From Visual Data Mining towards Visual Analytics

Fraunhofer Institut Intelligente Analyse- und Informationssysteme

universität bonn

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Dr. Natalia Andrienko

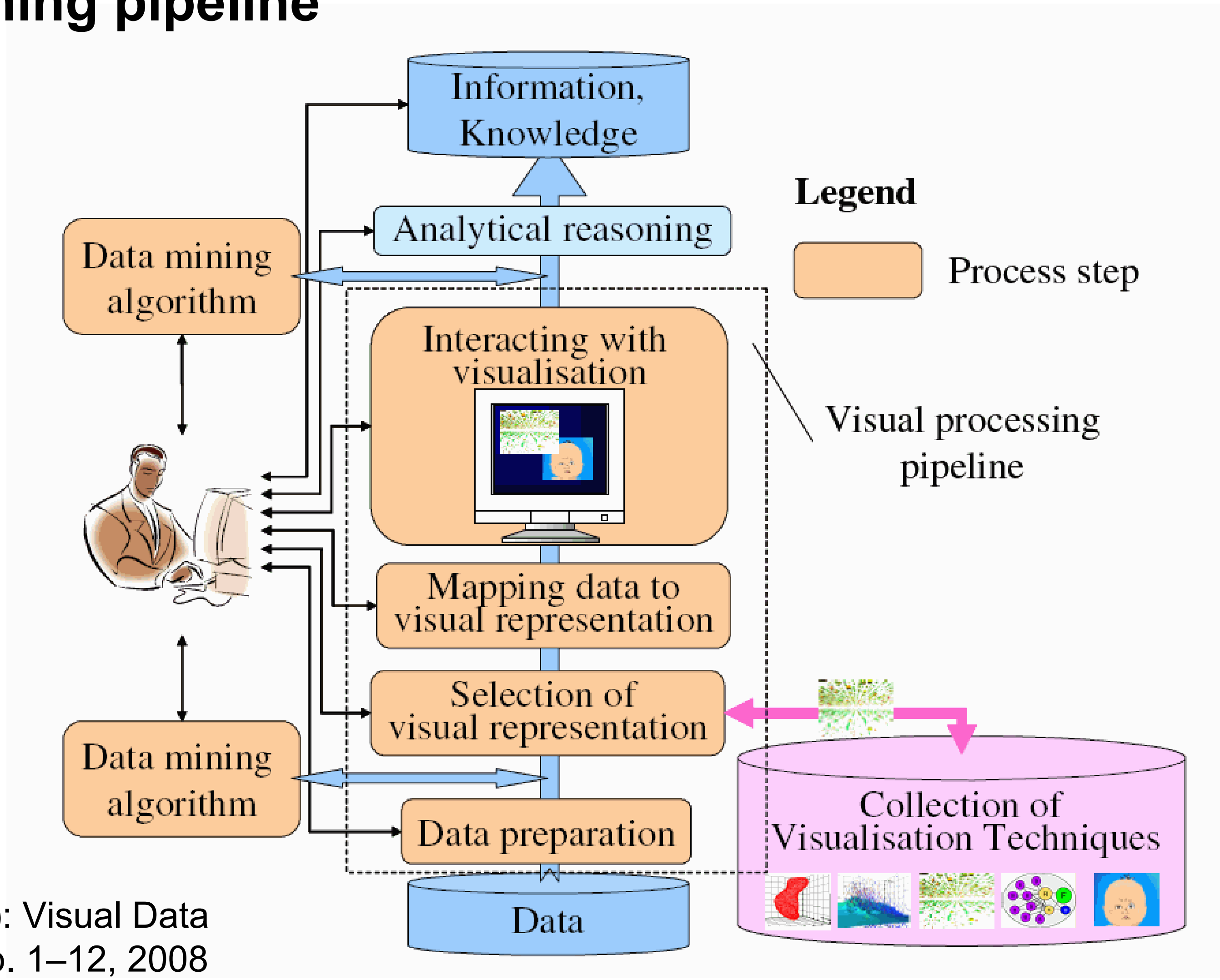
http://geoanalytics.net
http://visual-analytics.info

October 2009

The Value of Visualisation

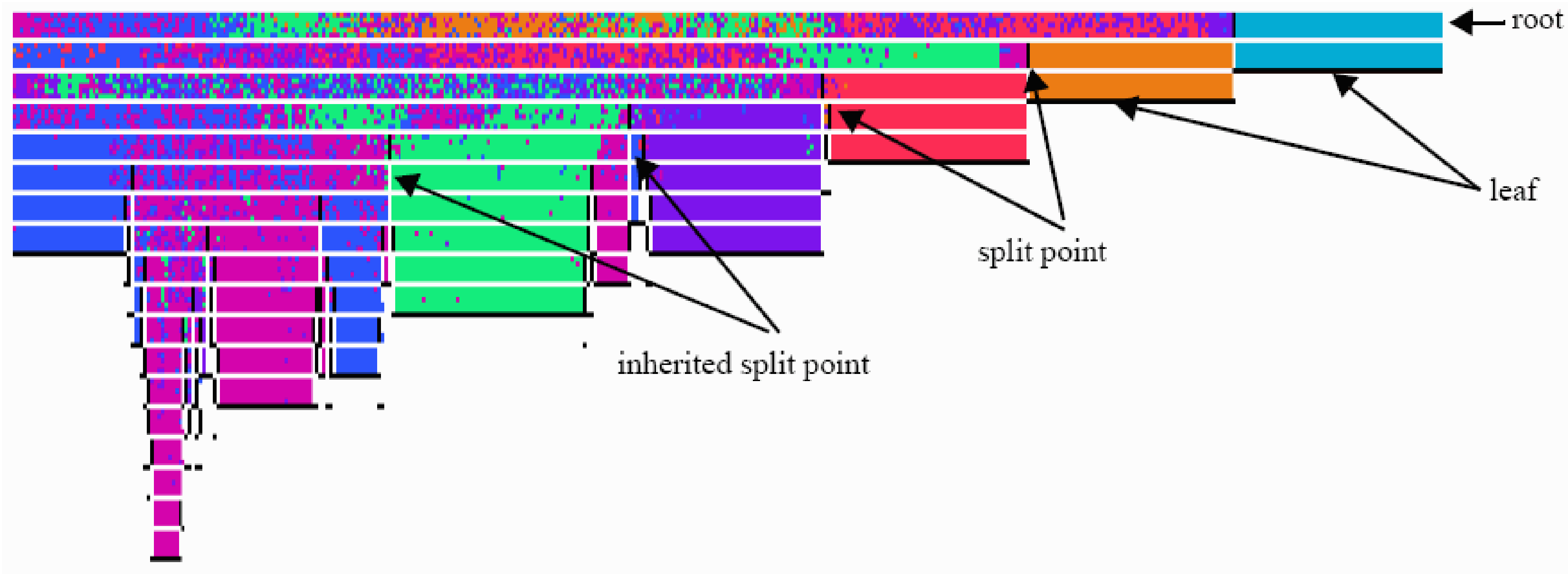
- Visualise: “to **make perceptible** to the mind or imagination”
  - Random House Webster’s College Dictionary
- “Visualisation is the process of representing abstract business or scientific data as images that can **aid in understanding the meaning** of the data.”
  - Whatis?com computer dictionary, http://whatis.techtarget.com/whome/
- “Visualisation offers a method for **seeing the unseen**.”
  - B. McCormick, T. DeFanti, and M. Brown. Definition of Visualization. ACM SIGGRAPH Computer Graphics, 21(6), November 1987, p.3
- “An estimated 50 percent of the brain's neurons are associated with vision. Visualization <…> aims to put that neurological machinery to work.”
  - Ibid.

Visual Data Mining pipeline



Source:
S.J. Simoff et al. (Eds.): Visual Data Mining, LNCS 4404, pp. 1–12, 2008

Examples of Visual Data Mining: Decision Trees



- Interactive tuning of decision trees by manipulating and visualizing
  - size of the node (number of training records corresponding to the node)
  - quality of the split (purity of the resulting partitions)
  - class distribution (frequency and location of the training instances of all classes)

