Visualization
Visual Analytics (VA)

SCHMALKALDEN UNIVERSITY OF APPLIED SCIENCES

Graphics+Interaction Laboratory

Based on Material by Marc Streit and Alexander Lex

VA Motivation

- Possibilities to collect and store data increase
- Faster than ability to use it for decision making

- Danger of getting lost in the data

- **Data** has no value in itself
- Extract the **information** contained in it!

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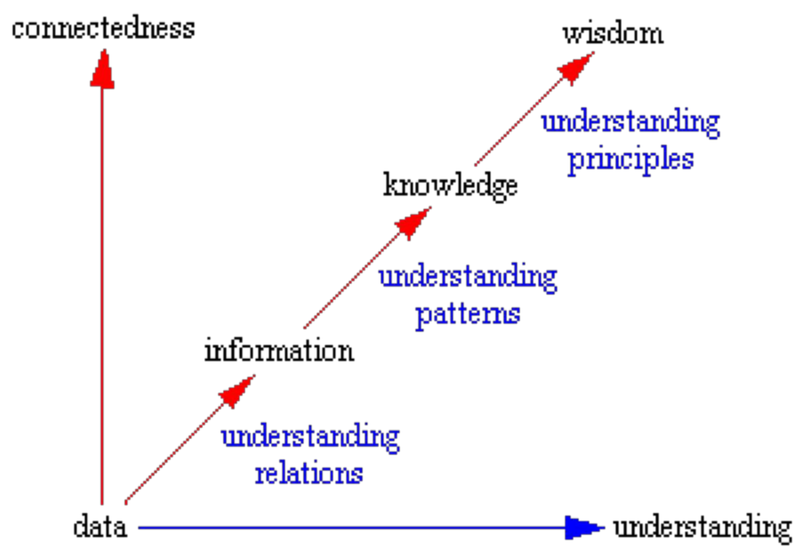
Data → Information → Knowledge → Wisdom

[Bellinger 2004]

- **Data**
  - Symbols
- **Information**
  - Data that are processed to be useful; provides answers to "**who**", "**what**", "**where**", and "**when**" questions
- **Knowledge**
  - Application of data and information; answers "**how**" questions
- **Wisdom**
  - Evaluated understanding



http://www.systems-thinking.org/dikw/dikw.htm

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History of VA

- Move from confirmatory to exploratory data analysis
  - John W. Tukey 1977 in “Exploratory Data Analysis” book
  - Confirmatory: charts and other visual representations to present data
  - Exploratory: interact with data
- Visual data exploration & visual data mining
- Visual analytics
  - 2004
  - Research and development agenda
    “Illuminating the Path”

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VA Definition

- "Visual Analytics is the science of analytical reasoning supported by a highly interactive visual interface." [WongThomas 2004]

- "Visual Analytics combines **automated analysis** techniques with **interactive visualisations** for an effective **understanding, reasoning and decision making** on the basis of **very large** and **complex datasets**" [Keim 2010]

- Detect the expected and discover the undetected

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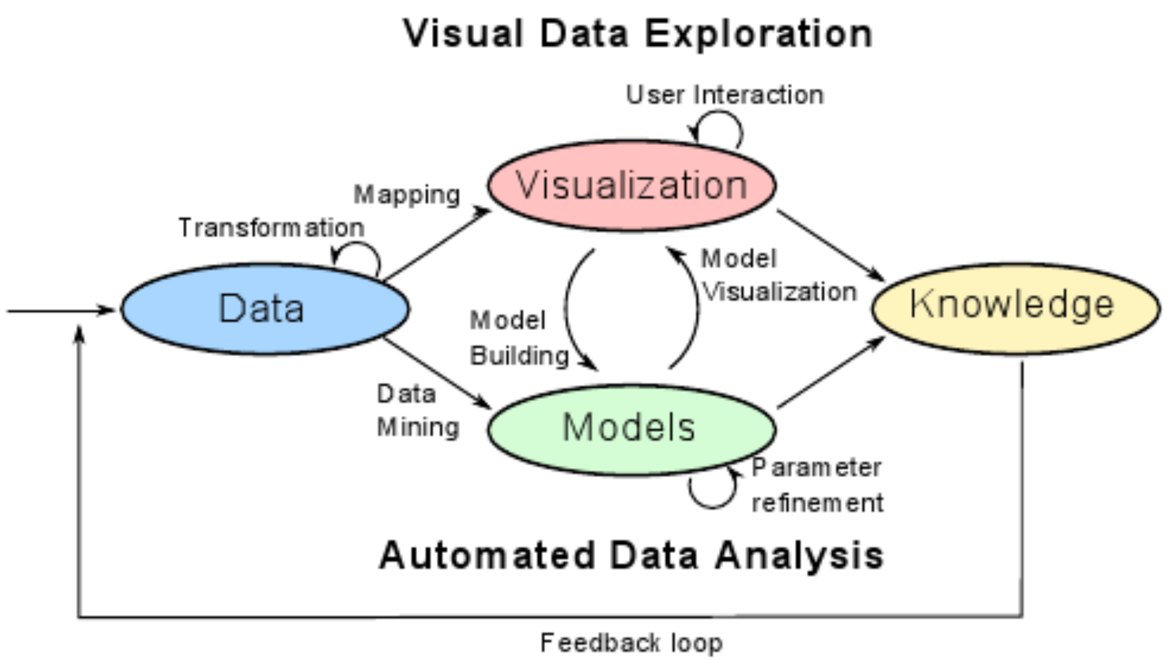
Visual Analytics Process

- First step: preprocess and transform data
  - Data cleaning, normalization, grouping, data fusion
- Alternating between visual and automatic methods



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Application Fields

- Physics
- Astronomy
- Climate and weather
- Biology
- Medicine
- Business Intelligence

