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Big Data Visual Analytics

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Big Data Visual Analytics

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1 Summary

High-throughput technologies have produced Big Data in many application domains in Science and Engineering including Biomedical Engineering, Genomics, Software Systems, Computer Networks, Finance, e-commerce, Cyber intelligence, and Homeland Security. The ability to analyze such Big Data for knowledge discovery and decision-making is critical to scientific advancement, business success, clinical treatments, cyber and national security, and disaster management.

Visual Analytics is the science of analytical reasoning supported by interactive visual techniques, which requires interdisciplinary science integrating techniques from visualization and computer graphics, statistics and mathematics, data management and knowledge representation, data analysis and machine learning, cognitive and perceptual sciences.

The main goal of the workshop is to promote Visual Analytics research in Asia-Pacific region, and form a research community to collaboratively solve complex problems arising in a variety of application domains. In particular, special emphasis on the *Big Data* is addressed.

Big Data Analytics is the biggest and fundamental challenge in IT research due to Scalability and Complexity. Innovative scalable techniques for Big Data Visual Analytics will be the key enabler for researchers and end users in many application domains and other disciplines.

This meeting aims to bring world-renowned researchers on Visual Analytics and collaboratively develop innovative scalable Visual Analytics solutions to solve the scalability and complexity issues for analyzing Big Data arising from various application domains including Systems Biology, Social Networks, Finance, Business intelligence, and Security.

Our specific objectives are:

- identify research opportunities in Big Data Visual Analytics, focusing on the Asia-Pacific context.
- form a broader research community with cross-disciplinary collaboration, including computer science, information systems, statistics, biology and sociology, with a focus on Visual Analytics of Big Data.

- foster greater exchange between visualization researchers and practitioners, and to draw more researchers in the Asia-Pacific region to enter this rapidly growing area of research.
- assist emerging researchers to find linkages to international researchers, industrial contacts, and competitive research grants and fundings.

2 Program

- Nov 7 Saturday Evening
  - Reception
- Nov 8 Sunday Morning
  - Introduction
  - Invited Talk 1: Peter Eades
  - Invited Talk 2: Wei Chen
  - Invited Talk 3: Steffen Koch
  - Group Photo
- Nov 8 Sunday Afternoon
  - Invited Talk 4: Vladimir Batagelj
  - Invited Talk 5: Shixia Liu
  - Invited Talk 6: Xiaoru Yuan
  - Open Problem Session
  - Group Formation
- Nov 9 Monday Morning
  - Group Discussion
- Nov 9 Monday Afternoon
  - Group Discussion
  - Group Report
- Nov 10 Tuesday Morning
  - Group Discussion
  - Group Report
- Nov 10 Tuesday Afternoon
  - Afternoon: Excursion to Kamakura
- Nov 11 Wednesday Morning
  - Group Discussion
  - Group Report and Planning
  - Wrap up

3 Invited Talks

How Do You Know Whether Your Visualization Is Good?

Peter Eades, University of Sydney, Australia

The Graph Visualization community has improved the scalability of graph layout algorithms for many years. However, only recently a discussion has started to verify the usefulness of established quality metrics, such as the number of edge crossings, in the context of increasingly larger graphs stemming from a variety of application areas such as social network analysis or biology. Initial evidence suggests that the traditional metrics are not well suited to capture the quality of corresponding graph layouts.

This talk proposes a new family of quality metrics for graph visualization; in particular, concentrating on big graphs. I will illustrate these metrics with examples and apply the metrics to data from previous experiments, leading to the suggestion that the new metrics are effective.

Challenges for Big Data Visual Analytics

Wei Chen, Zhejiang University, China

Nowadays big data brings us unprecedented opportunities for resolving problems that traditional approaches are not competent and building the next generation IT systems. Despite that data visualization has been applied for many fields, there remains many challenges. First, data analysis typically search known patterns from data. How to predict unexpected information remains a challenging problem. Second, despite many well-established software, toolkits and systems, a comprehensive visualization scheme and strategy that is adaptable to varied tasks and datasets is demanded. However, a general visualization software or system is impractical.