Source: Ankerst & Ester & Kriegel, ACM KDD 2000

Examples of Visual Data Mining: Association Rules

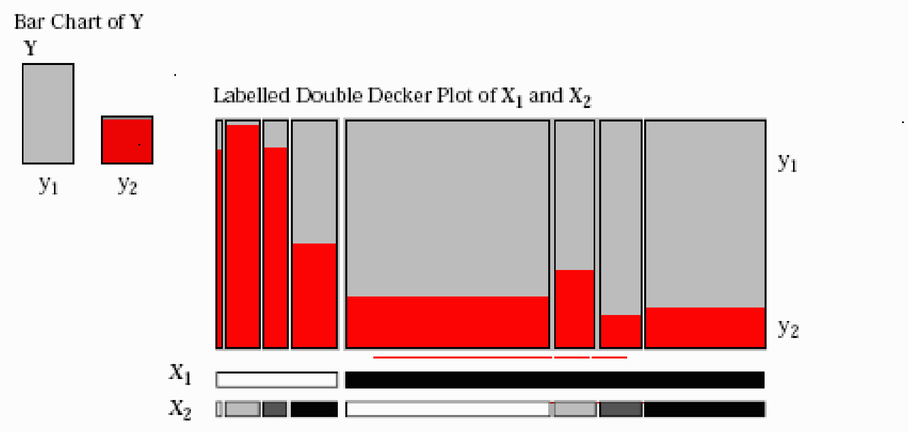


Figure 3: *(Labelled) Double Decker Plot of the mosaic*

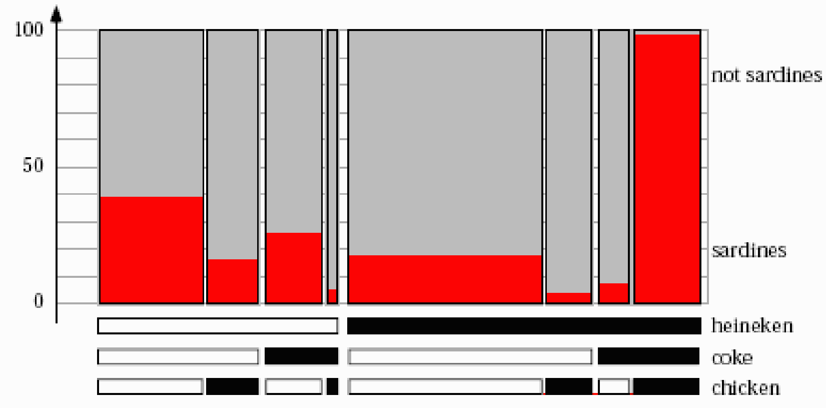
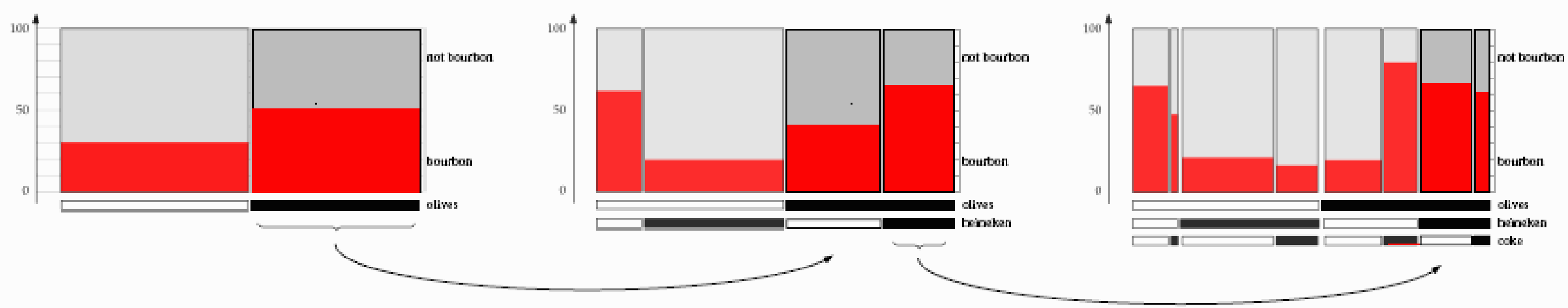


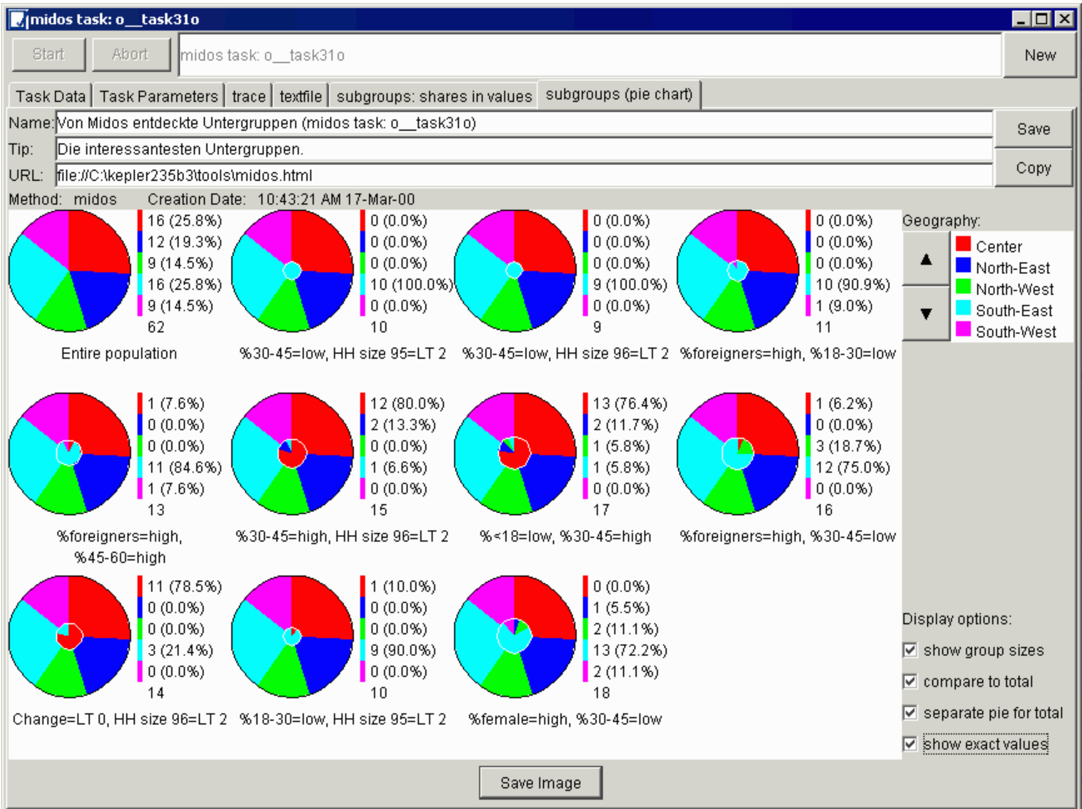
Figure 4: *Example of a "good" association rule: the bin heineken & coke & chicken is filled almost entirely with highlighting, while none of the other bins is filled*

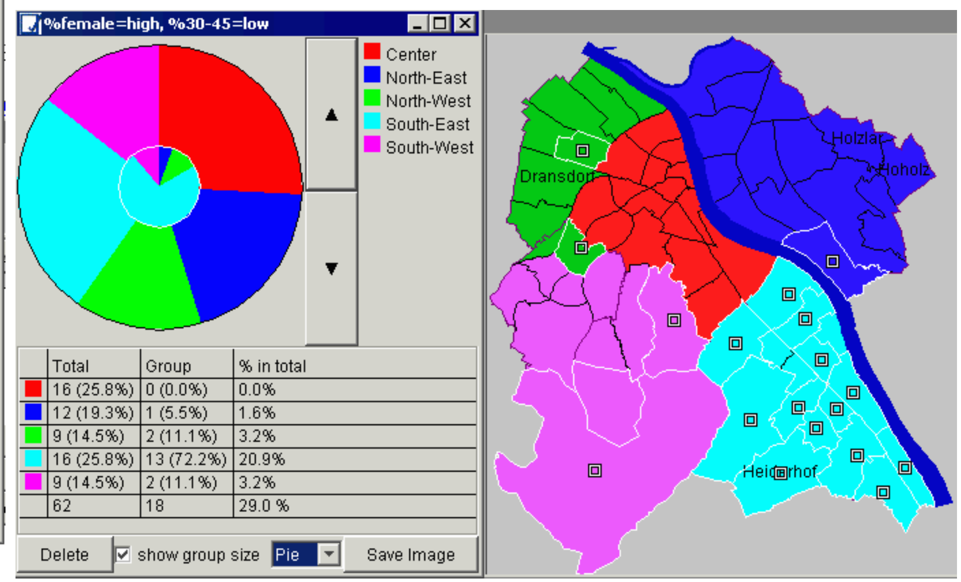


- Visual Inspection and interactive modification of association rules on mosaic plots

Source: Hofmann & Siebes & Wilhelm, ACM KDD 2000

Examples of Visual Data Mining: Subgroups

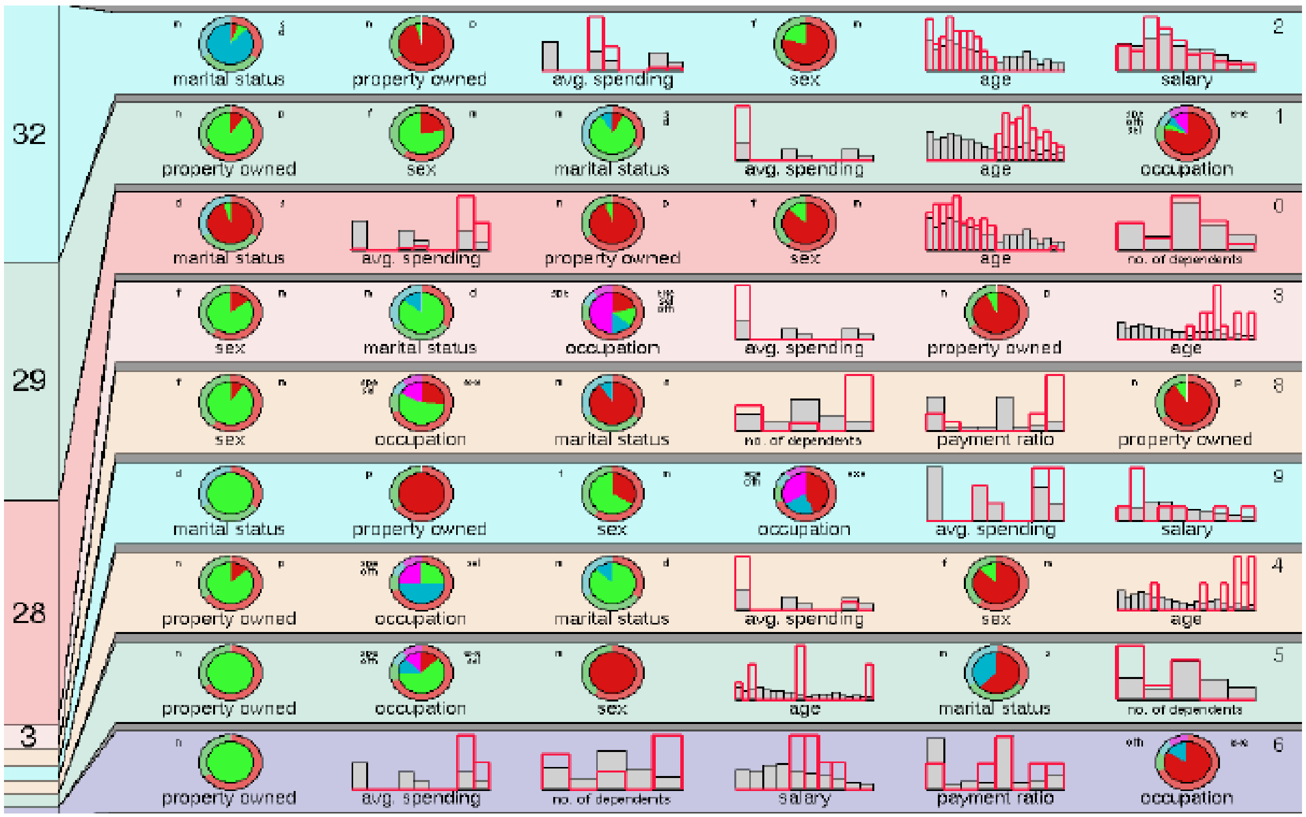




- Interpretation of subgroups in attribute and geographic spaces

  Kepler and Descartes. Wrobel, Andrienko, Andrienko, Lüthje, Handbook of DM & KD, 2002

