Chapter 12
Top Ten Interaction Challenges in Extreme-Scale Visual Analytics

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Abstract The chapter presents ten selected user interface and interaction challenges in extreme-scale visual analytics. The study of visual analytics is often referred to as "the science of analytical reasoning facilitated by interactive visual interfaces" in the literature. The discussion focuses on applying visual analytics technologies to extreme-scale scientific and non-scientific data ranging from petabyte to exabyte in sizes. The ten challenges are: in situ interactive analysis, user-driven data reduction, scalability and multi-level hierarchy, representation of evidence and uncertainty, heterogeneous data fusion, data summarization and triage for interactive query, analytics of temporally evolving features, the human bottleneck, design and engineering development, and the Renaissance of conventional wisdom. The discussion addresses concerns that arise from the different areas of hardware, software, computation, algorithms, and human factors. The chapter also evaluates the likelihood of success in meeting these challenges in the near future.

12.1 Introduction

Extreme-scale visual analytics, generally speaking, is about applying visual analytics to extreme-scale data. Thomas and Cook (2005) define visual analytics (VA) as "*the science of analytical reasoning facilitated by interactive visual interfaces*." By extreme-scale data, we are referring to both scientific and non-scientific data of a petabyte (10^{15}) today to the magnitude of exabyte (10^{18}) in the next five years.

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When the VA research and development (R&D) agenda (Thomas and Cook 2005) was published in 2005, the focus of the R&D community was largely on non-scientific data analytics and their applications. The agenda was not intended to be a static, final document but rather an evolutionary recommendation that guides the community based on its needs and priorities. In the years since the agenda was published, the VA community has continued to evolve and new requirements have emerged.

For example, the National Science Foundation (NSF)'s Foundations of Data and Visual Analytics (FODAVA) (FODAVA 2012) program has taken a particular interest in, among others, the mathematical foundations that enable and support data and visual analytics. The U.S. Department of Energy (DOE)'s Advanced Scientific Computing Research (ASCR) program (DOE 2010) has set a goal to address the exabyte data problem with a vision of future exascale computer systems comprising as many as a billion cores. Visual Analysis of Extreme-Scale Scientific Data is one of the six major R&D areas formally identified by DOE.

Size does count. When data size reaches the magnitude of an exabyte, it creates a significant set of unsolved and potentially unsolvable problems that challenges the conventional wisdom and assumptions in computing, computational reasoning, visualization, etc. In fact, some domain and computation scientists have already suggested that everything ranging from hardware to software must adapt and change, and change quickly (Ahern et al. 2011; Ahrens et al. 2010), to fully address the extreme-scale data challenges looming on the horizon.

Because we want to accelerate the pace of progress towards addressing the extreme-scale visual analytics challenges, we present a set of hard problems in this chapter and invite the readers to consider the challenges from different technical and intellectual viewpoints. These hard problems are presented as a list of top *interface and interaction design* challenges of extreme-scale visual analytics. The list was created based on what we have learned from our work and extensive discussion with domain experts in the community. We intend to continue to identify and rank additional top-problem lists in areas such as hardware and computation as related to extreme-scale visual analytics.

The chapter presents related work in extreme-scale data analytics in Sect. 12.2, describes what an extreme-scale visual analytics problem should be in Sect. 12.3, and identifies and ranks a list of top interface and interaction design problems in extreme-scale visual analytics in Sect. 12.4. We evaluate the likelihood of success of the selected challenges in Sect. 12.5 and conclude our discussion in Sect. 12.6.

12.2 Related Work

We highlight some of today's extreme-scale data problems found in scientific and technological communities, describe recent R&D efforts to address some of the extreme-scale challenges, and present three top-ten problem lists reported in modern data visualization and visual interface literature.

12.2.1 Some Well-Known Extreme-Scale Data Problems Today

The problem of managing extreme-scale datasets is real and growing more serious every year. In 2007, *The Wall Street Journal* (Swanson 2007) published an article on *Exaflood* information transmitted over the internet. Multiple datasets have since been identified in the literature that either have reached, or have the potential to reach, multi-exabyte in size. These datasets include the world's digital content (500 exabytes in 2009) (Wray 2009), broadcasted information (1900 exabytes compressed in 2007) (Hilbert and Lopez 2011), and telecommunication (projected to be two exabytes per month by 2013) (Cisco Network Index 2012).