Thus, we need to first standardize a visualization and visualization design. The standardization requires further revolutions for effectively improving the effectiveness and efficiency of visualization. Third, urban data is connected to cyber-and-physical spaces. To address practical problems in urban management and security, a suite of schemes are demanded for realizing urban data visualization.

On the Interplay of Dynamic Data Analysis and Interactive Visualization

Steffen Koch, University of Stuttgart, Germany

This talk focuses on velocity, variability and complexity in the context of Big Data Visual Analytics. Beyond the sheer mass of data, these Big Data characteristics require special attention because many data sources, such as sensor telemetry or social media, are flooding us with continuous data streams. Some visual analytics approaches that can handle them have been developed, but many important questions remain open. In particular the tight integration of automatic analysis techniques and visualization techniques that can deal with incoming data streams has to be improved in order to find better solutions for continuous monitoring and real-time situation awareness.

One problematic aspect is the changing data, which is especially difficult to handle with rigid analysis models that cannot be easily adapted to new situations. Another issue is that changes have to be reflected with a form of animation or the emergence of new data values in the visualization. Human perception can be hampered by change blindness and inattention blindness, thus requiring the development of adequate means for attention guiding in such situations.

The presentation summarizes related works in the field of text and document visual analytics that address the aspects of velocity, variability and complexity. Many of the problems are pointed out with examples and demos of first approaches, and open question are formulated accordingly.

On Visualization of Social Networks

Vladimir Batagelj, University of Ljubljana, Slovenia

A network is a graph with additional data on nodes and/or links. In analysis and visualization of a network they have to be combined. To explore a large network its overall structure has to be used (as a map) to interactively inspect interesting details. It would be useful to define a common (JSON based?) layout format so that independent viewer modules can be developed.

Visual Text Analytics: Towards Better Understanding of the Textual World

Shixia Liu, Tshinghua University, China

In many big data applications, it is important to survey and explore complex text data including heterogeneous data and streaming data. A core challenge is to connect big data with people, that is, to present such complex text data effectively in an understandable and manageable manner.

This talk presents major challenges in visual analytics of complex text data and exemplifies them with several text visualization techniques and examples. It aims at investigating how to best combine and leverage state-of-the-art technologies from multiple fields to help people analyze and understand high volume text data.

Visualization for Everyone

Xiaoru Yuan, Peking University, China

It is not trivial to provide easy accessible visualization and visual analytics tools for the general public. In this talk, I will address two sides of this problem. First, we will discuss how to develop suitable visual analytics approaches under situation with limited resources; Second, we will discuss visualization and visual analytical tool for pubic usage, using social media data as examples.

4 Group 1: High-Performance Extreme-Scale Visual Analytics

This group focused on the issues concerning the *BDVA (Big Data Visual Analytics)* within the context of *HPC (High Performance Computing)* environments. HPC systems are capable of generating vast amounts of time-varying complex data sets which can include multivariate, multi-field data, and makes the visual analytics a challenging task. The group discussion was not limited on how to deal with vast amounts of generated data, but also involved the entire life cycle of the simulation, visualization, and analysis as shown in Fig. 1.

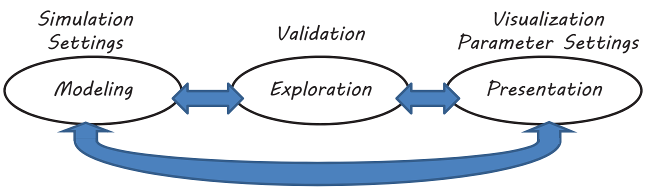

Figure 1: Overview of life cycle of the simulation, visualization and analysis

Our discussions were concerned with both the current and expected future problems faced by the group members within the context of extreme-scale visual analytics in HPC environments. Many of the common problems are related to the data movement cost, and the data and parameter space reduction. Considering HPC systems are shared resources, there was a consensus to focus our discussion on the *Batch Mode* operations inherent to the HPC environments. Within this *Batch Mode* context, the aforementioned problems may be considered in the three scenarios shown in Fig. 2, which also match the life cycle shown in Fig. 1 involving *modeling*, *exploration*, and *presentation*.