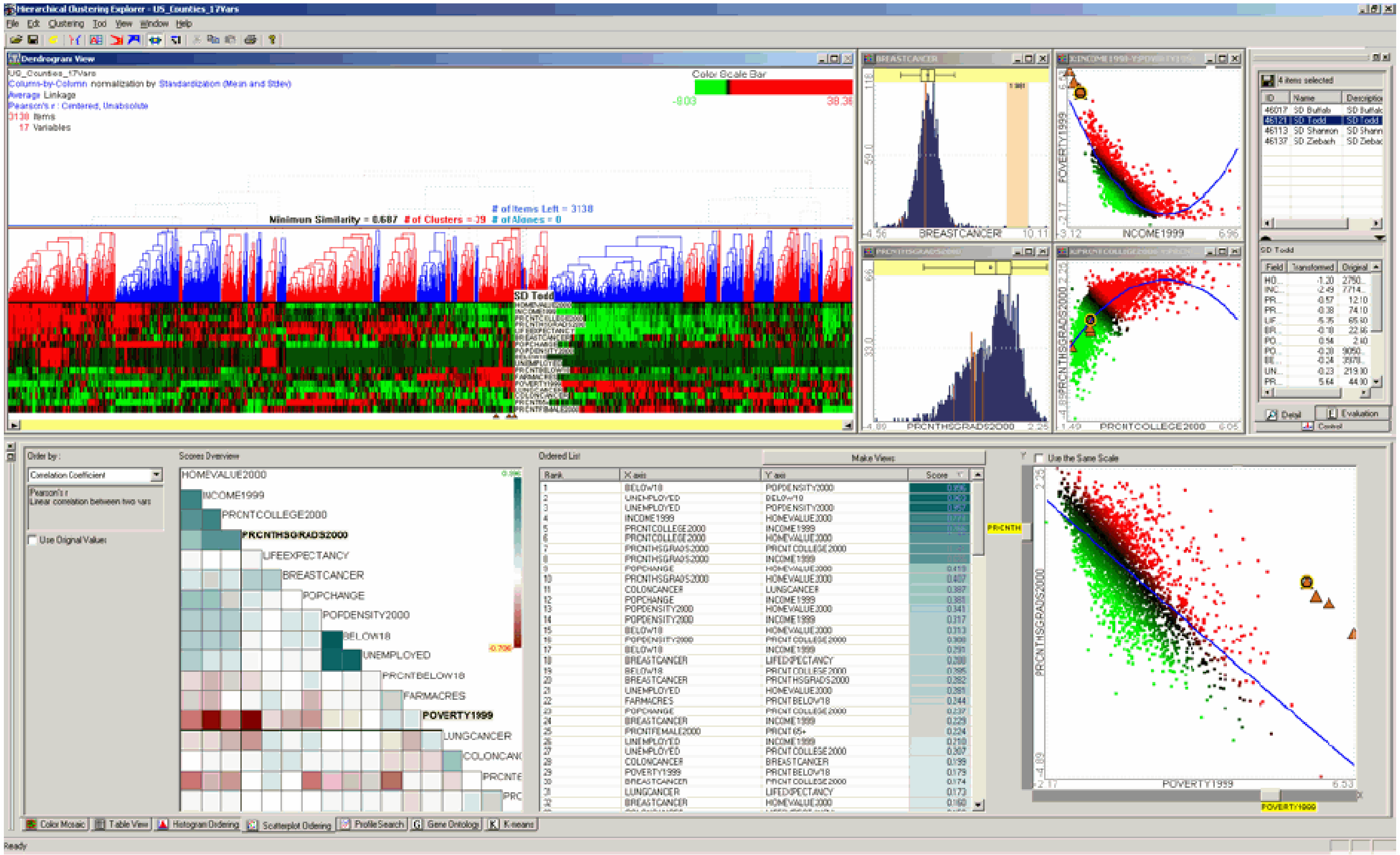
Examples of Visual Data Mining: Clusters



- Visualisation of the attribute values statistics for the clusters in comparison to the whole dataset

Source: IBM DB2 Intelligent Miner; http://www-3.ibm.com/software/data/iminer/fordata/

Examples of Visual Data Mining: Hierarchical Clusters



- Visually-driven hierarchical clustering

Source: Seo and Shneiderman, InfoVis, 2004

Visual Analytics: Similar Techniques, Different Focus

- Data Mining is **computer-centred**:
  - Computer performs data analysis, human somehow uses the results
  - Visualisation may be involved for
    - (mainly) helping the user to understand the results;
    - (sometimes) enabling the user to select and prepare input data;
    - (sometimes) enabling the user to direct the work of the algorithm
- Visual Analytics is **human-centred**:
  - Human solves a complex problem, computer helps the human
  - Visualisation is needed for activating the perceptual and cognitive capabilities of the human:
    - perception of patterns;
    - identification and association;
    - abstraction and generalisation;
    - reasoning and insight.

Computer and Human Can Work Synergistically

Computers

- can store and process great amounts of information
- are very fast in searching information
- are very fast in processing data
- can extend their capacities by linking with other computers
- can efficiently render high quality graphics, both static and dynamic

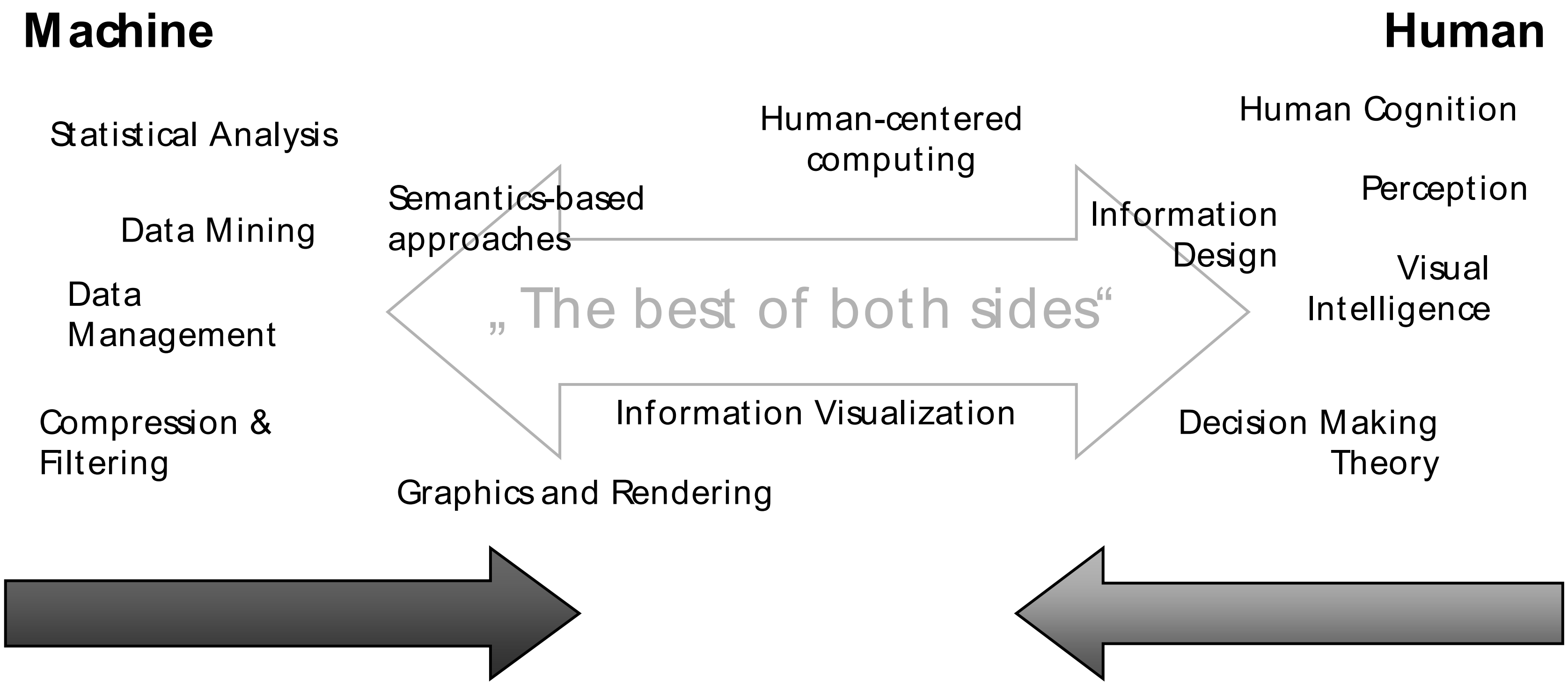
Humans

- are flexible and inventive, can deal with new situations and problems
- can solve problems that are hard to formalise
- can reasonably act in cases of incomplete and/or inconsistent information
- can simply *see* things that are hard to compute
- can employ their knowledge and experience