12.2.2 Extreme-Scale Data Visualization and Management

There are a number of recent U.S. Department of Energy (DOE)-sponsored workshop reports that discuss the mission and R&D opportunities in exascale data management and visualization (Ahern et al. 2011; Ahrens et al. 2010). Within the scientific visualization community, both VACET (2012) and Institute for Ultra-Scale Visualization (2012) have continuously developed new and innovative visualization technologies for petabyte data applications.

In his keynote speech at the ACM SIGMOD/PODS Conference in 2008, Ben Shneiderman (2008) discussed the challenges of visualizing extreme-scale datasets with a limited number of display pixels. Most of the examples discussed are related to non-scientific data visualization applications.

12.2.3 Top-Ten Visualization and Visual Interface Challenges in Literature

A number of top-ten problem lists have been presented in the visualization and visual interface literature. Hibbard (1999) presents perhaps the first ever top-ten list of problems in visualization, which includes topics from virtual reality to direct data manipulation with visualization, and focuses mainly on early scientific visualization problems found in the 1990s.

In 2002, Chen and Börner (2002) presented their top-ten list in visual interface to digital libraries. Although the topic area is somewhat similar to the Hibbard list, the Chen and Börner list has a wider topic scope that emphasizes information analytics.

Finally, Chen (2005) presented a bona fide list of unsolved problems in information visualization. The list, which was published just before Thomas and Cook (2005), contains modern analytical topics from prediction to quality measure studies that align well with the visual analytics R&D agenda presented in Thomas and Cook (2005).

12.3 Three Fundamental Elements of Extreme-Scale Visual Analytics

During the preparation of this chapter, we attempted to define extreme-scale visual analytics among ourselves by looking at the underlying data (scientific, non-scientific, social, etc.), the analytical techniques (mathematical, cognitive, immersive, etc.), and the ultimate goals (presentation, reasoning, sensemaking, etc.) of the problem. In the end, instead of providing an elegant definition of the emerging area, we suggest three fundamental elements that characterize an extreme-scale visual analytics problem to facilitate the rest of the discussion, and leave the formal definition open for others to contribute to and elaborate further.

The first element, of course, is the *size* of the underlying data. The reason we emphasize size is that the traditional *post-mortem* approach of storing data on disk and visualizing it later is going to break down at the petascale and will undoubtedly have to change for exascale (Ahern et al. 2011; Ahrens et al. 2010). Extreme data size is the root of many computational and analytical difficulties. However, it also provides the broadest possible opportunity for R&D in the area.

The second element is the inclusion of both visual and analytical means in the solution of the problem. Following the recommendations in Thomas and Cook (2005), a visual analytics process normally involves a combination of visual representation, data transformation, interactive manipulation, and sensemaking. In other words, visualizing an extreme-scale dataset as a static display or a video is not visual analytics. Such visualizations are sometimes referred to as *presentation visualization* in the literature.

The third and final element is the active involvement of a human being in reasoning and sensemaking during the visual analytics process. To borrow a term from the data mining community, visual analytics is indeed a *supervised data analysis* process that involves active interactions between the computer and human being. The interaction element as implemented on a parallel high-performance computer (HPC) has subsequently become a top challenge in our discussion in Sect. 12.4.

12.4 Imminent Challenges of Interface and Interaction Design

We present ten selected *interface*-focused and *interaction design*-focused challenges for extreme-scale visual analytics. The order of the challenges does not reflect relative importance, but rather the content correlation among individual challenges.

12.4.1 In Situ Interactive Analysis

We mentioned earlier that the traditional post-mortem approach of storing extreme-scale data on disk and then analyzing it later may not be possible beyond petascale in the near future. Instead, the *in situ* visual analytics approach attempts to perform as much analysis as possible while the data are still in memory. This approach can greatly reduce the cost of I/O and maximize the ratio of data use to disk access.