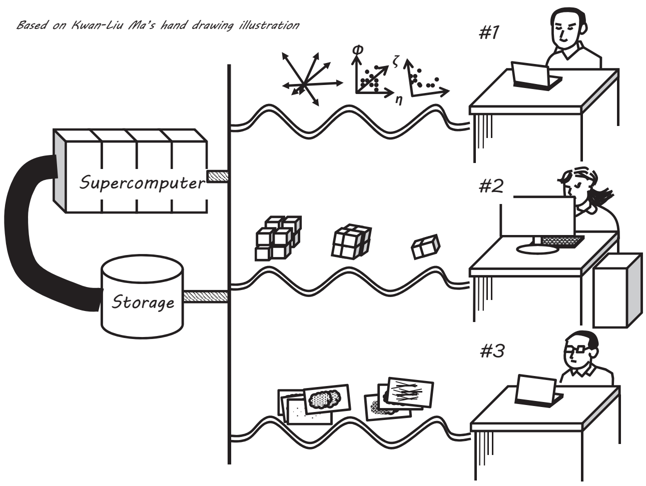

Figure 2: three scenarios involving modeling, exploration, and presentation

4.1 Scenario 1: Large-Scale Simulation Parameter Space

Conducting a large number of runs of simulations is often required in a wide range of scientific and engineering studies, such as climate simulation and during the design process of complex engineering products. In such simulations, normally executed in *Batch Mode*, extensive parameter sweep calculations might be required, generating a vast parameter space for exploration and mining. In this situation, visual analytics can become an important tool for optimizing the multi-run simulations by assisting in the reduction of simulation parameter space, and for the selection and extraction of the key parameter set. For this scenario, the problem and the possible solutions are summarized as follows:
Problem:

- The need to reduce the simulation parameter space and identify the key parameters.

Solutions:

- Interactive *InfoVis* design. [1]
- Interactive multiple linked views between physical and abstracted spaces.
- Parameter space reduction. [2]
- Uncertainty evaluation.

4.2 Scenario 2: Interactive Exploration of Large-Scale Multivariate Data

The importance of interactive visualization for data exploration and mining was highlighted in our discussion. To enable interactive navigation over different aspects in large-scale multivariate data sets on the user desktop side, there is the need to select and pack data subsets of interest on the HPC side. In this scenario, the main issues are related to tasks of data encoding and selecting the region of interest, which can be done by extracting some feature representation of the entire data. On the HPC side, the data encoding as well as the generation of different projections of the data can be executed in the Batch Mode. For this scenario, the problem and the possible solutions are summarized as follows:
Problem:

- The need/challenge to select and pack data subsets to enable interactive visualization of large multivariate data.

Solutions:

- Feature guided encoding of the data.
  - A way to formulate feature descriptions (for computing derived variable(s)).
  - Encoding designs.
  - Direct visualization processing of the encoded data.
- Batch mode computing of different projections of the data. [3][4]

- User-guided process.
- High-dimensional data visualization.
- Transformations between the projected space and the physical space for viewing and selection.
- Views of 4D correlation analysis results and so on.
- Parallelization of all processes.

4.3 Scenario 3: High-Quality and High-Fidelity Visualization

The use of the abundant hardware resources on the HPC side for generating high-quality and high-fidelity visualization of large-scale data sets has also been discussed. One of the main challenges in this approach is setting the visualization parameters since the usual *trial & error* approach would not be feasible because of the shared nature of the HPC systems. For this scenario, the problems and the possible solutions are summarized as follows:
Problems:

- The challenges of setting visualization parameters.
- Trial and error does not work because a supercomputer is a shared resource.

Solutions:

- *In situ* or batch model preprocessing of the data (likely based on sampling) to derive statistics or overviews of the data.
- *"Explorable Images"* technique. [5]
- History/Provenance driven machine learning to derive/recommend visualization parameters (*Machine Learning Group* results).