The Goal of Visual Analytics

- Visual analytics must develop solutions
  - enabling analysts to focus their **full perceptual and cognitive capabilities** on their analytical processes
  - while allowing them to **apply advanced computational capabilities** to augment their discovery process

Visual Analytics Integrates Scientific Disciplines to Improve the Division of Labour between Human and Machine



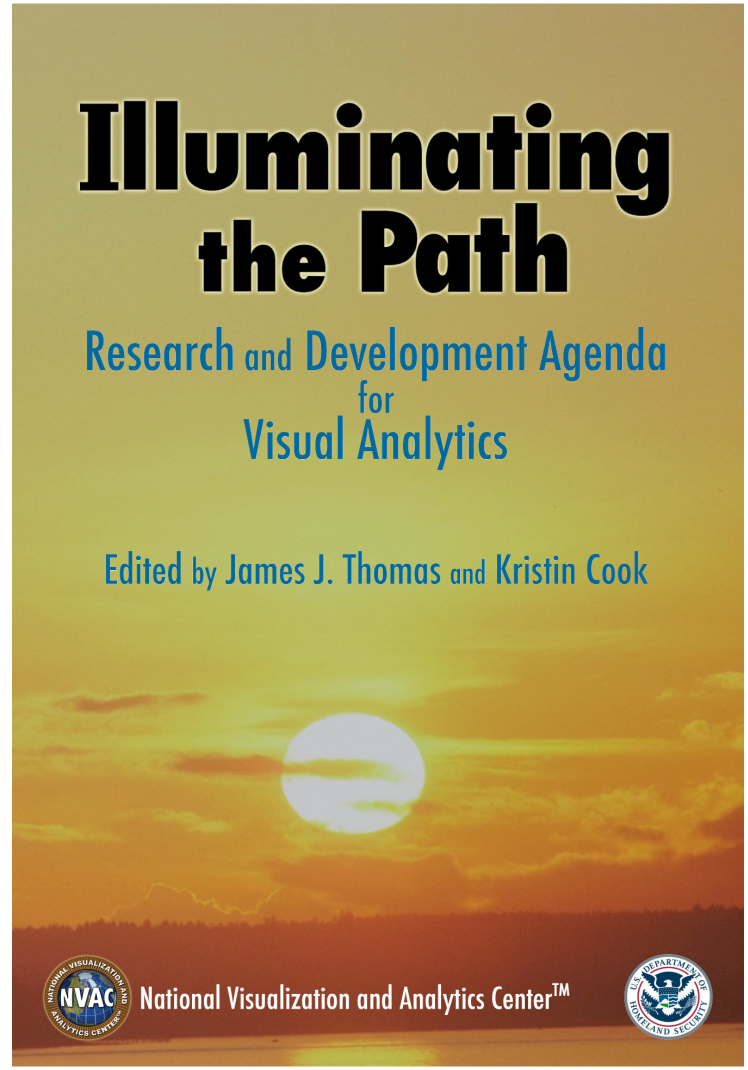
Definition of Visual Analytics

Visual Analytics is the science of <u>analytical reasoning facilitated by interactive visual interfaces</u>.

People use visual analytics tools and techniques to

- Synthesize information and derive insight from massive, dynamic, ambiguous, and often conflicting data
- Detect the expected and discover the unexpected
- Provide timely, defensible, and understandable assessments
- Communicate assessment effectively for action

The book (IEEE Computer Society 2005) is available at http://nvac.pnl.gov/ in PDF form



Components of Visual Analytics

- **Analytical reasoning**
  - How to maximise human capacity to perceive, understand, and reason about complex and dynamic data and situations?
- **Visual representations and interaction techniques**
  - How to augment cognitive reasoning with perceptual reasoning through visual representations and interaction?
- **Data representations and transformations**
  - How to transform data into a representation that is appropriate to the analytical task and effectively conveys the important content?
- **Production, presentation, and dissemination**
  - How to convey analytical results in meaningful ways to various audiences?

Emergence of Visual Analytics

Initially driven by the USA Homeland Security…

…but now has a much broader scope and impact

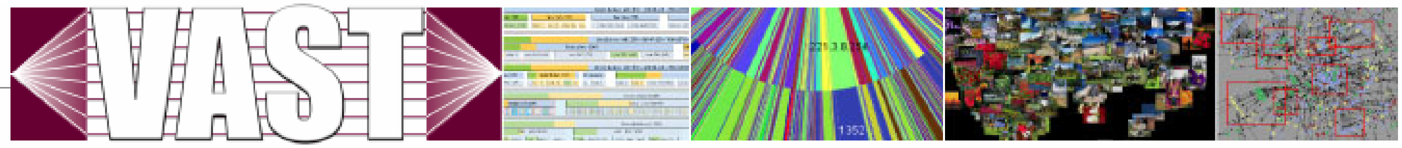
Conferences, symposia, workshops

EU Workshop on Visual Analytics
18. January 2007

Downloads

Agenda

- Agenda



IEEE Symposium on Visual Analytics Science and Technology 2007 • October 30 to November 1, 2007

GIScience 2006

Visualization, Analytics & Spatial Decision Support

Call for papers for the Workshop on Visualization, Analytics & Spatial Decision Support at the GIScience conference (September 20, 2006, Münster) and for a special issue of the International Journal of Geographical Information Science

Research programs and projects

National Science Foundation
WHERE DISCOVERIES BEGIN

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Funding

Division of Computing and Communication Foundations
Foundations of Data and Visual Analytics (FODAVA)

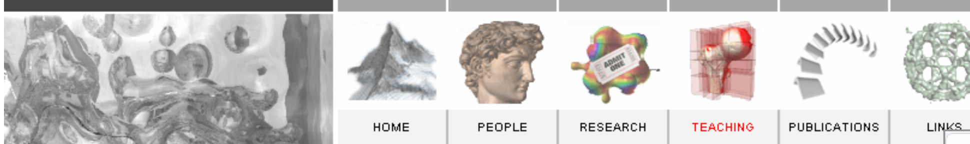
DFG Priority Program

Scalable Visual Analytics: Interactive Visual Analysis Systems of Complex Information Spaces

University courses and seminars

Visualization and MultiMedia Lab
Department of Informatics, University of Zürich

VMML visualization and multimedia lab university of zürich



HOME PEOPLE RESEARCH TEACHING PUBLICATIONS LINKS

vmml:/teaching/seminar

Organisation
Voraussetzung

Seminar in Visualization and Visual Analytics (V-Nr. 43

TECHNISCHE UNIVERSITÄT DARMSTADT

Courses and Lectures
Comment: Visual Analytics: Inte

Visual Analytics

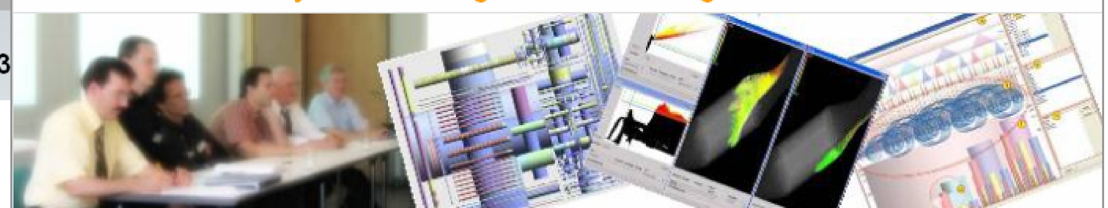
Department of Computer Science
UNC Charlotte

ITCS 4122 (Undergraduate)
ITCS 5122 (Graduate)

RHEINISCHE FRIEDRICH-WILHELMS-UNIVERSITÄT

From Visual Data M

VisMaster: Visual Analytics - Mastering the Information Age



VisMaster
Visual Analytics - Mastering the Information Age

What is VisMaster?

Visual Analytics - Mastering the Information Age

VisMaster is a European Coordination Action Project focused on the research discipline of Visual Analytics: One of the most important challenges of the emerging Information Age is to