However, today's HPC architectures generally do not support or promote *interactive* operations. Even though an interactive operation is technically possible, the time spent waiting for user responses in an interactive operation will quickly increase the cost of the computation to a prohibitive level. Thus, one of the major challenges is how do we optimally share the cores within the hardware execution units and alleviate the overall disruption of the workflow brought by the human-computer interactions.

12.4.2 User-Driven Data Reduction

While many agree that more aggressive data reduction needs to be done for extreme-scale applications, it is not clear where and how such data reduction should take place. Traditionally, data reduction is often performed via compression. However, given that the size of data is overwhelmingly large, and many datasets have single or double precision, the effectiveness of compression will be extremely limited.

Several other data reduction mechanisms are possible. For example, data can be stored at a much lower resolution if little or no interesting features exist. The definition of features can be geometrical, topological, or statistical. Because different applications will have different requirements, it is risky to perform data reduction without involving the humans that produce the data. Thus, the challenge of data reduction for extreme-scale application is to develop a flexible mechanism that can be easily controlled by users based on their needs. It is likely such a customized mechanism will be multi-level (data level, feature level, and application level), and all levels will need to work seamlessly together. Furthermore, unnecessary details such as the lower level storage and I/O also need to be encapsulated and hidden from the user.

12.4.3 Scalability and Multi-level Hierarchy

Scalability has been a continual challenge for any big data problems. Whether it is algorithmic, visualization, or display scalability issues, the multi-level approach has always played a vital role in the computation, analysis, and final outcomes. We discuss the multi-level concept and different mechanisms for user-driven data reduction in the last section. But no matter what mechanism is applied to the dataset, the corresponding hierarchical outcomes will often result in additional challenge to the rest of the visual analytics tasks.

Given a big dataset G, a prevailing multiresolution approach is to generate an increasingly coarsened hierarchy $G_0, G_1 \dots G_i \dots G_n$ such that the fine levels provide local details and the coarsened levels give the overall structures for both computation and visualization. The multi-level concept has addressed the big data problem for years when the data size remains in the terabyte range. When the data size increases further, the number of hierarchical levels can quickly escalate. For example, if we generate a multi-level hierarchy from an exabyte dataset using a dyadic approach, there will be as many as 60 levels between the coarsest and finest levels. Navigating such a *deep* hierarchy, and searching for the optimal resolution (and details) at the same time, has become one of the major challenges for scalable analysis.

12.4.4 Representation of Evidence and Uncertainty

Evidence synthesis and uncertainty quantification are two fundamental data analytics problems in their own right. Evidence and uncertainty often both supplement each other and underscore each other's inferiority. In a visual analytics environment, this information is frequently united by visual representation for further reasoning and sensemaking.

The issue of evidence representation is that the interpretation of evidence is subject to the person doing the interpretation. The process often depends on prior knowledge, subjective settings, and the analyst's viewpoint (Chen 2008). As data size grows, the problem becomes more complicated and more human decisions are involved. Uncertainty quantification attempts to model the consequences of various machine and human decisions based on the presented evidence and to predict the qualities of the corresponding outcomes. The primary challenge is how to represent the evidence and uncertainty information of extreme-scale data clearly and *without bias* through visualization.

Additionally, humans are cognitively vulnerable, especially when dealing with large-scale data visualization. A secondary challenge is how to help humans to be aware of cognitive biases and pitfalls that could potentially alter what they believe they are seeing. As one can lie with statistics, one can also lie with perceptual illusions and cognitive patterns, whether it is intended or not.

12.4.5 Heterogeneous Data Fusion

We seldom see fully homogeneous datasets at extreme-scales in real life. Most of the known extreme data problems today are highly heterogeneous and proper attention must be paid to analyzing the interrelationships among the heterogeneous data objects or entities. As the size and complexity of a heterogeneous dataset continue to grow, extracting the data semantics and interactively fusing them together for visual analytics will significantly add additional burdens to both computation and complexity of the problems.