4.4 References

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5 Group 2: Challenges for Interactive Machine Learning in Big Data Visual Analytics

It is important to properly utilize machine learning components in big data visual analytics. To this end, however, there exist numerous challenges, which hinders the effective use of machine learning in visual analytics. We have discussed and enlightened various challenges.

First of all, the pipeline of using machine learning can be summarized as shown in Fig. 3. In this process, user intervention can occur at any stage, and depending on how we view the machine learning module, one can think of two different perspectives: a white-box or a black-box approach. The former considers a machine learning module as what users can intervene in the middle of its process while the latter view the machine learning module where users can only control its input and output. Each perspective has its own pros and cons, and we discussed the following challenges from each perspective.

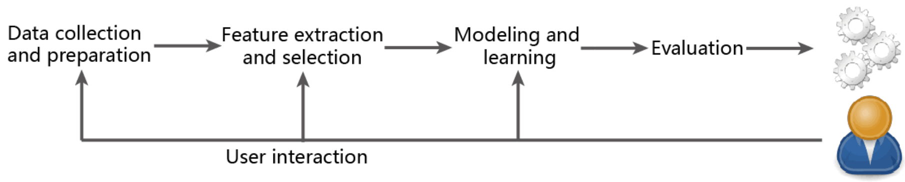

Figure 3: Overview of a machine learning process

5.1 A Black-box perspective:

1. How to provide an effective mechanism to explore big data for choosing the right analysis model, such as K-means, SVM, or neural network.

   (a) Providing different perspectives with different algorithms.

      i. Human-guided sampling - check the distribution - heat map for the original data, scatter the sampling data over the heat map

   (b) Presenting the algorithm results in an interpretable and intuitive way.

5.2 A White-box Perspective:

1. How to provide a scrutable user feedback mechanism, i.e., provide user with an understanding of how his/her input affects the underlying algorithm/method.

   (a) Infer user intent from user interactions or feedback: interactions with raw data and transformed data (e.g., clusters)

      i. Single data item: efficient (possible feedback grows linearly w.r.t. #data items), but requires users to have a clear idea about user feedback in advance. For example, users could assign the exact label of a particular data item.

ii. Relative comparisons between data items: inefficient (possible feedback grows quadratically w.r.t. #data items), but it is more suitable when users have only rough idea about their pairwise decision or preferences. For example, users could only specify the two data items should belong to the same cluster or different ones.

(b) Active learning from machine learning context could be utilized to lead users to answering the most critical question that is maximally helpful to the system.

i. The main issue is how to provide intelligent user interfaces that can efficiently and effectively collect the user inputs.

ii. Gamification could be one interesting way of enhancing user participation in the context of the active learning tasks.

(c) Transparent communications between a computer and a user: reveal how a user's feedbacks will influence the model and then guide the user to provide further feedback in the right direction.

2. Human-guided feature selection

(a) Examine the data from different angles, e.g., Interaxis system for user-driven axis forming via data selection of users' preference

(b) Interactive feature selection/engineering

3. User-steerable machine learning

(a) Machine learning that can support various user feedback and serve user intent. Traditionally, machine learning methods have incorporated user feedback in several classes of methods such as semi-supervised learning and active learning. However, how the user intent is incorporated into a machine learning model has been considered in a limited form. For instance, in the context of clustering, most of the methods assume user input is given as pairwise clustering constraints such as cannot-link and must-links. However, user feedback can be in much more flexible and diverse forms, and thus machine learning models should be re-invented to better incorporate such human needs.

(b) Real-time responsive machine learning due to user feedback in a highly interactive environment. The algorithm can be too fast for user to respond, or on the other side too slow for human (e.g. because of the long running time). The challenge is to keep the user and algorithm synchronised.

(c) Progressive visual analytics: 1) mark the stable results so that the model will not process them later; 2) iteratively merge similar results and modify the parameters for fast convergence.

4. Uncertainty

(a) Data noise (Gaussian or shot), missing data, conflict, errors in data (some ML algorithms are sensitive to such errors). The challenge is to visualise such data uncertainties to make the users (who runs algorithms on the data) aware of them.