Current affairs

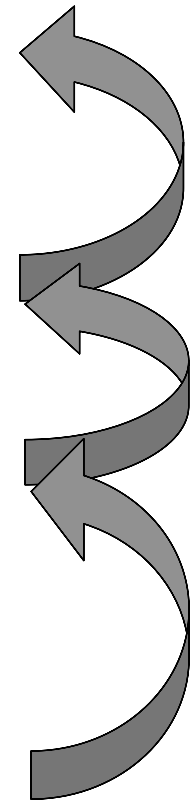
News

Events

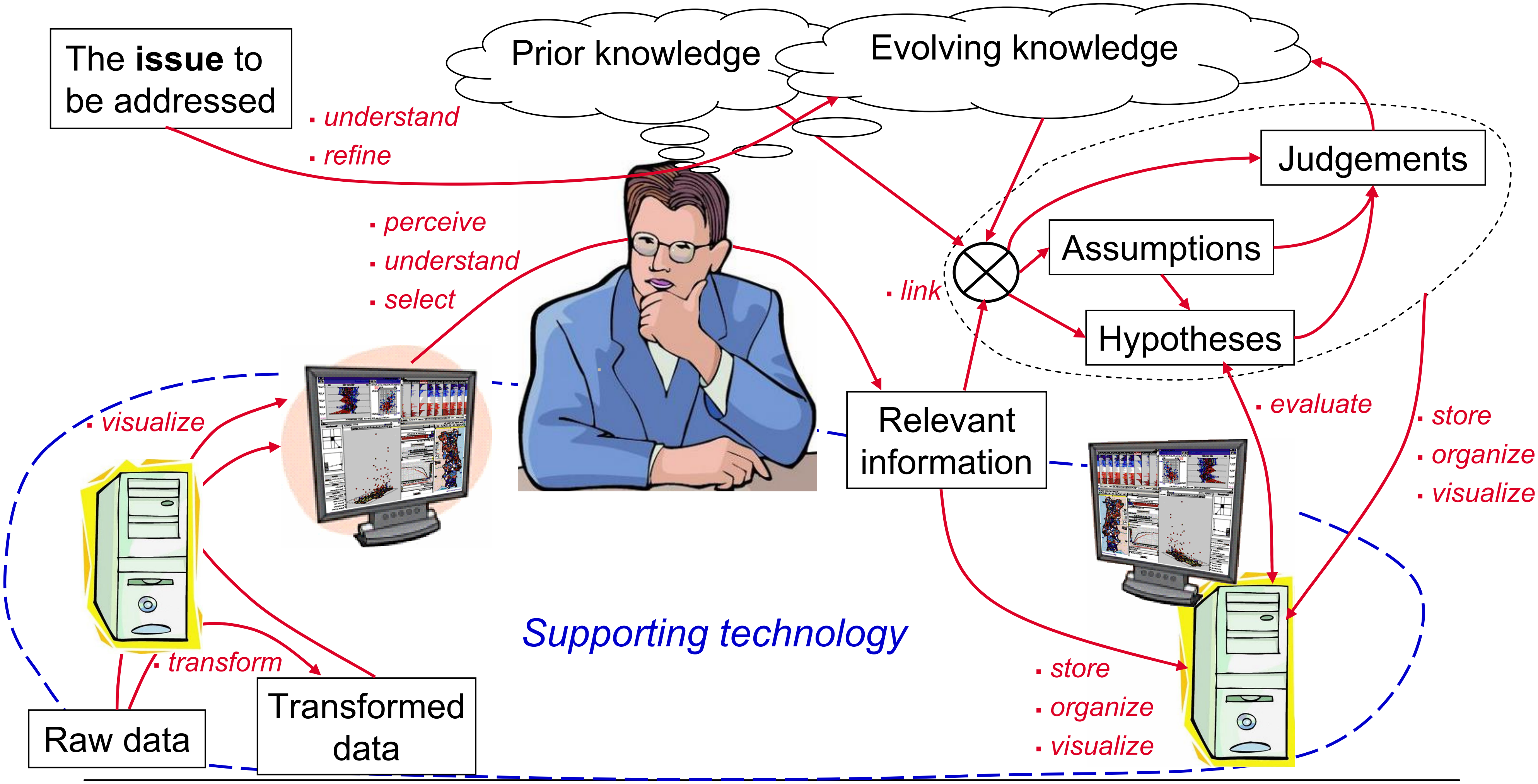
Kontakt »

Visual Analytics Aims at Supporting the Whole Analytical Process

- Plan the process
- Gather relevant information and become familiar with it
- Incorporate the relevant information with the existing knowledge
- Generate candidate explanations (hypotheses)
- Evaluate the hypotheses in light of evidence and assumptions
- Develop a judgement about the most likely explanations or outcomes
- Try to find other possible explanations that were not previously considered
- Draw conclusions
- Create a report or presentation of the results; explain why
- Collaboratively review the results and the arguments
  (with colleagues and/or external experts)
- Share the results with customers or other audience



Analytical Discourse



Supporting Technology

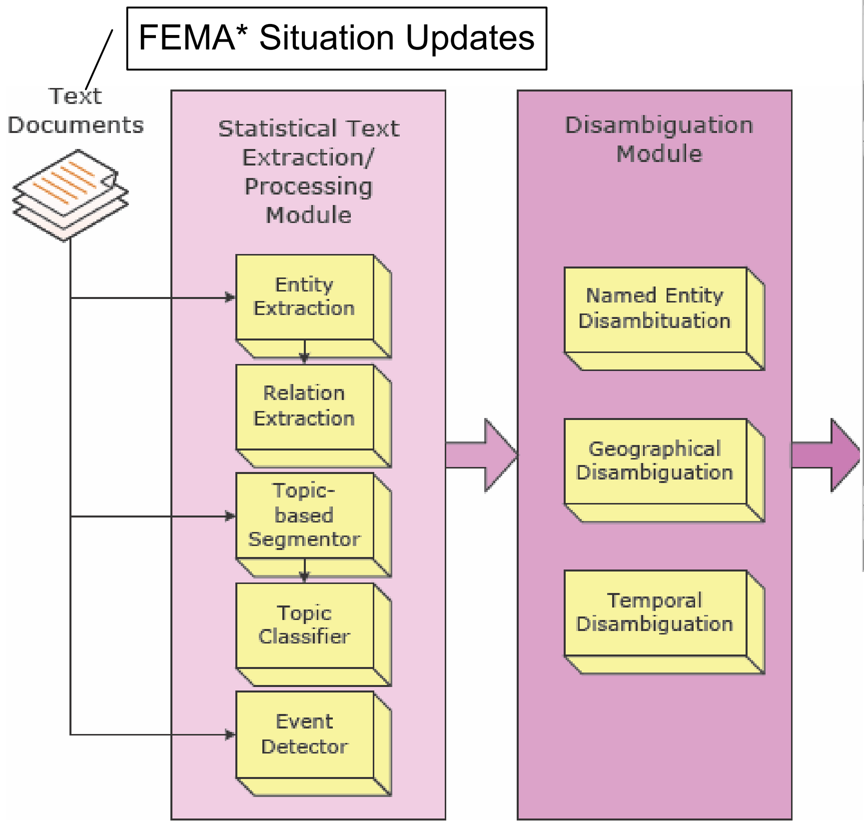
- Data pre-processing and computer-adapted representation
  - e.g. extraction of structured data from images, video, texts
- Data transformations
  - e.g. aggregation; clustering; dimensionality reduction; interpolation; smoothing
- Automatic extraction of potentially interesting features and patterns (relations, regularities, anomalies, trends)

Visualization of data (original and derived)

- Techniques for hypotheses testing (statistics)
- Annotation support
- Support for workspaces and workflows
- Support for collaborative analyses

Visualization of derived knowledge, argumentation, and analysis process

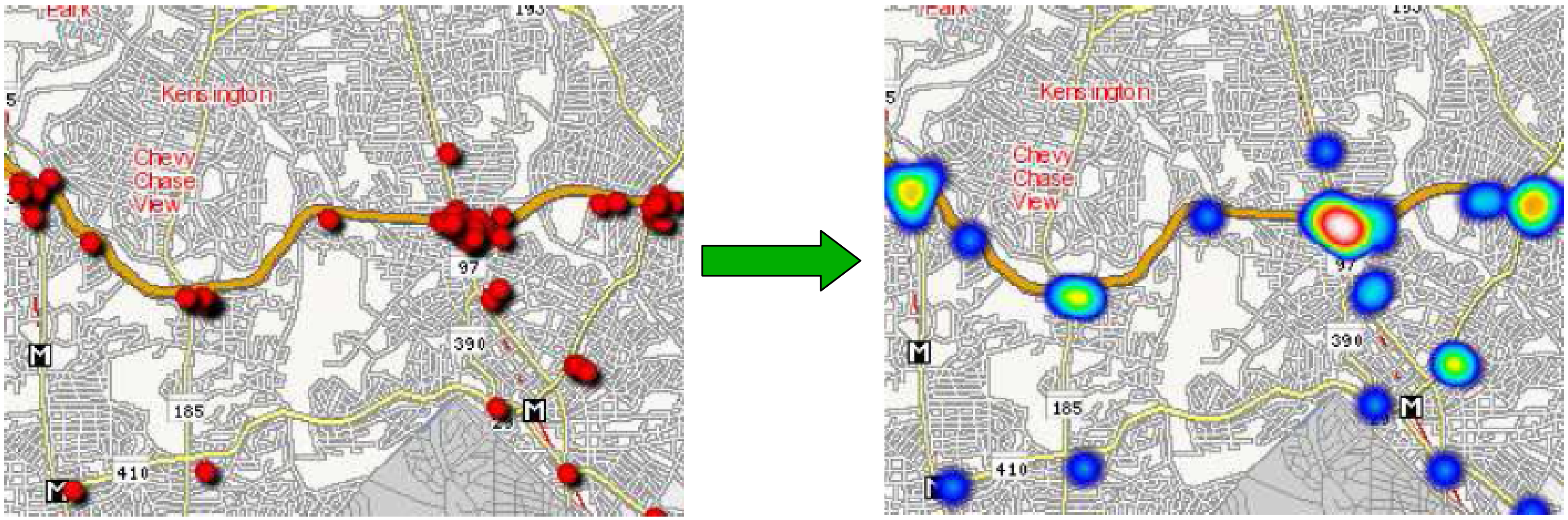
Example of Data Pre-processing (Text Processing)