For example, we used to harvest multimedia data—such as text, images, audio, and video—and then analyze them independently. As multimedia becomes increasingly digital and connected, knowledge is potentially embedded in data of all types/sources and in the aggregate. Extracting knowledge may require mining the entire dataset in order to measure and assess the relative relevance of the information. Thus, the data size directly, and in many cases non-linearly, affects the dimensionality and scope of the underlying analytical problem. Similar challenges can also be found in scientific computing domains such as climate modeling, where scalar fields meet flow fields referenced by both geographic coordinates and topological structures. Overall, the data heterogeneity problem makes the extreme-scale visual analytics challenge even more formidable.

12.4.6 Data Summarization and Triage for Interactive Query

As the size of data exceeds petabytes, it becomes very difficult, if not impossible, to examine the complete dataset all at once. Instead, the model of visual analytics and data analysis for extreme-scale datasets will be more like database queries—that is, the user requests data with particular characteristics, and only the corresponding results are presented.

One key to support interactive data query is effective data summarization. The goal of data summarization is to organize the data based on the presence and the type of features, which can be defined by certain general criteria as well as domain-specific input. For scientific data, features can be roughly classified as geometrical, topological, and statistical. For non-scientific datasets, features are often related to the semantic or syntactic components of the data. Extraction of meaningful features can be a major challenge. As the dimensionality of features can be high, it is necessary to reduce the dimensionality of feature descriptors to a manageable space that allows efficient exploration by the users. Finally, after data summarization is completed, the data needs to be stored and indexed in an I/O efficient format that allows rapid runtime retrieval. One technical challenge is to make the underlying I/O components work hand in hand with the data summarization and triage results, which together facilitate interactive query of the extreme-scale data.

12.4.7 Analytics of Temporally Evolving Features

We live in a dynamic world, and hence data generated from most applications will evolve with time. For example, the topics of interest in Twitter messages can change daily, if not hourly. The evolution of data characteristics often contains important information about the underlying problem and therefore should be a focus of data analysis and visual analytics.

Several challenges exist when analyzing temporally evolving extreme-scale data. One is that the size of data is often quite large, which makes lengthy calculation or preprocessing impractical for daily use. Another challenge is that when the features occur at different spatial and temporal scales, traditional visualization methods such as animations, or displaying small multiples, often fail. The key challenge for analyzing extreme-scale temporal data is to develop effective visual analytics techniques that are computationally practical and that can take advantage of humans' unique cognitive ability to track moving objects.

12.4.8 The Human Bottleneck

HPC experts have recently predicted that all major components related to computational science—from power, memory, storage, I/O bandwidth, to total concurrency, etc.—will improve by a factor of three to 4444 times by 2018 (Ashby et al. 2010). Human cognitive capabilities, however, will undoubtedly remain constant. The human is rapidly becoming the bottleneck in extreme-scale visual analytics.

We know that humans are not good at visually detecting patterns in a large amount of data. When data grows to a certain size, patterns within the data tend to become white noise. Human cognitive biases also tend to distort or inhibit understanding of data patterns in large data. Researchers have used large, tiled displays to increase the visualization space and alleviate the big data visualization problem, but there is a visual acuity limitation (Yost et al. 2007) that potentially hinders the effectiveness of the large screen approach. There is no Moore's Law for any cognitive activities. The human bottleneck problem in extreme-scale visual analytics will stay relevant for a long time.

12.4.9 Design and Engineering Development

The HPC community has offered little to motivate the adoption of API and framework standards for general user interface development on HPCs. Much of today's large scale data analytics interface development is implemented and executed on desktop-based environments such as a desktop computer. It is nevertheless a feasible, and often the only, solution for today's large-scale visualization and visual analytics efforts. In other words, community-wide API and framework support on an HPC platform is still not an option today.

