus alternative threads of work as first-class citizens directly in the system [35]. Then one could start an ensemble solver, any form of optimization process, or some system that automatically explores the solution space, and be assured that the results of that computation are, once they are available, easily integrated into the whole workflow as a separate alternative or have the option to merge these results (wholly or partially) into the work by humans or other algorithms, as appropriate or needed.

5.4.2. Human Control of Computational Analytical Processes

Immersive analytics offers new opportunities for human-centered interactive analytics. By focusing on the sensemaking loop, we make clear that human sensemaking tasks are the central considerations around which computational analytics can be designed and situated [20]. Immersive analytics whole-heartedly takes this point of view by immersing the user in the sensemaking process and contextualizing computational support in the immersive sensemaking space. This leads to new challenges in the design of immersive interactive controls for computational analytics.

The large physical and/or virtual spaces offered by immersive environments can be exploited to support the synthesis portion of sensemaking, such as schematizing, by giving analysts “space to think” [2] (Figure 4). Analysts use the space to interactively externalize cognitive schemas by organizing information into series, clusters, and other spatial structures. Over time, analysts “incrementally formalize” their hypotheses via course- or fine-grained adjustments to these spatial structures [49]. These immersive interactions can be exploited as human-in-the-loop feedback for computational analytics and semi-supervised machine learning algorithms that support the sensemaking process, such as user-guided dimension reduction for spatialization of text corpora [18].

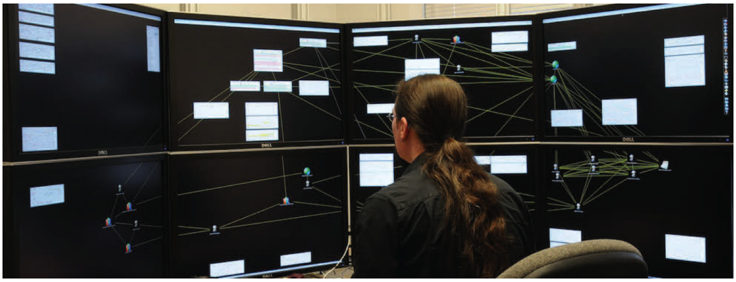

Fig. 4: Space to think: An analyst is immersed in a large sensemaking space, organizing a schema of textual data in collaboration with machine learning algorithms [2, 4].

A key challenge is designing immersive interactions that provide relevant input to computational analytics and designing computational analytics that appropriately support such user feedback [35]. One of the principles of Semantic Interaction [18] is to exploit existing cognitive operations that sensemakers naturally apply in physical environments, such as organizing and annotating, and re-casting these cognitive-level interactions into low-level feedback required by computational algorithms. Since these interactions are likely to be incremental in nature, it is important that the algorithms are designed such that they (1) do not require complete specification of all parameters up front, and (2) support incremental model learning [49].

Immersive environments offer opportunities for rich, multi-modal interactions, through many kinds of input devices and tracking many kinds of human analytic behaviors, to control computation. Subtle cues can be recognized and used to steer computational analytics. For example, big data computation can be steered onto areas of human focus of attention in the space, such as via gaze tracking, to provide just-in-time results [26]. Multiple degrees of freedom in the interaction space can offer more fluent control for parallel input. This enables the possibility for more efficiently steering multidimensional parameter spaces of complex analytics, manipulating multiple parameters and constraints for ensembles, or simultaneously specifying operations and target data. Immersive analytics can also support interaction with larger amounts of data at multiple levels of scale, such as manipulating many data objects via multi-touch [42] or physical-navigation aware cone-casting [43] methods. Multiple input devices can be used to exploit the most appropriate interactive affordances for each sensemaking task [13]. These complex interactions, such as simultaneously controlling several parameters, are typically a skill that requires training and thus create new usability challenges.

However, immersive environments also pose some difficulties for user input to computation. Immersive environments may have less precise input controls that would need to be supplemented with computational support. Also, text input in immersive systems is a notable challenge. Text input is useful for many tasks that cannot easily be solved when using pointing, such as annotating, formulating a hypothesis, or building a case. Speech recognition is a potential solution, but error recovery (after either the speech recognizer or the human makes a mistake) typically requires a surprisingly large amount of time with speech recognition.

Another design challenge is supporting transitions into and out of the immersive environment or between forms of immersive environments. For example, a user takes off an HMD to sketch on a tablet for designing a new computationally-generated visualization and then goes back into the HMD to see how the final result looks. Such transitions might be necessary due to the limited display resolution of the HMD or the limited tracking of pen-based input in an HMD environment. Similar transitions need to be considered for transitioning between individual and collaborative sensemaking tasks.