** Federal Emergency Management Agency*

Chi-Chun Pan, Prasenjit Mitra
Pennsylvania State University

Example of Data Transformation: Aggregation, Smoothing

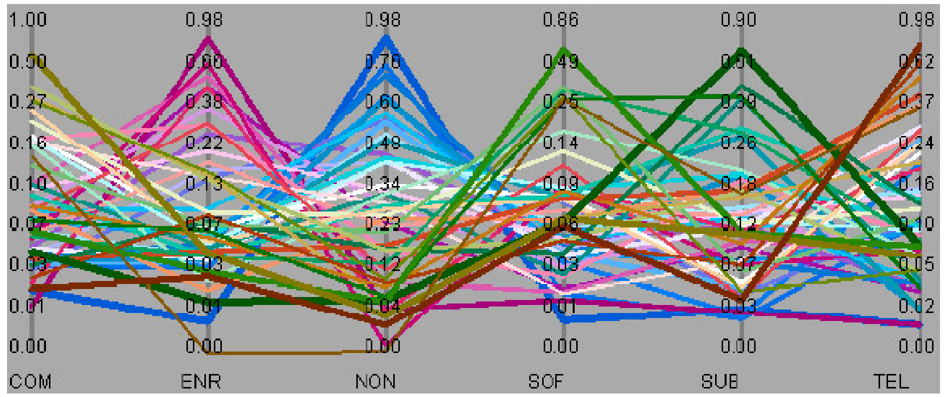


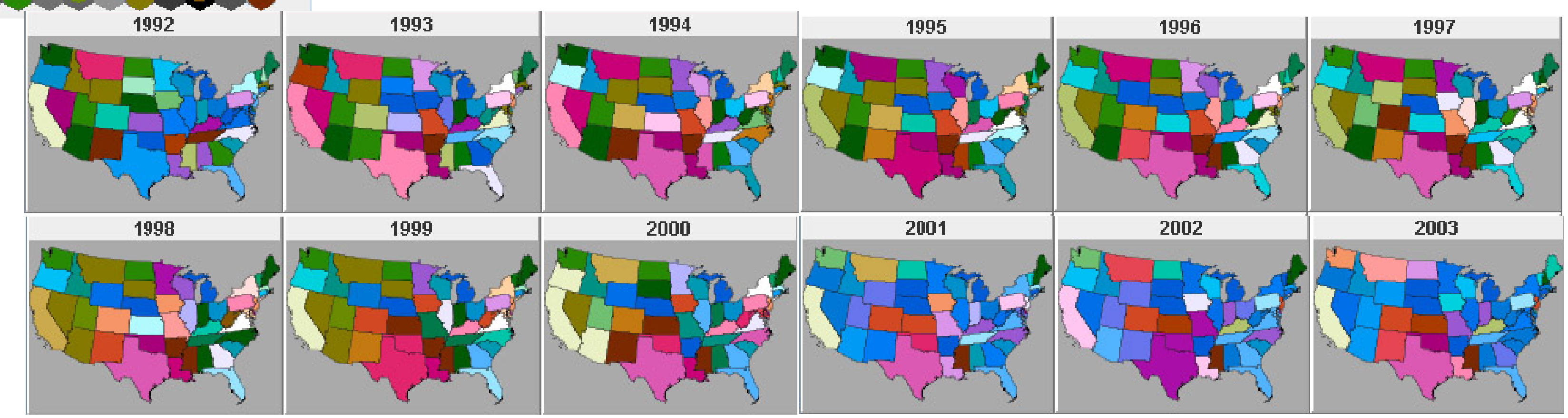
Events (traffic accidents)

Densities of events

Darya Filippova, Joonghoon Lee, Andreea Olea, Michael VanDaniker, Krist Wongsuphasawat
University of Maryland, College Park

Example of Data Transformation: Clustering, Classification

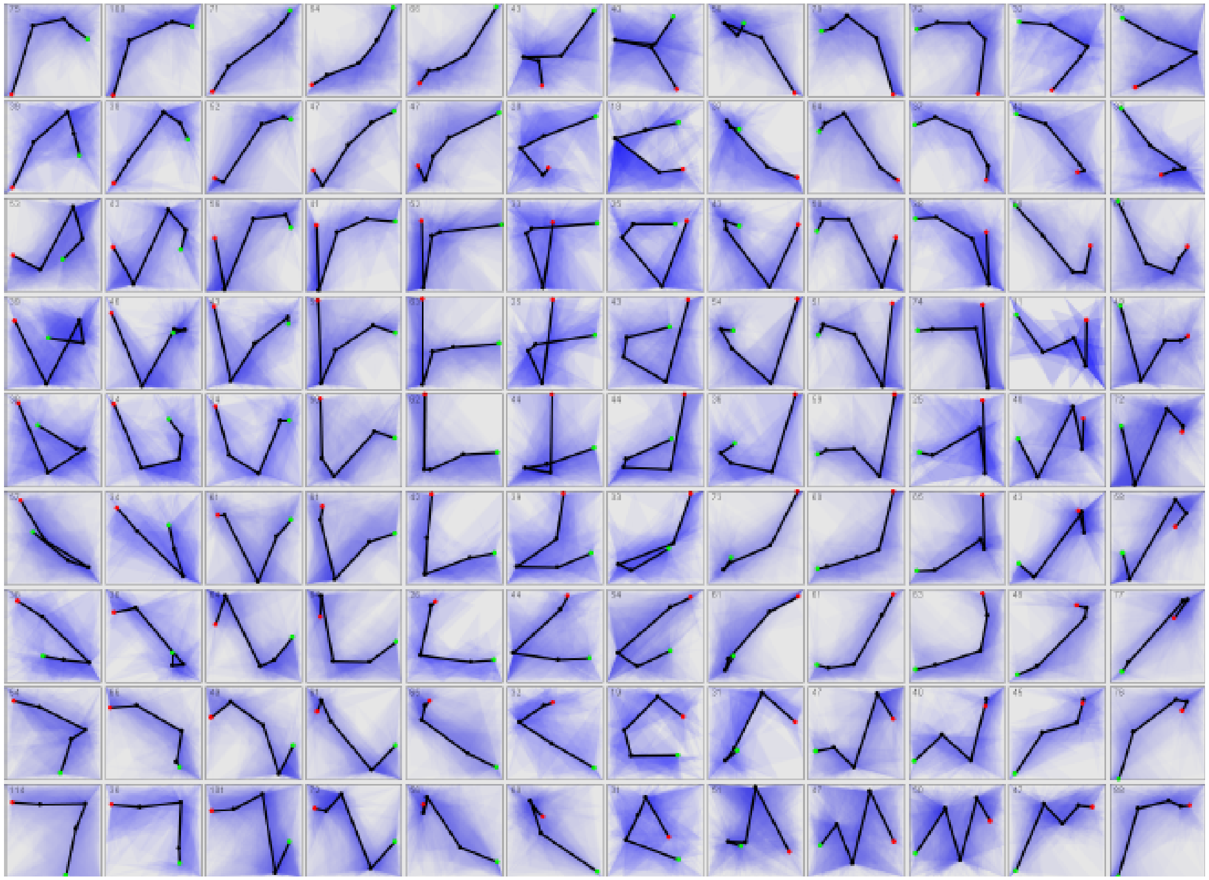




Diansheng Guo, Jin Chen, Alan M. MacEachren, Ke Liao
University of South Carolina; Pennsylvania State University

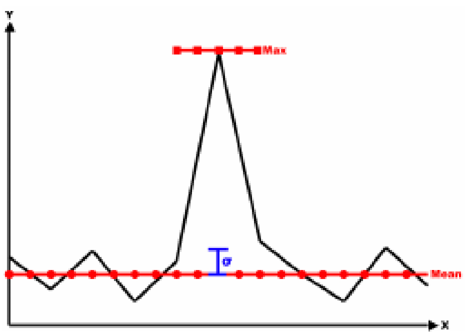
Example of Data Transformation: Clustering, Dimensionality Reduction

Time series of 2 variables clustered using SOM (Self-Organizing Map)

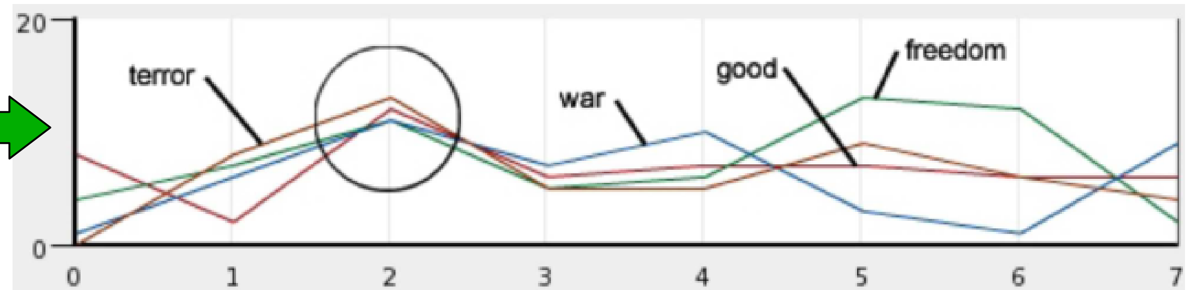


Tobias Schreck, Tatiana Tekušová,
Jörn Kohlhammer, Dieter Fellner
Technische Universität Darmstadt
Fraunhofer IGD Darmstadt

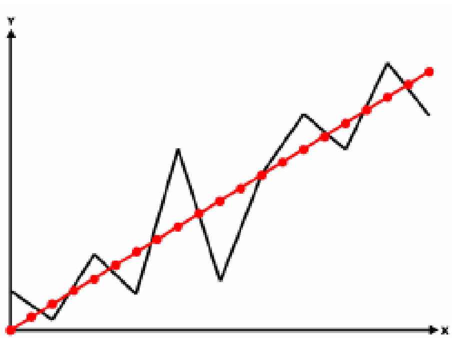
Example of Feature Extraction



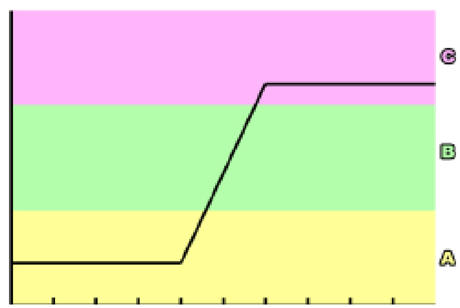
Spike



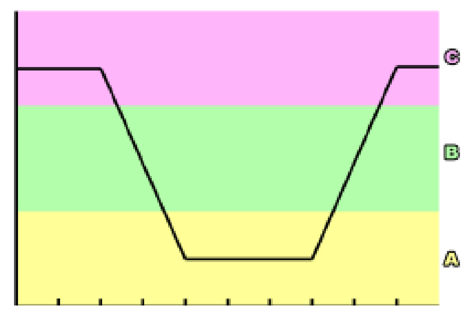
Search for certain types of features in time series data