Beside the hardware challenges, software support for user interaction development is also a major problem today. Programs will need to be compiled using a 64-bit compiler to allow access to a much larger memory address space. Unfortunately, some of the prevailing user-interface frameworks such as Qt (Qt Framework 2012) still do not fully support 64-bit Windows OS, which allows much greater memory space and thus larger datasets. Additional compatibility challenges also come from programming languages, operating system platforms, customized domain software, and threading programming problems on today's desktop computers. This will remain a problem until either there is a massively parallel desktop computer or a new HPC that addresses some of the above-mentioned challenges.

12.4.10 The Renaissance of Conventional Wisdom

Throughout the years, our community has acquired nuggets of wisdom that are widely adopted by both researchers and practitioners when working on information analytics problems. Many of these once seemingly infallible nuggets will inevitably be confronted by the above challenges when dealing with extreme-scale data. Among the well-known controversies, for example, is Ben Shneiderman's "*overview first, zoom and filter, then details-on-demands*" mantra for navigating or viewing big data.

We agree that full-blown interactive analytics on HPC will be possible eventually but probably not any time soon. For now, we will need a secondary machine such as a desktop computer to support post-mortem visualization. But writing such an extreme amount of data on disks is also not likely to happen soon. All these, plus *the-human-bottleneck* challenge, work against Shneiderman's mantra that requires effective access to all information at one time and in one place. So our final, and perhaps most important challenge, is to spark the Renaissance of conventional wisdom in visual analytics as applied to extreme-scale data. Successfully bringing back the conventional wisdom will most likely foster solutions to many of the problems described in the chapter.

12.5 Evaluation and Likelihood of Success

The *In-Situ Interactive Analysis* challenge could theoretically be solved even today. The potential solution would require a radical change in the operation, regulation, and policy of the HPC-wide community as well as the system and engineering support of the commercial hardware vendors.

The *User-Driven Data Reduction* and *Scalability and Multi-Level* challenges are both related to the size of the extreme-scale data. As HPC is becoming increasingly mainstream, many problems with respect to these challenges can potentially be addressed, or at least alleviated, by building more powerful machines and developing more advanced data and computation algorithms.

The *Representation of Evidence and Uncertainty* challenge is a hard problem to solve because it often involves human bias in the process, which may not be fully addressed by machine-based automated systems. The problem also coexists with two other difficult, non-visual problems (evidence synthesis and uncertainty quantification), which further exacerbates the challenge.

With a wider range of applications and stronger demand in growth for the HPC community, the *Heterogeneous Data Fusion* and *Data Summarization and Triage* challenges for many database-oriented problems can potentially be addressed in the near future. The increasing availability of low-cost, high-performance data warehouse appliances such as Netezza Data Warehouse (2012) also offers alternative solutions to the data challenges.

Both *Analytics of Temporally Evolving Features* and *The Human Bottleneck* challenges push the human performance to the limit. These challenges are not meant to be solved entirely. Remedies that alleviate some of the problems may potentially come from a combination of better computation hardware and more advanced human-computer interaction hardware devices and interfaces.

The *Design and Engineering Development* challenge will be addressed when the demand rises for HPC-based user interface and interaction science and technology and outweighs the cost of development. The success of this challenge also lies in the availability of solutions that meet the *In-Situ Interactive Analysis* challenge above.

As for the *Renaissance of Conventional Wisdom* challenge, we fully expect that it will eventually happen as the high-performance computer is becoming increasingly popular and will be the norm of everyday computation in the future.

12.6 Conclusions

This chapter discusses the emerging area of extreme-scale visual analytics and presents some of the top user interface and interaction design challenges facing the current and future research and development of the area. Much of the discussion is drawn from the experience of our ongoing work, as well as the experiences of our colleagues in the exabyte data visualization and management areas. While the scientists and researchers of the extreme-scale data analytics community may have a different priority on these and other challenges, solving some of these challenges can certainly lead to very desirable outcomes for scientific discoveries and advances in technology for the society.

Like Thomas and Cook (2005), the discussion of this chapter is not meant to be a static, final document. It will most likely evolve as both hardware and software technologies advance in the future. We hope the discussion of these important issues can inspire enthusiasm and creative solutions to the challenges, and ultimately lead to a vibrant and engaged community for extreme-scale analytics.

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