(b) Model approximate solution

(c) Bi-directional function: smooth communication between the high dimensional space and low dimensional space. For example, if the user find one pattern in the low dimensional space, he should check it in the high dimensional space to verify this. If he changes something in the low dimensional space, the high dimensional space should be changed accordingly. Potential issue: how to handle the distortion in the low dimensional space.

5. Lack of ground truth given large-scale streaming data; sliding window

6. Challenges specific to Big Data: distributed/parallel processing of ML algorithms, which may have implication for 'white box'-related issues, as users need to understand the details of how the algorithms run.

There should be much more challenges we have not covered from our discussion, but at least we strongly believe this list should give a comprehensive guideline about which challenges should be mainly tackled when trying to achieve a true integration and machine leanring and visual analytics for big data analysis.

6 Group 3: Visual Analytics of Complex Streaming Data

In the current era of continual data production, Volume is not the only BigData challenge to address. Velocity and Variety are two key problems often faced together when data is continuously streamed from various sources. More and more streaming data sources are available and many tasks arise that require Visual Analysis of this data in a timely manner. This is generally the case when real-time situational awareness is required such as in crisis management, or real-time intelligence analysis. Analysis methods, visualization techniques, and interaction methods have to take into account the specific characteristics of such sources.

What we consider here as *streaming data* is any type of information that is continuously produced and which needs to be read and captured once released – otherwise it would be quickly forgotten and left unreachable. Such examples can be CCTV camera recordings, sensor readings, or also instant messages.

This type of Big Data challenges Visual Analytics in all its design stages. The proper nature of the data with a continual modifications influences the data analysis from its earliest stages. Changes of such steps might render the visualization of past data invalid with respect to recently changed analysis goals. Depending on how the system records and encodes past informations, this has consequences on what could and should be done especially when we bring in user interaction. For example, changes in the data may be small or dramatic, and both the analysis and views may be influenced either locally or globally - when local changes may also trigger larger global changes.

6.1 Visual Analytics Challenges

We have identified six domains where strong contributions can be brought to perfect stream data visual analysis:

- *Computational complexity and scalability:* We need fast algorithms for real time processing even for the visualization itself. We should think of incremental methods, that could update analysis and visualization locally and globally. Sampling data is imposed when facing huge streams. Useful investigation leads: blue noise, reservoir sampling, computational models from high performance, extreme-scale, and cache oblivious computing.

- *Analytic complexity:* Here we are interested in what analysis is relevant to perform in real-time. And this is relative to the proper analytical task dedicated to stream data. As for example, we need to fuse in real time data sources so we can build comprehensive analysis from heterogeneous and multiple data. We should also take into account that data is often integrated from different time scales, comes at different rates and speed, and is visually analyzed on even different time frames. This integration and the continuous production of data often forces the system not to keep all data as is, but to progressively integrate it and sometimes even forget it – creating different abstraction stages for a same piece of information. How can we manage in this condition integrative analysis which builds similarity and tries to derive causality – critical for situation awareness.

- *Visual complexity:* This is the step where perception and cognition for visualisation come into play. What can we deliver in a static manner, and what should be delivered in an animated manner? Many challenges rise here because of the very dynamic nature of the data itself, and our own brain's tendency to focus all cognition on pre-attentively detected dynamic changes.

- *Interaction complexity:* How can users interact with the streaming data? We need new interaction paradigms. Traditional interaction tasks are not left aside, such as search and query, but how to interact to emphasize on facts and events? For example, in an animated visualization, we can intervene on the animation speed, to slow it down to relay important events, although this may be specific to the application. How do we translate the classical Visualization user interaction tasks taxonomy into streaming manipulation?

- *Evaluation complexity:* Evaluation has always been difficult to assess in visualization. How do we compare and evaluate a system in constant motion? We need to figure out tasks and data out there so we can build a test suite for contesters to compare different approaches on the same data with different tasks in mind. A multilevel task taxonomy that is comprehensive and descriptive of what a system intends to achieve, if not a proper validation, makes a good baseline to understand and evaluate a system.