A final challenge is recording interaction history for provenance purposes, such as computational checkpointing. This is already a challenge in current visual analytics systems but becomes an even bigger challenge in immersive analytics systems due to the need to consider the current viewpoint and/or location in space of the users at any given time. For augmented reality applications, provenance systems may also need to take snapshots of how the world looked at each point in time, for example, to determine if a given person or object was present.

5.4.3. Computational Output in Immersive Analytics

There are a number of challenges and opportunities that arise in embedding computational analytical results in interactive immersive environments in ways that support the collaborative sensemaking process.

Holistic approach to the collaborative sensemaking loop: Rather than treating each step in the sensemaking process as a distinct tool, immersive analytics seeks to integrate the processes in a common space with common operations. A holistic approach can help to better support the many interconnections between the looping steps of the sensemaking process. This is important because analysts make many rapid iterations through portions of the sensemaking loop during the course of an analysis. This is exacerbated by the presence of multiple collaborating human and computational agents, each potentially working at different stages within the sensemaking loop. For example, in the sensemaking concept of "dual search", analysts must seek to simultaneously find hypotheses that explain the given evidence and also find evidence that supports their hypotheses [44]. An integrated approach can help analysts to more efficiently propose, and confirm or refute hypotheses.

A challenge for immersive analytics is the design of such unified spaces, and the design of the visual representations, interactive links, and computational processes that connect the steps of the sensemaking process. Designs should seek to minimize breaks in immersion across task boundaries. For example, with "synthesis driven foraging" (e. g., Starspire [4], as in Figure 4), human interactions in the later synthesis-oriented stages of sensemaking, such as schematizing and hypotheses generation, can automatically drive computational re-foraging for supporting evidence in the earlier stages of sensemaking. Results would then be immediately visualized for their impact on the hypotheses and enable further synthesis operations by the analysts. A particular opportunity with the holistic approach is overcoming confirmation bias. Since human analysts frequently suffer this problem, computational agents can be utilized to specifically seek and display refuting information.

Embedding users in computational workflows: An important opportunity in immersive analytics is to exploit the large physical and/or virtual spaces offered by immersion to visually represent complex analytical workflows, along with concomitant parameters and results at each stage. Increasingly complex computational analytic workflows lead to an overload of human short-term memory and difficulties in human understanding of the results. As an initial solution, visualization researchers have explored the use of visual representations of computational workflows, such as iconic representations of process steps (e. g., VisTrails [3]). This is particularly important in human-in-the-loop analytics, where the computational workflows are designed to reflect the steps of the human sensemaking loop.

A challenge of immersive analytics is the design of representations that visually embed the user and the computational results directly into the workflow representation. This approach can simultaneously represent the parameters and full outputs of multiple stages of the workflow, potentially enabling the user to navigate and compare results along the computational pipeline, thus supporting rapid progress through the sensemaking loop [46]. Multiple users can be simultaneously embedded to analyze different portions of the workflow while maintaining awareness of each other, similar to analogous physical organizations of collaborative human activity such as air traffic control [33].

With these methods, immersive analytics can help to open the analytical black-box by enabling users to see inside the workflow, participate in various steps of the workflow, and directly relate inputs to process to outputs. Such an introspection capability could lead to better user control of computational analytics and increased trust in algorithmically generated results [12]. Additional opportunities arise in annotating and examining the provenance of process and results, such as visualizing which source data contributed to certain output results throughout the entire analytical workflow [45].

Contextualizing computational feedback in human sensemaking: To support human sensemaking, computational analytic results can be contextualized directly within the human sensemaking process. Previously we have described how sensemakers exploit immersive spaces to externalize their cognitive process and construct organized schemas of information. Supervised learning algorithms can use such input to compute relevant results, and then display these results directly in connection to the inputs. A principle of Semantic Interaction [18] is to represent computational feedback within the context of the cognitive constructs in the immersive space. This can help analysts to better connect computational results to their own cognitive work than if the results were displayed separately elsewhere. The resulting space is a blending of computational and human-created schemas, representing a collaborative effort between cognition and computation.

Immersive environments provide meaningful space for such computational enrichment of the user input. In a sense, the large spaces offered by immersive environments provide a form of common ground between cognition and computation. The principles of spatial and distributed cognition emphasize the role of the physical spatial environment in human cognition [27]. Meanwhile, many data analytic methods exploit spatial metaphors such as distance metrics and triangle inequalities. Thus, space offers a rich medium for interaction between the computer and human.

A challenge is designing visual representations that re-cast computational output into task-oriented elements in the human sensemaking process. For example, in StarSpire [4], the user interest model that is learned by the computational algorithms in the form of keyword weights is visualized to the user by highlighting those keywords directly in the documents that they are reading with a color brightness that is proportional to their weight in the model. This explicitly supports the human sensemaking task of foraging for relevant information in the documents, but also implicitly gives the user feedback about the model state.