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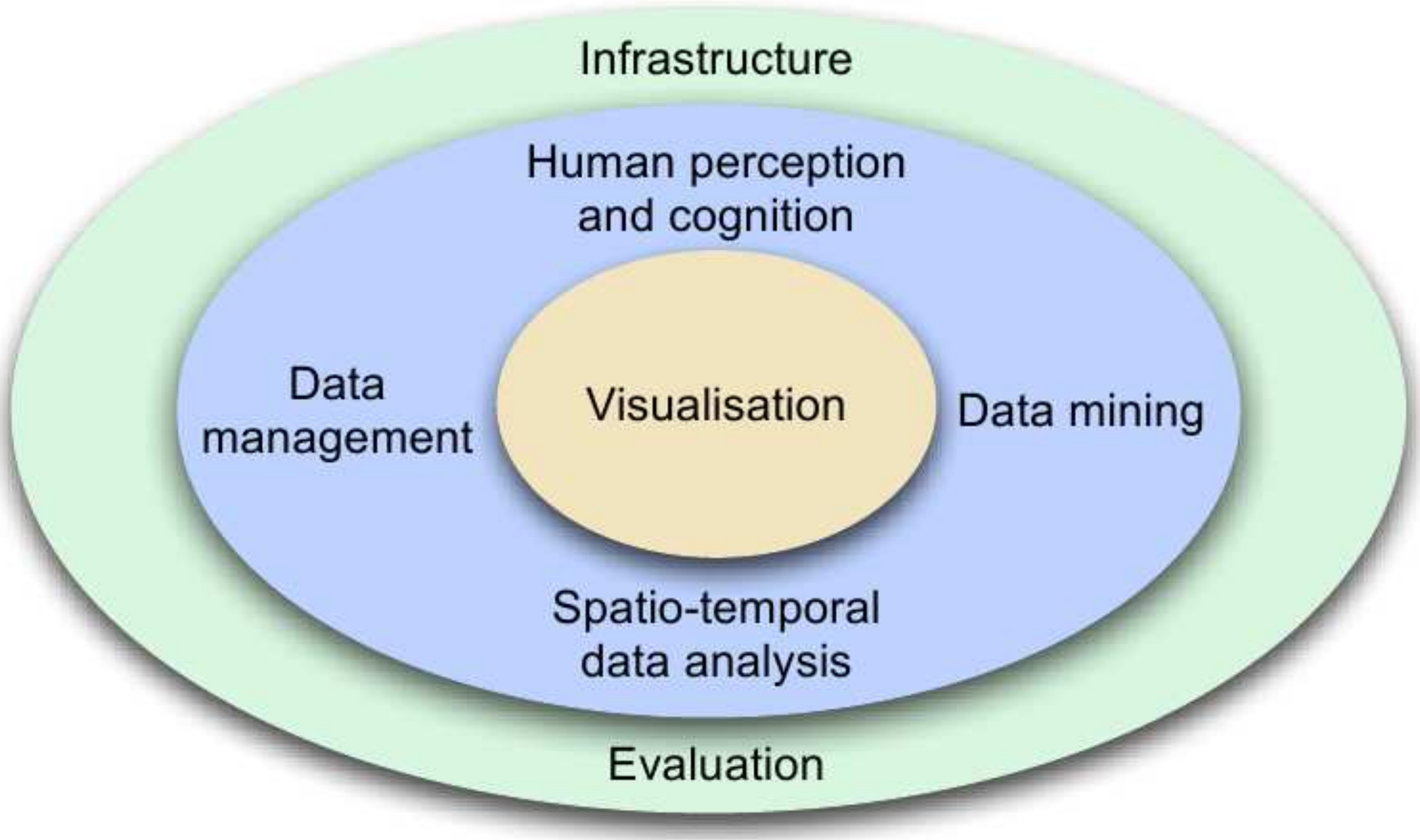
VAST

- IEEE Conference on Visual Analytics Science and Technology
- Founded 2006
- Co-located with IEEE VisWeek (Vis, InfoVis)

- New: EuroVA
  - Co-located with EuroVis

Interdisciplinary!



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VISUALIZATION

Already covered in other lectures!

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DATA MANAGEMENT

Heterogeneous Data

- Until last decade
  - Focus on efficiency and scalability
  - Uniform, structured data
- Numeric data, graphs, text, audio, video, etc.+
- Different formats
- Different sources
- Dealing with missing and inaccurate data values

- Users get overwhelmed
  - Data/information overload problem!

Data Types

- Numeric Data
- Text
- Graphs
- Audio
- Video signals
- etc.

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Data Management

- Data Management is a well understood field
  - Research over past 30 years
- Dynamicity problem
  - Data Management: Static two step interaction
    1. Query formulation
    2. Result collection
  - Interactive analysis
    - Response in < 100 msec necessary
- User interaction life-cycle
  - Data Management: Single user, one shot
  - Interactive analysis:
    Long-term activities and collaborative tasks

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Ways to manage data in VA

- Flat files
  - Lack of typing and metadata
  - E.g., spreadsheets, CSV
- Structured file formats
  - Adds typing
  - E.g., XML
- Traditional (relational) databases
  - Row-based
  - Robust / mature

Ways to manage data in VA (2)

- Analytical databases
  - Column-based architecture
- NoSQL systems
  - Cloud Storage
- Workflow and dataflow systems
  - Apply a previous or well-known process repeatedly

- Interactive analysis needs in-memory storage!

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Data Cleaning

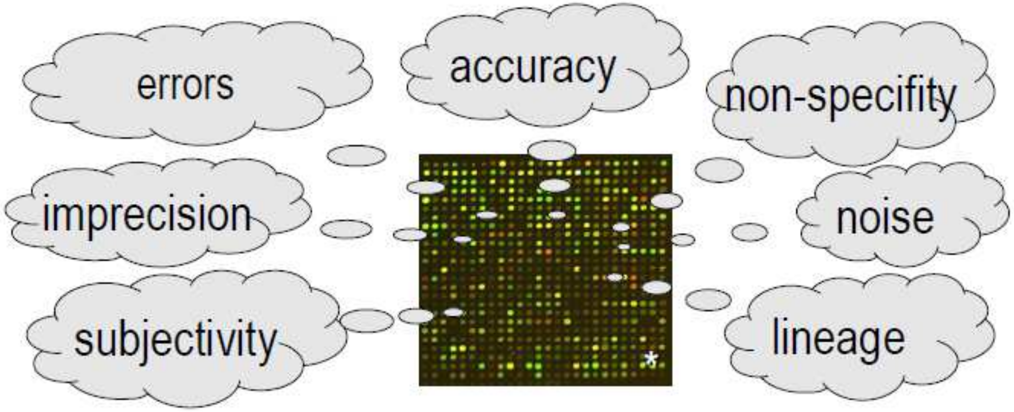
- Missing values
- Inaccurate values
- Null values

- Curative algorithms: Providing an alternative
  - Interpolation
  - Statistically computed
- Visualization