Increasing slope



Rise

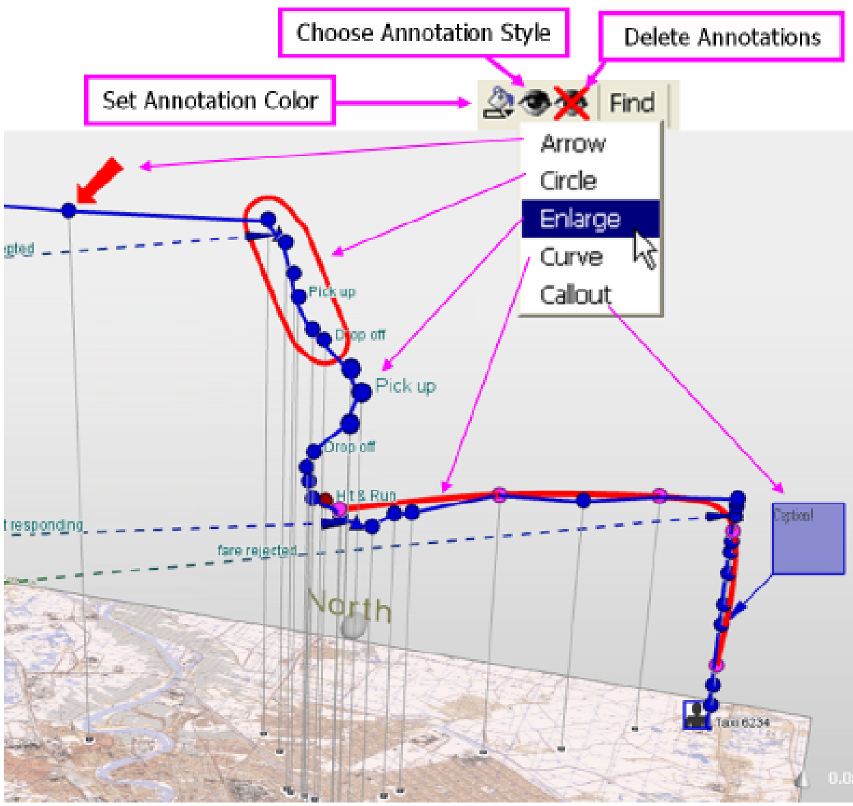


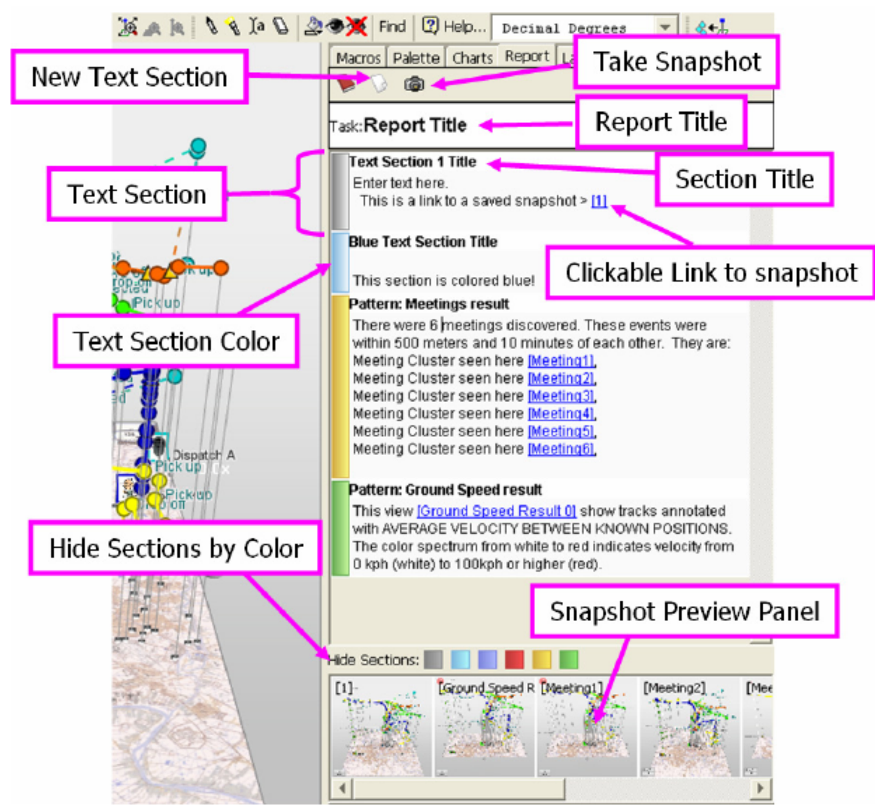
Valley

...

Machon Gregory, Anthony Don, Elena Zheleva, Sureyya Tarkan, Catherine Plaisant, Ben Shneiderman
University of Maryland, College Park

Example of Annotation Support

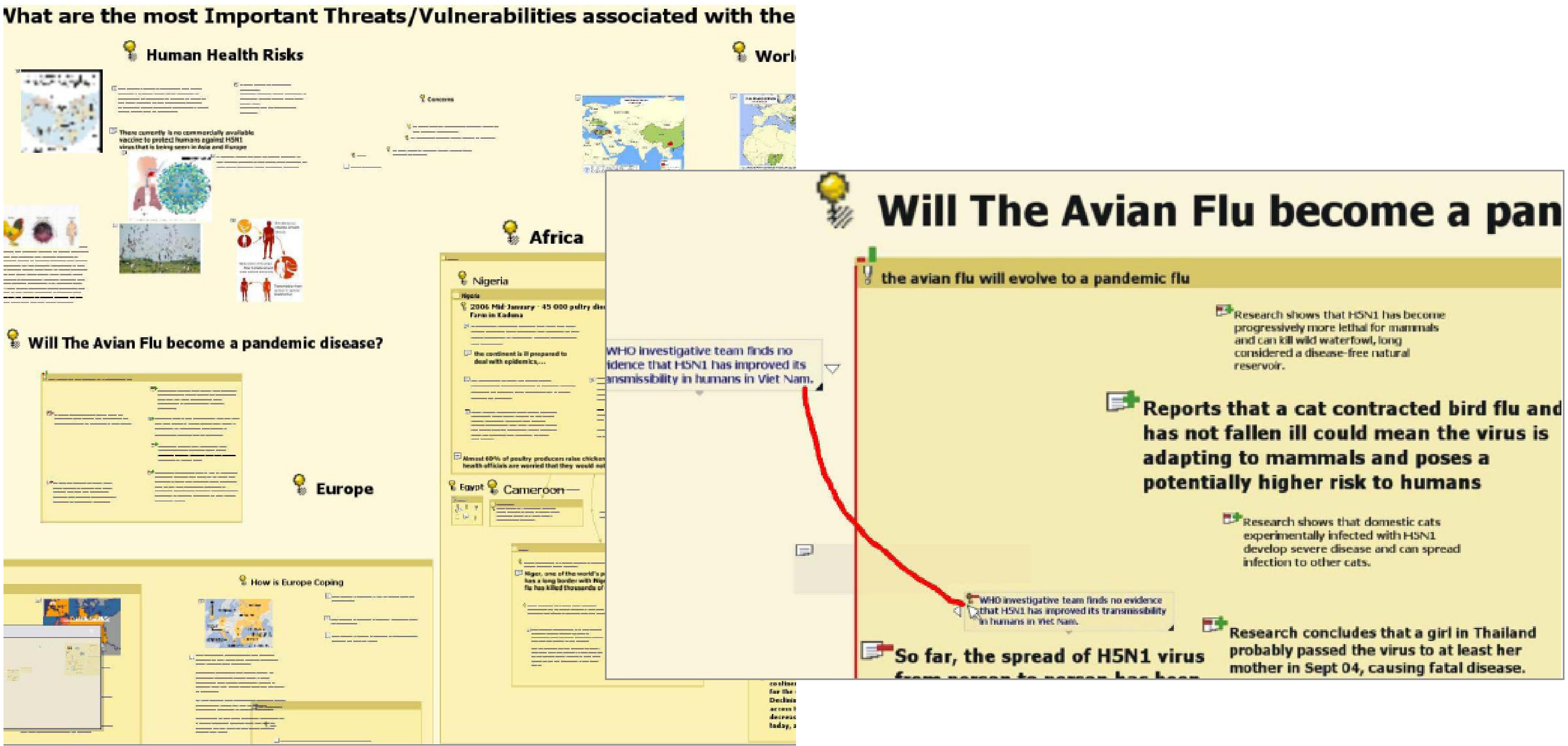




Ryan Eccles, Thomas Kapler, Robert Harper, William Wright
Oculus Info Inc.