- *Domain/application complexity:* There is wide panorama of domains that provide streaming data, from social media, to personal visual analytics and crisis management. We need to understand what is needed from expert users, and what is expected from non experts and the general public. Should the Visual Analytics be in-situ, on mobile devices, or accessible in a mixed manner? These constraints define all the analysis and visualization steps, such as the computing power available or the visualization design.

6.2 Formal Definition of Streams

We propose the following general definition of streams to identify the potential parameters which can influence visual analytics.

We will first consider streams as discrete content of information (such as transaction data). A stream σ will be defined as $\sigma \subseteq L \times A \times T \times S$; for which the quadruple $(l, a, t, s) \in \sigma$, with: $l \in L$ the labels, and can be a unique label, a set of labels, or links in a subgraph; $a \in A$ the value of the stream; $t \in T$ the time stamp of the stream; and $s \in S$ the source emitting the stream item.

We can then define operations on streams, starting with $start(\sigma)$ and $next(\sigma)$ to get the next quadruple from the streams.

When the set of labels L is too large we can partition it into interesting classes $L = L_1 \cup L_2 \cup \ldots \cup L_n$ and replace streams labels with labels of the corresponding classes.

Now, we can also bring the focus on a given time window $[t_0, t]$ $t_0 < t$ and study the characteristics of a collection of streams within this time window, such as:

- the sum of stream values:
  $f_\Sigma(l, s, t) = \sum\{a : (l, a, \tau, s) \in \sigma \wedge \tau \in [t_0, t]\}$
- the maximum stream value:
  $f_M(l, s, t) = \max\{a : (l, a, \tau, s) \in \sigma \wedge \tau \in [t_0, t]\}$
- the frequency of quadruples:
  $c(l, s, t) = |\{(l, a, \tau, s) \in \sigma : \tau \in [t_0, t]\}|$
- the list of q most important labels with respect to characteristic f in the time window: $Top(q, f, s, t)$
- and other graph-based metrics, such as connectivity, (l_1, l_2)-reachability, degrees, bipartiteness (fractional approach to link weights), ...

With such framework in mind, we can operate analytically on streams, and visualization operations may be translated into such operations. In the monitoring of streams we include also automatic "alarms" signaling critical or unexpected behaviour of the streams.

6.3 Stream VA framework

The main idea is to integrate an updater module that will come between data, user, and the classical visual analytics framework. Given the multiple potential source updates at different points in time, and based on usersínput, the *Updater* will manage with changes must be local, global, and which local changes can trigger bigger global changes. The updater also needs to manage time, and the different abstractions of the data (old data may be kept only as an average for example). See Fig. 4.

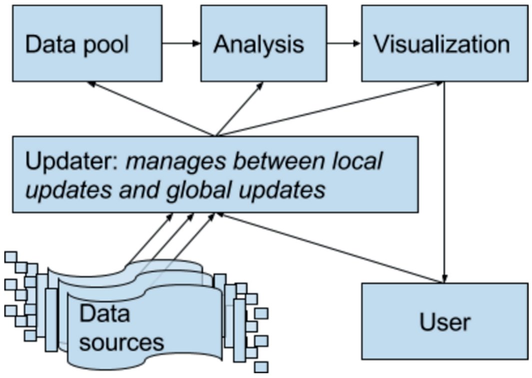

Figure 4: Stream VA framework

6.3.1 Analysis

Analysis component include:

- Detection of events: Monitoring for situational awareness
- Data fusion, Cross-media analysis
- Comparison with historical data (Min, max, etc)
- Searching for relevant information from data streams
- Pattern identification, Pattern matching
- Similarity/correlation/causality analysis: Bringing in heterogeneous data to reveal new findings (from the crossing of information)
- Data mining/text mining: topic modeling
- Network analysis : Diffusion, Opinion leader
- Clustering analysis: forming groups, spread, splitting groups

6.3.2 Visualization

Visualization component include:

- Timeline: snapshot (history)
- Main visualisation: integrated visualization
- Multiple window: each source (for details on demand)
- Sedimentation
- Visual hierarchy
- Animation (local update, global update)
- Change of layout: subtle changes/radical changes

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