- Complex and time consuming!
  - Even for small data sets

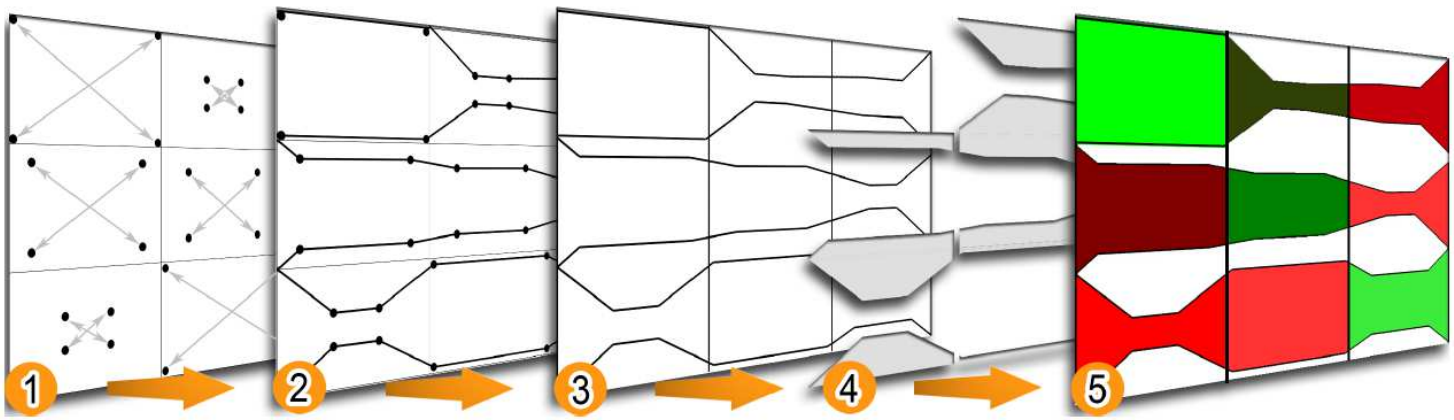
Challenge: Uncertainty

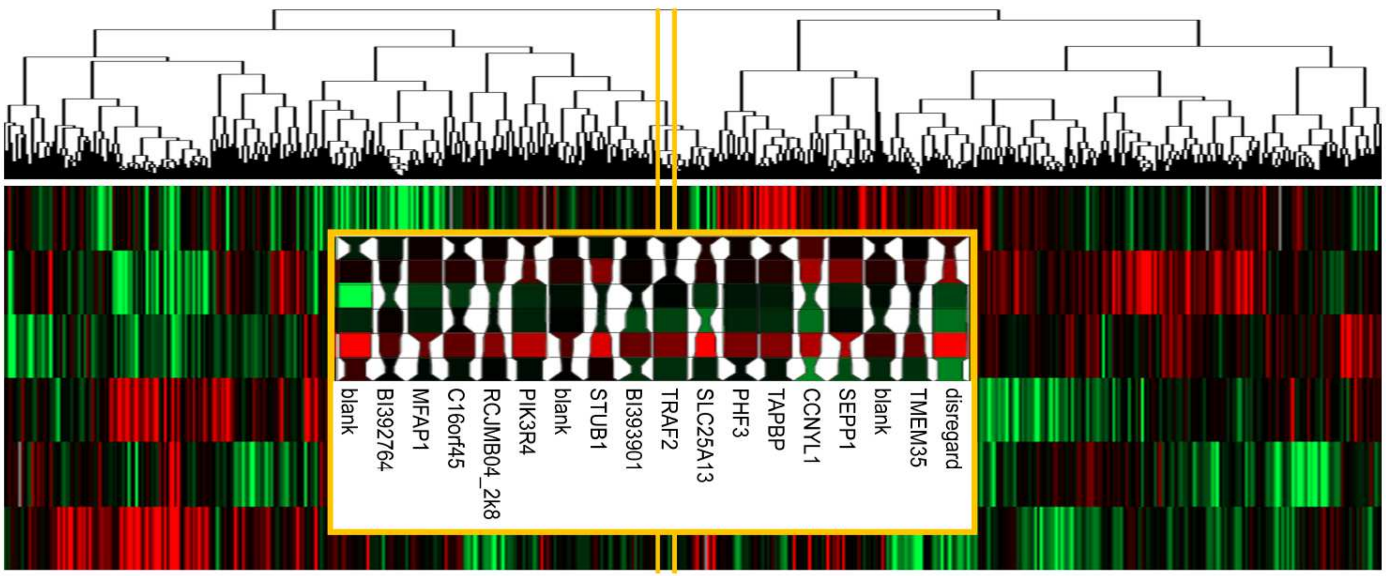
- Definition
  - “Degree to which the lack of knowledge about the amount of error is responsible for hesitancy in accepting results and observations with caution” [Hunter 1993]
- Measurement data
  - E.g., DNA microarray expression data



[Holzhüter 2010]

Uncertainty Visualization Example





[Holzhüter 2010]

Challenge: Semantics Management

- Manage not only data itself
- But also
  - Meta data
  - Abstraction levels
  - Hierarchical structures

- Needed for automatic and semi-automatic analysis

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Challenge: Data Streaming

- Dynamic data
- Example
  - VA of social network with life feed data
- Re-calculating everything is not a solution

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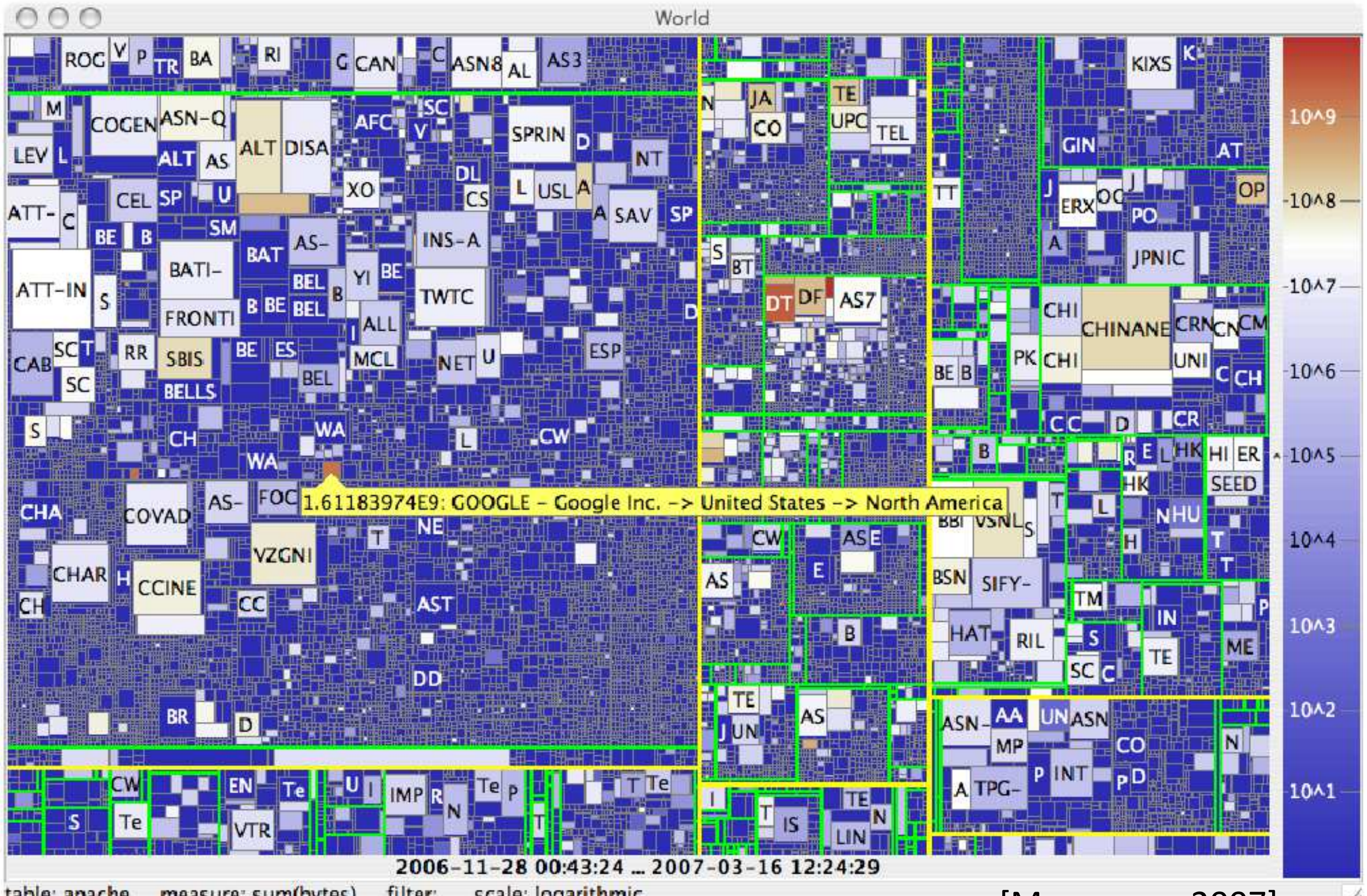
Network Traffic Analysis