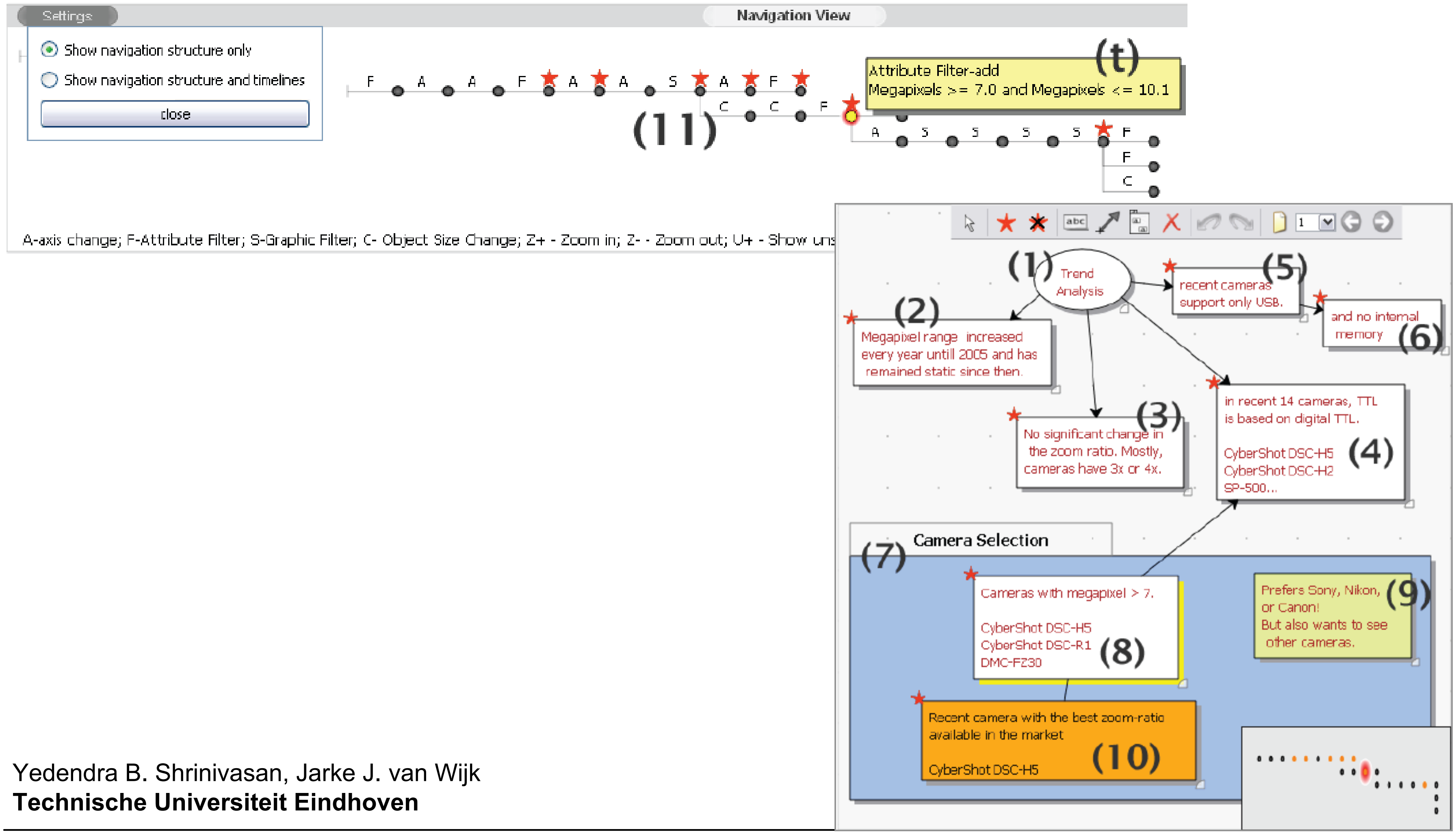
Example of Workspace Support

Relevant Information, Hypotheses, Evidence, Arguments, …



Pascale Proulx, Sumeet Tandon, Adam Bodnar, David Schroh, Robert Harper, William Wright
Oculus Info Inc.

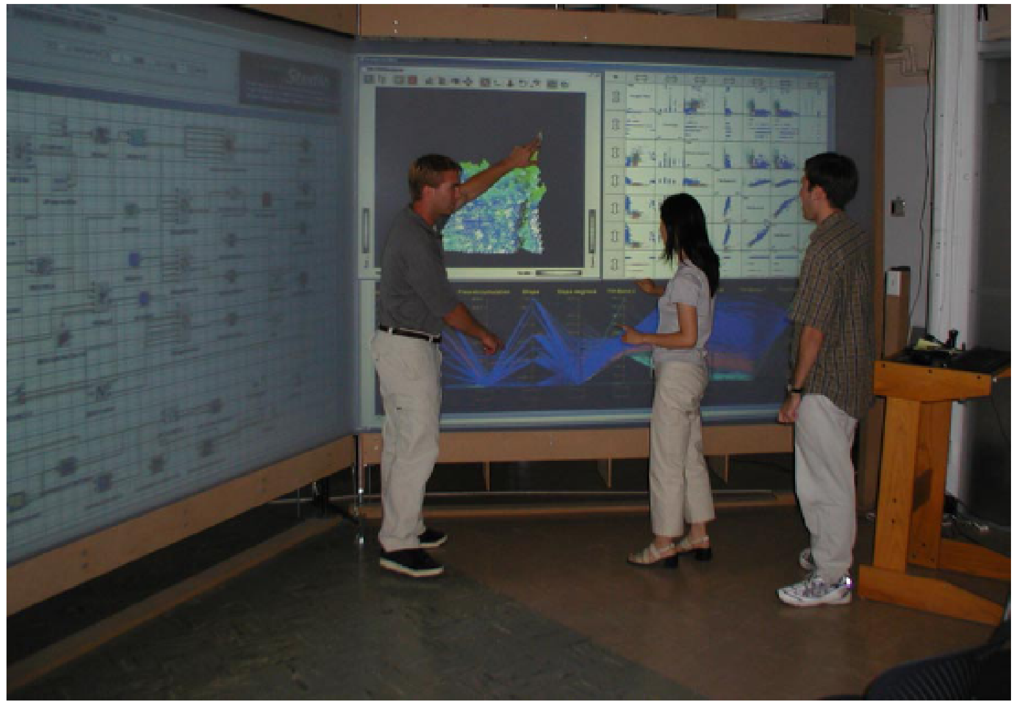
Example of Workflow and Workspace Support



Yedendra B. Shrinivasan, Jarke J. van Wijk
Technische Universiteit Eindhoven

Examples of Support for Collaborative Analyses

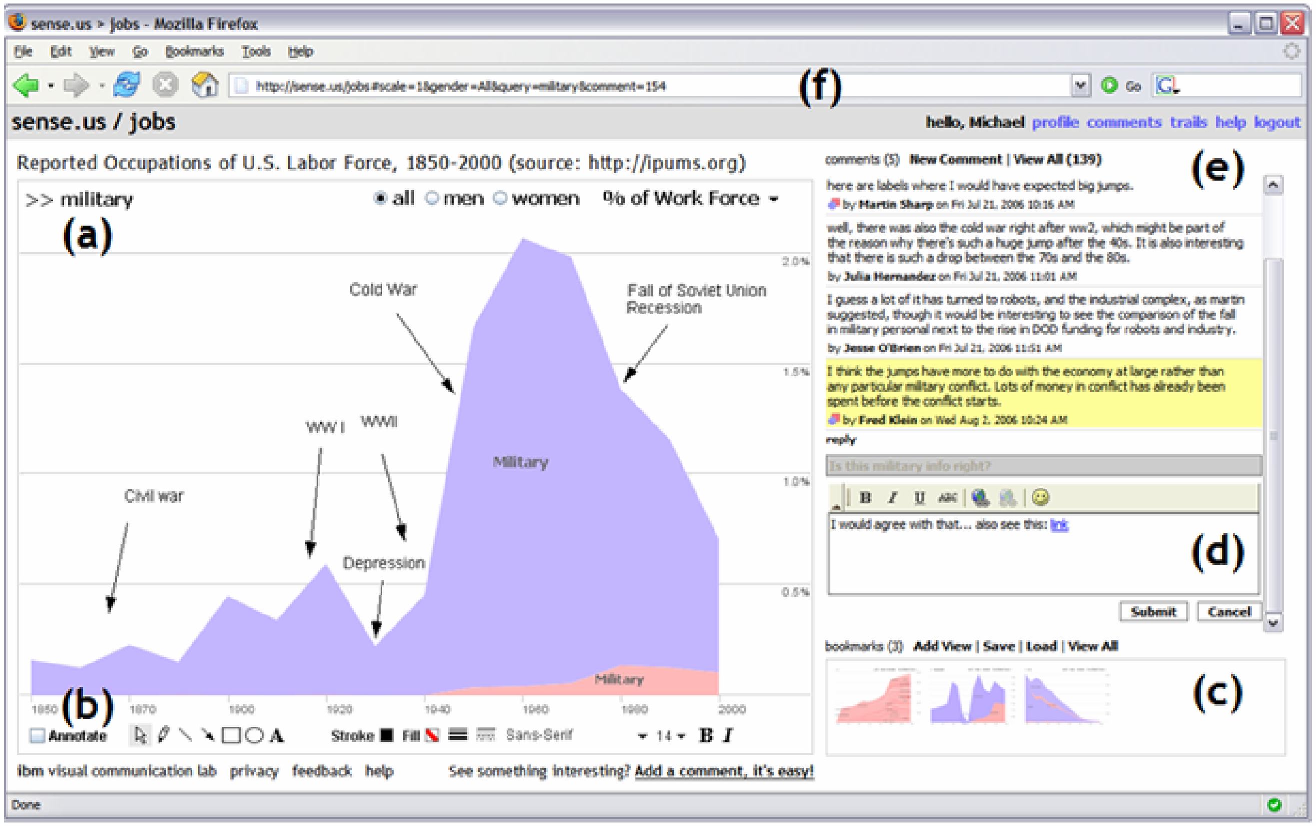
(synchronous, co-located collaboration)



Alan M. MacEachren, Isaac Brewer
Pennsylvania State University

Example of Support for Collaborative Analyses

(asynchronous, distributed collaboration)



sense.us

Jeffrey Heer, Fernanda B. Viégas, Martin Wattenberg
University of California, Berkeley

Conclusion

- Visual Analytics science and technology is meant to help people to make sense from complex data and solve complex problems
- Complexities: massive amounts, high dimensionality, heterogeneity, multiple facets, time variance, incompleteness, uncertainty, inconsistency
- Visual Analytics combines interactive visual interfaces with algorithmic methods for data pre-processing, transformation, and feature/pattern extraction
- Visual Analytics also includes interactive visual tools supporting reasoning, knowledge synthesis, and knowledge management
- Interactive visual interfaces help analysts to utilize their perceptual and cognitive capabilities fully and effectively
- Computer technologies compensate for the natural limitations in human skills and abilities and augment the discovery process
- The ultimate goal is to enable a synergistic collaboration of human and computer where each side can utilize its intrinsic capabilities in the best possible way