Managing user attention: A particular challenge in immersive analytics is managing users' attention in the immersive space in the presence of new or changing information that results from computational processes. For example, computational processes can be used to suggest regions of particular interest in a large space of results (e. g., Voyager [57]), to find latent connections between spatially distant information on the display (e. g., VisLink [14]), or to progressively refine streaming data or large computations on big data (e. g., [21]).

When small or non-obvious changes take place, such as new computational results appearing out of the user's current viewing frustum, the notification problem arises [36]. The question is how to alert users to the new information in a clear and yet unobtrusive fashion. Immersive environments can exploit additional human embodied resources such as peripheral vision or sonification to subtly notify users of changes [26].

At the other end of the spectrum, when very large changes take place, such as a complete re-organization of the space based on the results of a dimension reduction algorithm, they can be overwhelming and disorienting to an immersed user. This leads to the need for methods analogous to "smooth and efficient zoom and pan" [56] that attempts to minimize optical flow during navigation by zooming out before significant panning, making use of the larger frame of reference. Similarly, incremental approaches such as incremental learning algorithms or animated force-directed layouts, combined with landmark persistence, can help users maintain orientation while exploring new results (e. g., ForceSpire [18]).

Representing sensemakers: In immersive analytics, actors in the sensemaking process can be visually represented in the sensemaking space to make the collaboration more clear. A challenge is creating avatars or other forms of representations of both human and computational agents, enabling collaborators to see what part of the data or sensemaking process activities others are working on and potentially share perspectives [34]. With augmented reality, actors might be represented physically. For example, "Be the Data" [10] enables collaborating students to take on the perspectives of individual data points as they are manipulated by dimension reduction algorithms, and directly visualize distances between points as distances between people in the space.

5.5. Conclusion

In this chapter, we discussed higher-level concerns of the sensemaking process around data, corresponding to *Strategic Immersion*, similar to high-level problem-solving in games [1], and analyzed how immersive environments can help here. We also looked at how immersive environments can help with the integration of automatic processes, such as machine optimization and learning, into the analytics workflow and the user's role in a large-scale collaborative analytics process with both other people and machine assistance. This is a natural step in the integration of interactive data analytics capabilities with modern machine learning methods. Such integration also satisfies the growing need to be able to explain data analytics results to others. Consider having to defend the choices made–by human or algorithmic data analyst–to a superior or a judge. Finally, we also looked at some of the technical requirements associated with doing data analytics in immersive environments.

There are a variety of avenues for future research. These include:

- Can–and if so, how can–immersive environments enable users to think about, and deal with, more complex problems than is currently possible on desktop platforms. This is especially a challenge when one considers that it may be necessary to employ multiple actors, both human and automatic, working together to solve such problems.
- How can we use immersion to amplify human intelligence, intuition, and creativity? Specifically, this targets the higher-level process and provenance tasks described in Section 5.2., schematization and hypothesis generation (and testing). These high-level cognitive processes remain relatively poorly understood and thus this is a significant research challenge.
- How can immersion be used to advance human collaboration with computational processes? In particular, what new opportunities do immersive environments provide to enable human interaction with the inputs and outputs of computational analytics?
- Many of the current limitations for immersive analytics are technological. Research needs to provide an understanding of human capabilities for understanding analytics, given future technological capabilities. For example, by lifting the arbitrary limitation imposed by the display space of current desktop environments, can we imagine or prototype environments that overcome those limitations in order to discover where the next challenges lie?
- How can we minimize artificial breaks in immersion/engagement–especially across task boundaries? And if we require users to break their immersion, e. g., when switching from an HMD to keyboard input and back, how can we keep their engagement intact?

– One of the premises of this chapter has been that ideas from game design which promote immersion, engagement, and flow, can be beneficially brought to data analytics and sensemaking. Are there additional opportunities in this vein? For example, another potential avenue of future work is to explore the gamification of the immersive analytics process.
– A final future consideration is the evaluation of sensemaking activities in immersive analytics environments. There are opportunities for evaluation of immersive systems, for example, in many such systems gesture control and immersive rendering necessitate head and body position tracking. Thus, we can collect a fairly complete model of user interaction which could be further enriched with other biometric data collection, e. g., pulse-rate, affective measures or even cortisol levels. With such a complete model we can study peoples' patterns of interaction during sensemaking and ultimately better understand this complex activity.

Acknowledgements

Dwyer acknowledges support by the Australian Research Council Discovery Scheme, project DP180100755.

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