[Mansmann 2007]

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Challenge: Distributed and Collaborative VA

- Interdisciplinary analysis problems
- Single domain expert may not be enough
  → Need for collaboration
- Annotating data and insights
- Share findings with different users

- Co-located vs. distributed

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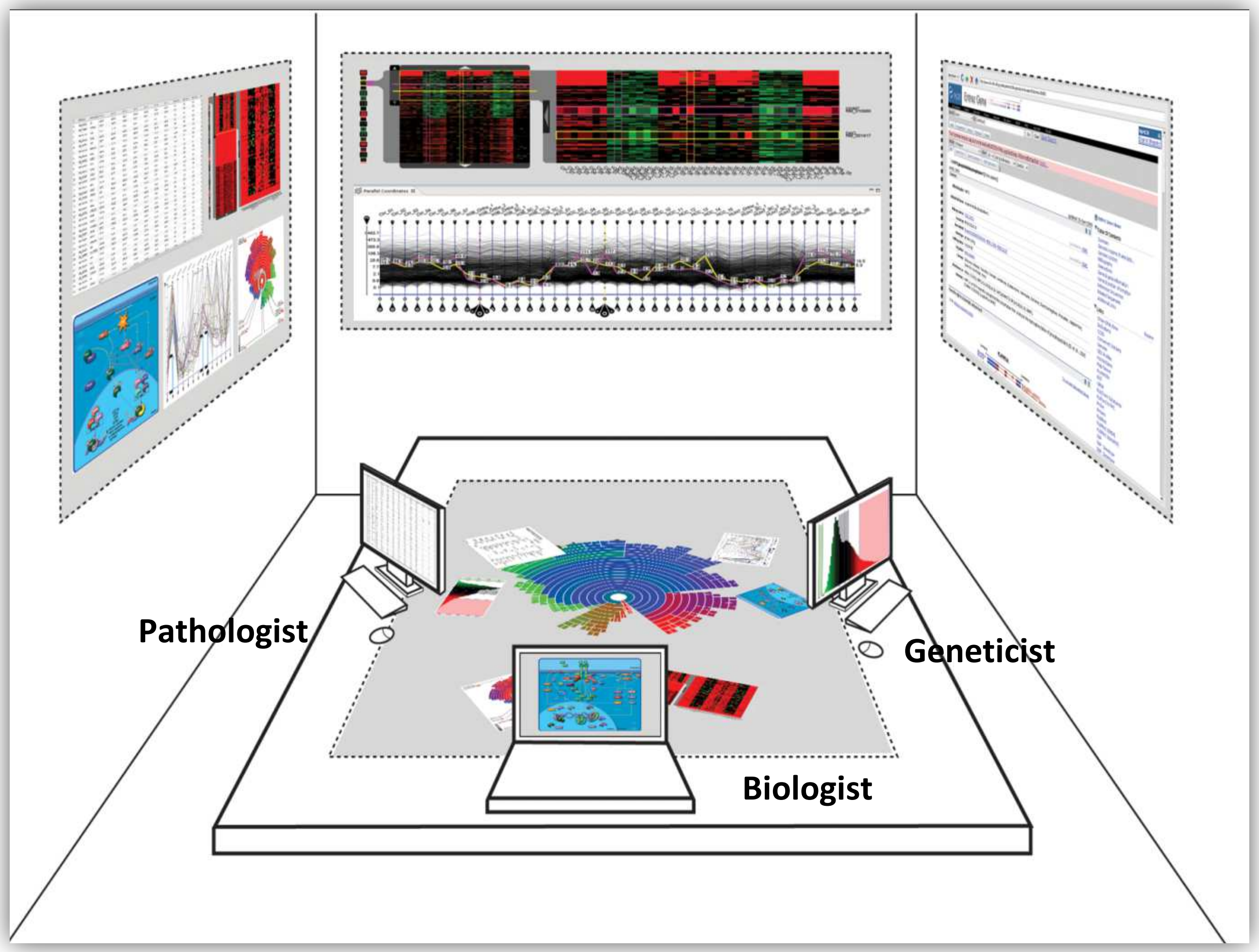
Co-Located Visual Analytics



[Streit, CoVis 2009]

Deskotheque Lab at ICG

[Waldner, CoVis 2009]

Challenge: VA for the Masses

Web-based system

+

Integrated data management

+

Interactive visualization

=

Visual Analytics for the Masses

- Home user becomes naive analyst
- Challenges
  - Raises heterogeneity (data sources and devices)
  - User Acceptance Issues
  - Scalability

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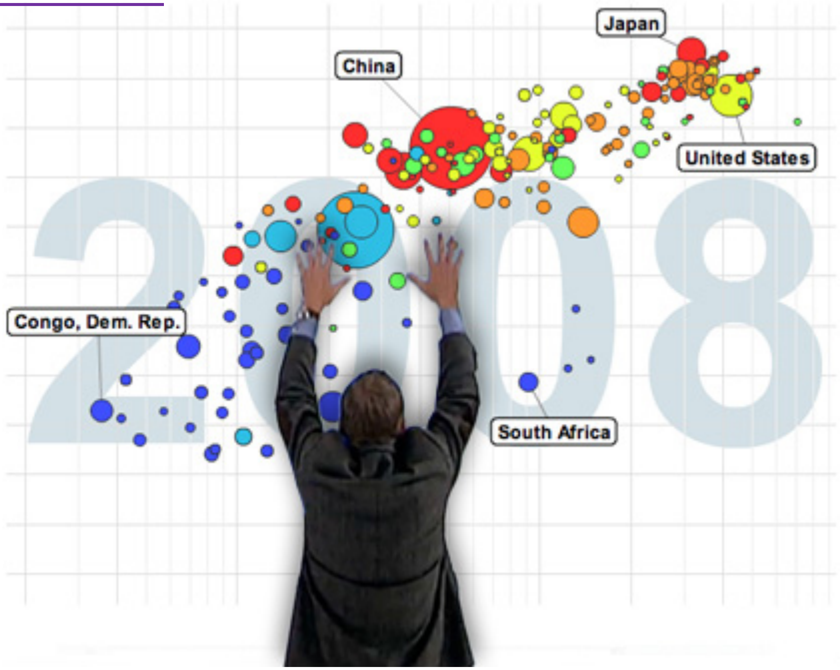
VA for the Masses: Gapminder

- World census data
- http://graphs.gapminder.org/world



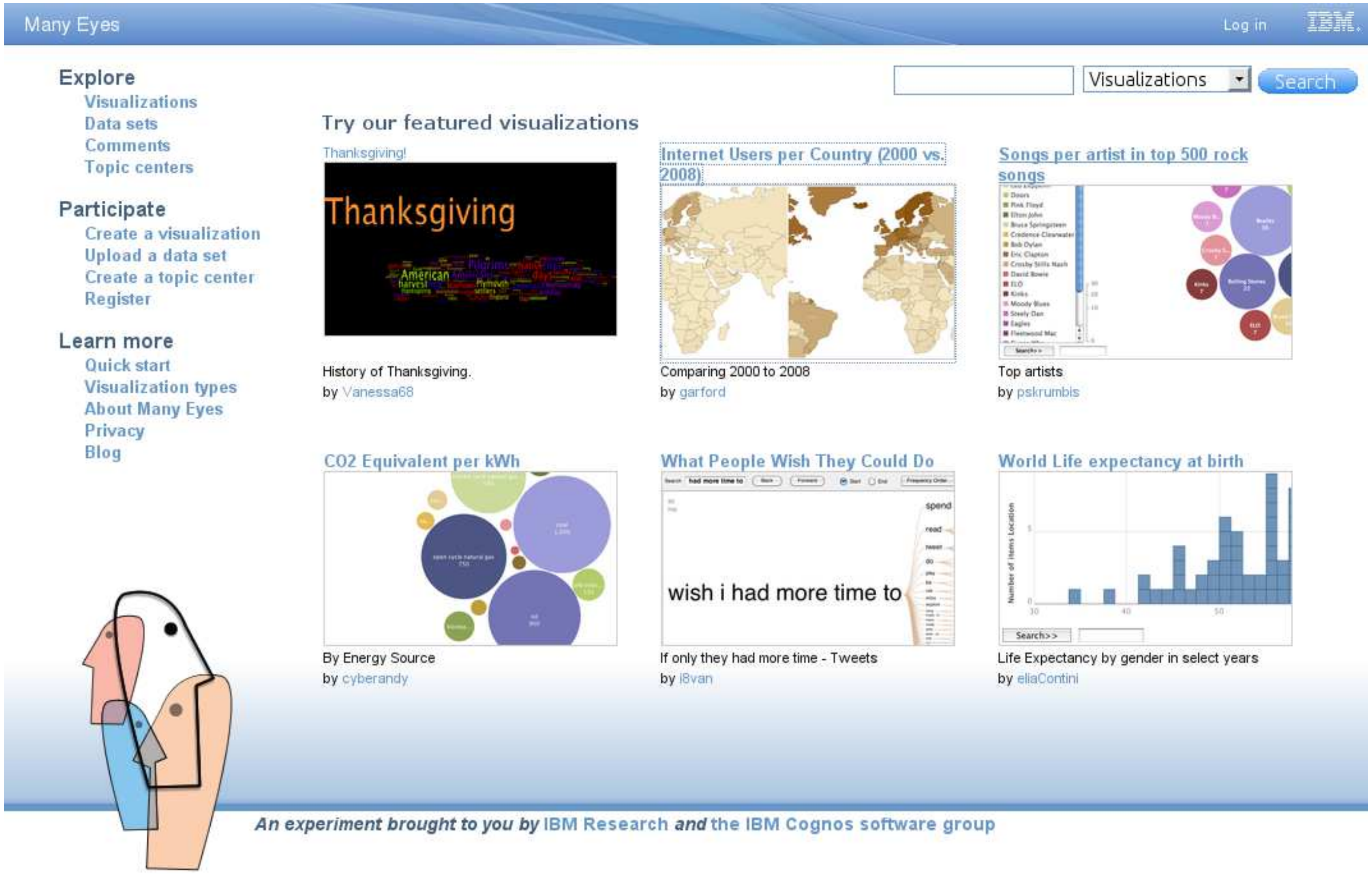
- Software: Trendalyzer
  - Acquired by Google in 2007
  - Interactive 2D-Scatterplot
  - Plus color and size
    for additional attributes
  - Linking and brushing
    - Sliders

VA for the Masses: Gapminder (2)

- Hans Rosling – TED talks
  - http://www.gapminder.org/videos/
  - http://www.youtube.com/watch?v=jbkSRLYSojo

VA for the Masses: ManyEyes

- IBM Research
- http://www-958.ibm.com/software/data/cognos/manyeyes/



DATA MINING

Data Mining Intro

- Definition
    - Automatic algorithmic extraction of valuable information from raw data
- Find interesting facts in large datasets

Statistics vs. Visualization

- Ascombe's quartett
- Statistics profile is the same for all!
  - Mean of x = 9.0
  - Mean of y = 7.5
  - Sums of squared errors = 110
  - Correlation coefficient = 0.82
  - Coefficient of determination = (
  - etc.

I		II		III		IV	
x	y	x	y	x	y	x	y
10.0	8.04	10.0	9.14	10.0	7.46	8.0	6.58
8.0	6.95	8.0	8.14	8.0	6.77	8.0	5.76
13.0	7.58	13.0	8.74	13.0	12.74	8.0	7.71
9.0	8.81	9.0	8.77	9.0	7.11	8.0	8.84
11.0	8.33	11.0	9.26	11.0	7.81	8.0	8.47
14.0	9.96	14.0	8.10	14.0	8.84	8.0	7.04
6.0	7.24	6.0	6.13	6.0	6.08	8.0	5.25
4.0	4.26	4.0	3.10	4.0	5.39	19.0	12.50
12.0	10.84	12.0	9.13	12.0	8.15	8.0	5.56
7.0	4.82	7.0	7.26	7.0	6.42	8.0	7.91
5.0	5.68	5.0	4.74	5.0	5.73	8.0	6.89

(a) Four datasets with different values and the same statistical profile

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Simple Visualization: Dot plot

I		II		III		IV	
x	y	x	y	x	y	x	y
10.0	8.04	10.0	9.14	10.0	7.46	8.0	6.58
8.0	6.95	8.0	8.14	8.0	6.77	8.0	5.76
13.0	7.58	13.0	8.74	13.0	12.74	8.0	7.71
9.0	8.81	9.0	8.77	9.0	7.11	8.0	8.84
11.0	8.33	11.0	9.26	11.0	7.81	8.0	8.47
14.0	9.96	14.0	8.10	14.0	8.84	8.0	7.04
6.0	7.24	6.0	6.13	6.0	6.08	8.0	5.25
4.0	4.26	4.0	3.10	4.0	5.39	19.0	12.50
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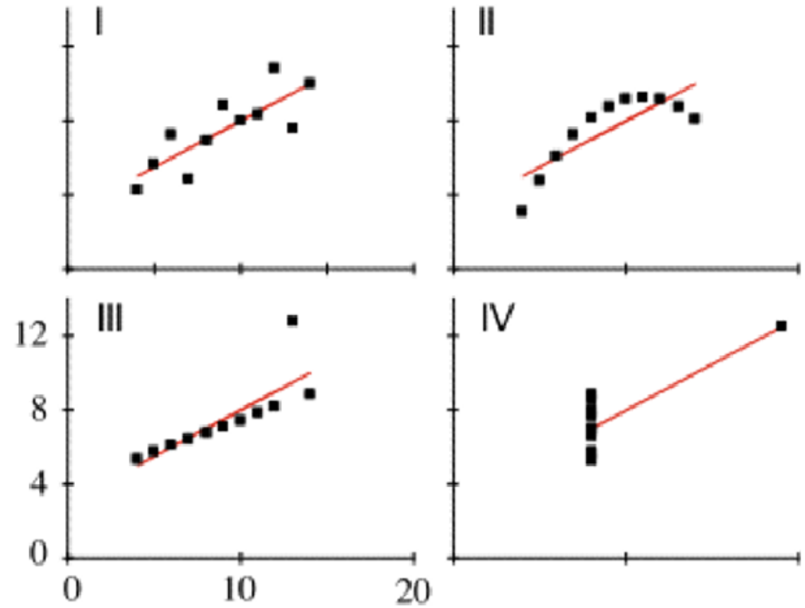
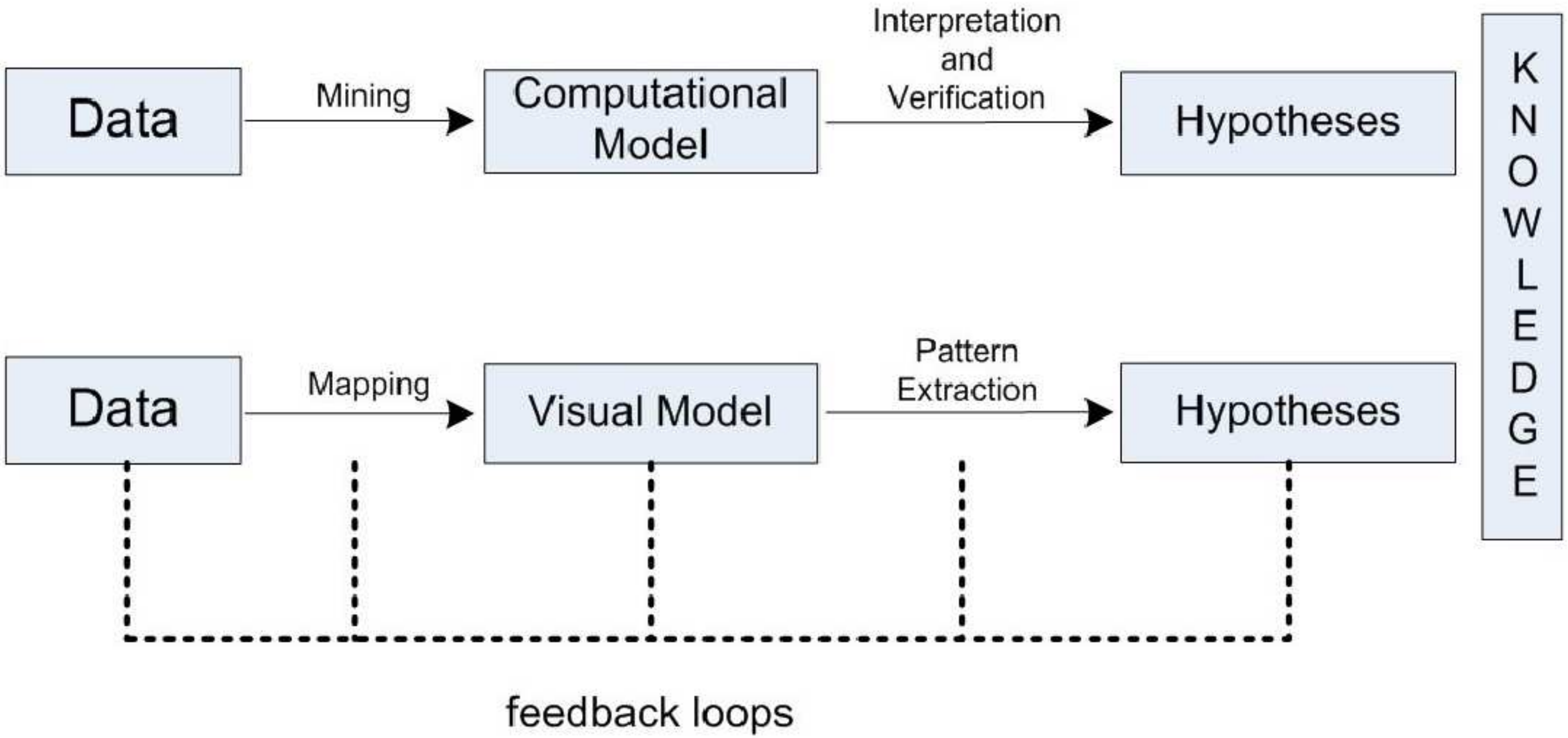


(b) Dot Plot of the four datasets

Fig. 6. Anscombe's Quartet

Traditional Data Mining vs. Visual Analysis Processes



Knowledge Discovery and Data Mining (KDD)

- Semi or fully automated analysis of massive data sets
- Contributions are more about general methodologies
- Black-box methods in the hands of end users
  - Users need to understand the algorithms for using them
  - What attributes to use? What similarity measure? etc.
  - Often trial and error

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In Contrast: Visualization

- Incorporate
  - Experts' background knowledge
  - Creativity
  - Intuition
  - But: only relatively small data sets

- VA has to bridge these two fields!

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Supervised vs. Unsupervised Learning

- Supervised learning
  - Based on set of training samples
  - Learn models for classification of previously unseen data samples
- Unsupervised learning
  - Extract structure form data without prior knowledge
  - Example: Cluster analysis
  - Example: Dimensionality reduction

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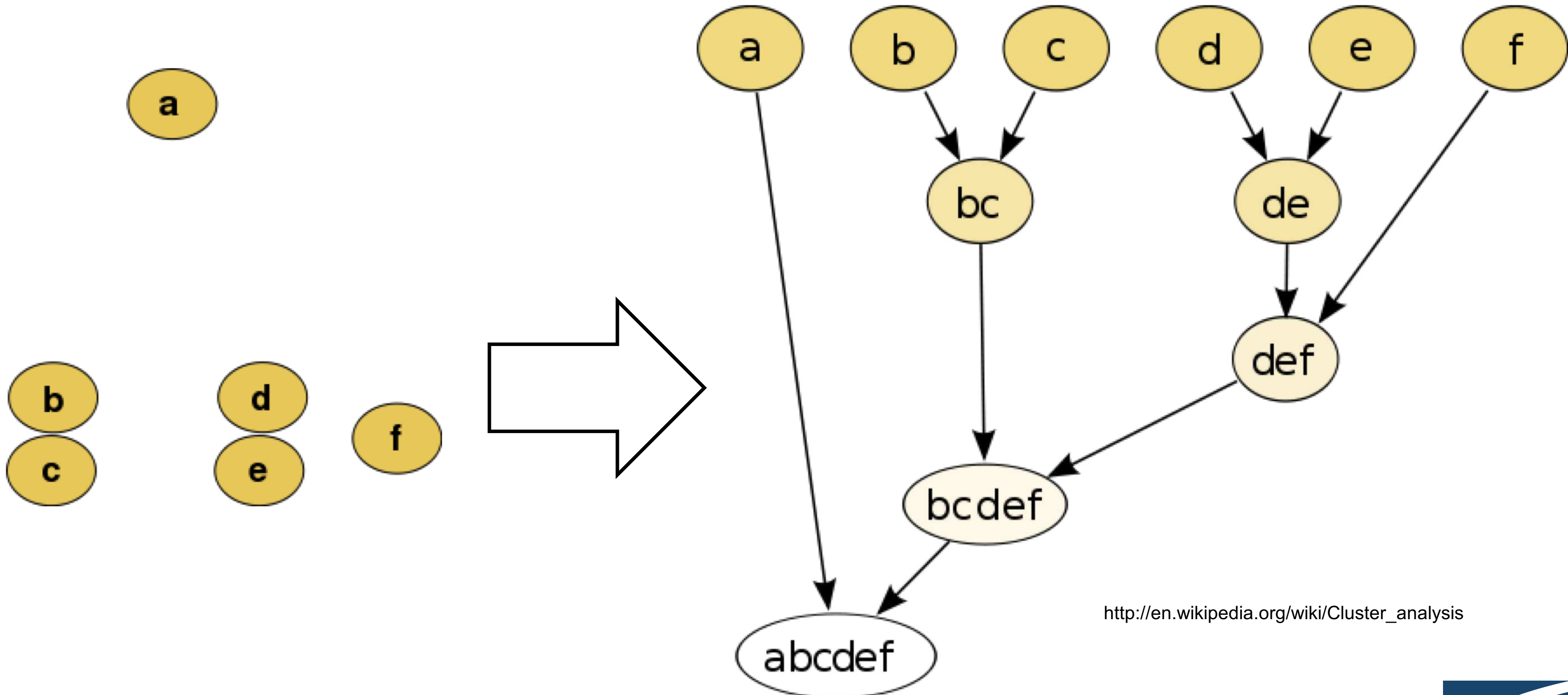
Cluster Analysis

- Automatically group data instances into classed based on mutual similarity
- Distance metric

- Hierarchical
- Partitional
  - K-Means
- Bi-clustering
  - Simultaneous clustering of rows and columns
- Fuzzy

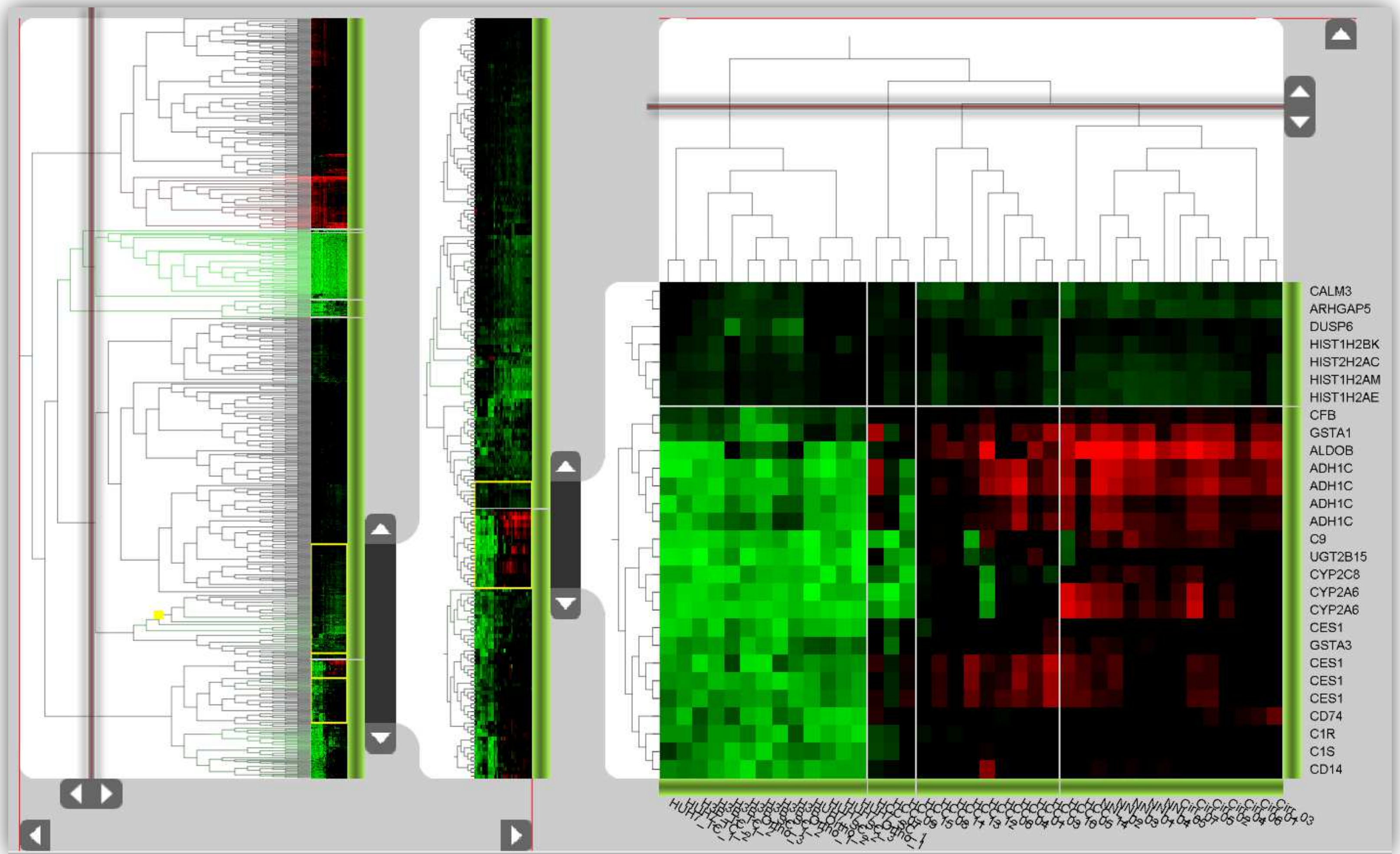
Hierarchical Clustering

- Distance metric: Euclidean distance



http://en.wikipedia.org/wiki/Cluster_analysis

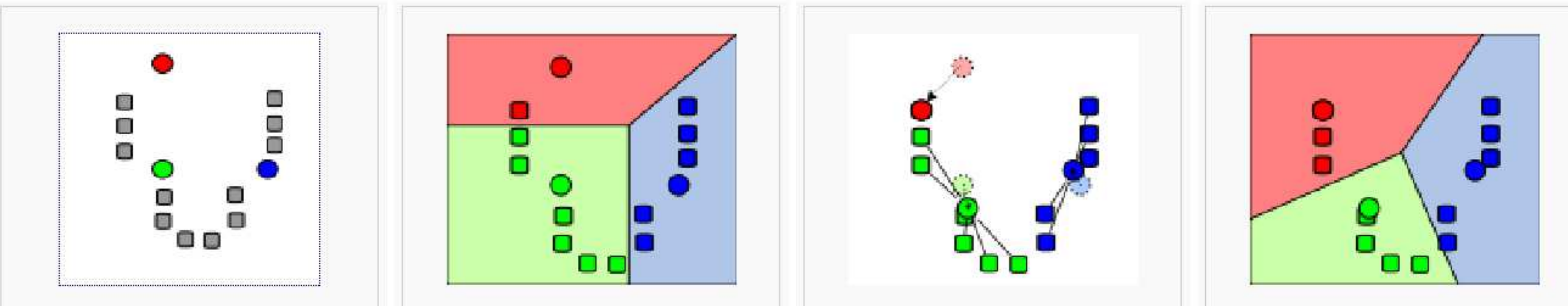
Hierarchical, Clustered Heat Map



[Lex, PacificVis 2010]

K-Means Clustering

- Partition n observations into k clusters
- Each observation belongs to the cluster with the nearest mean



1) *k* initial "means" (in this case *k*=3) are randomly selected from the data set (shown in color).

2) *k* clusters are created by associating every observation with the nearest mean. The partitions here represent the Voronoi diagram generated by the means.

3) The centroid of each of the *k* clusters becomes the new means.

4) Steps 2 and 3 are repeated until convergence has been reached.

http://en.wikipedia.org/wiki/K-means_clustering

Dimension Reduction

- High-dimensional data
- Transform to space with fewer dimensions
- Linear and non-linear approaches
- Example
  - PCA (Principle Component Analysis)

- Disadvantages
  - Hard to preserve semantics of single dimensions
  - Hard to understand and interpret

INFRASTRUCTURE

Infrastructure

- Linking together all the processes, functions and services required by VA applications
- Current state
  - Custom-built stand-alone applications (ad-hoc systems)
  - In-memory data storage (rather than DBMS)
  - No off-the-shelf systems
  - Need to implement them with limited domain skills
  - No intercompatibility / interoperatibility
- Problematic commercial market

Data Analysis Environments

- Statistical analysis
  - R, SPSS, SAS
- Scientific computation
  - Matlab, Scilab
- Machine learning toolkits
  - WEKA
- Textual Analysis
  - GATE, UIMA, SPSS/Text, SAS Text Miner
- Video/image analysis
  - OpenCV, IRIS Explorer

PERCEPTION AND COGNITION

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Differentiation

- Perception
  - How people interpret the surroundings
- Cognition
  - Ability to understand visual information
  - Largely based on prior learning

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EVALUATION

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Evaluation

- Goal
  - Compare approaches
  - Identify problems
- Assess
  - User acceptance
  - Effectiveness
    - doing "right" things, i.e. setting right targets to achieve an overall goal (the effect)
  - Efficiency
    - doing things in the most economical way (good input to output ratio)

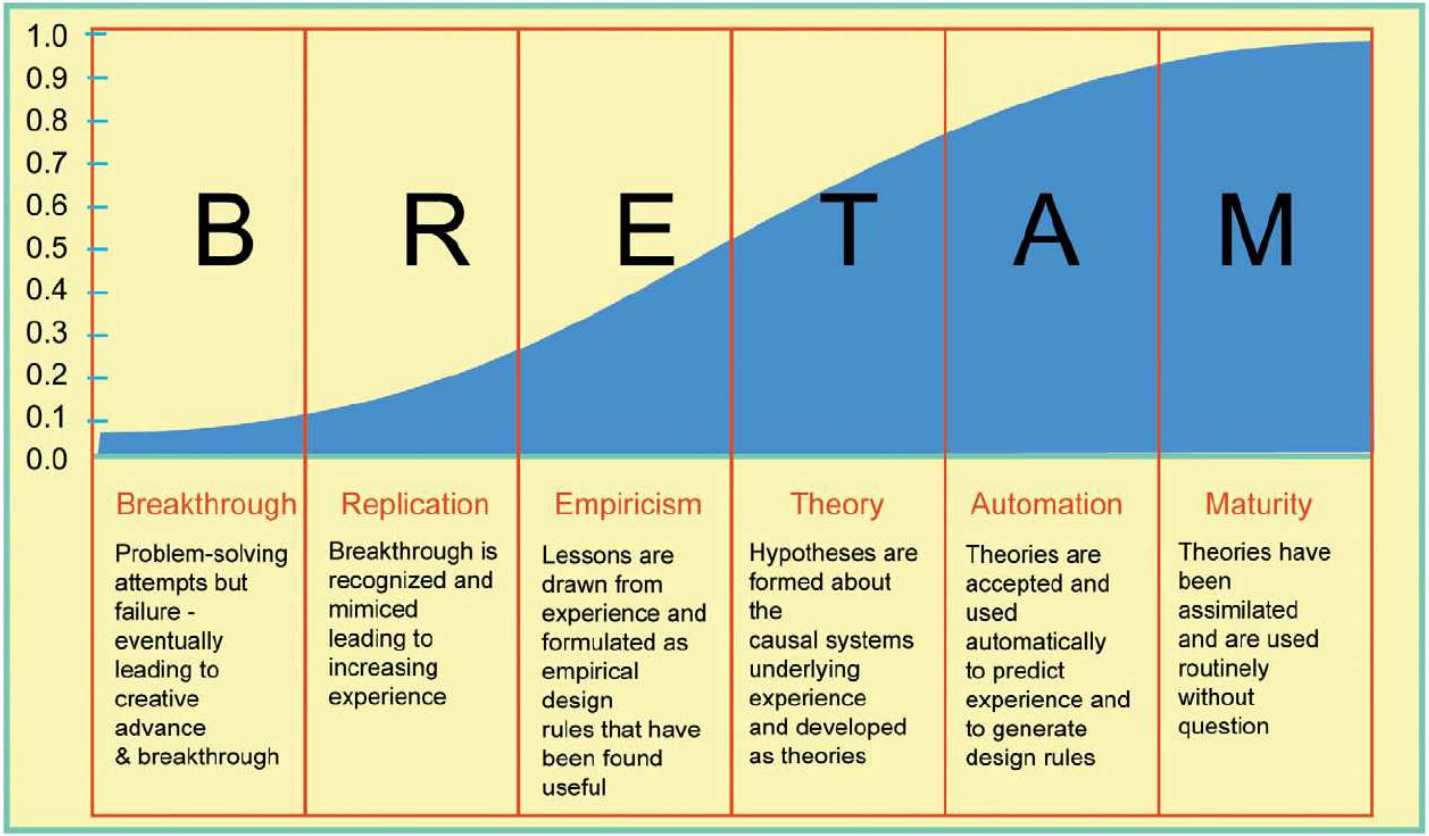
Evaluation (2)

- Quantitative vs. Qualitative methods

- Recently evaluation becomes more prominent
- Challenge
  - How to evaluate interactive, explorative visual data analysis?

VA Conclusion

- Every research field runs through same stages
- BRETAM Model -- VA is only at replication stage!



[Gaines 1991]

The End

QUESTIONS?