

Compromises and Added Value in Visual Analytics

Helwig Hauser (Univ. of Bergen)



Plan



~~So what is Visual Analytics?~~

OK, OK, ..., not this question, again, ... ☺

Instead:

**Five selected characteristics (C1–C5)
of Visual Analytics (VA solutions)**

leading to
a discussion of
– **compromises**
– **chances**

C1: problem size
C2: visualization richness
C3: interaction pace
C4: computational analysis
C5: comprehensiveness

* So let's start with **C1: Problem Size...**

C1: Large Data



- A recurring statement: there's **sooo much data...**
... therefore **visual analytics!**

Daniel Keim, 2007:

Dagstuhl Seminar Talk

Challenge of the Information Age

- 100 million FedEx transactions per day
- 150 million VISA credit card transactionen per day
- 300 million long distance calls in ATT's network per day
- 50 billion e-mails worldwide per day
- 600 billion IP packets per day DE-CIX backbone

Visual Analytics – Keim – May, 31 2007

Why is the topic highly relevant today?

- **Very Large Data Collections** are available in Databases and Data Warehouses
- On the Basis of the Data Complex Decisions have to made in a timely fashion
- Pure Visualization Methods (Information Visualisation) do not work for **Billions of Data Records**
- Full Automatic Knowledge Discovery Approaches only work for well-defined and clearly specifiable problems.
- Especially for adversarial situations:
Fraud, Viruses, SPAM, Attacks, Competition, ...

Visual Analytics – Keim – May, 31 2007

Thomas Ertl, 2009:

Visual Computing Trends, Wien

Information Explosion

- Today: the Peta (10^{15}) era
- Computer Simulations
 - Weather 1 Petabyte per year
 - High-performance computing center 1 Petaflop per second
 - Game PC graphics card 1 Teraflop per second
- Sensors
 - Satellite astronomy 1 Petabyte per year
 - Particle physics (CERN) 1 Petabyte per year
 - Bio-chemical high-throughput 1 Petabyte per year
- Digital Events
 - Credit card transactions 100 Mio per day
 - Long distance calls ATT 300 Mio per day
 - Internet packets through DE-CIX 500 Bill per day

Information Explosion

- Tomorrow: the era of Exa (10^{18}) and Zeta (10^{21})
- Digital Information (created, captured, replicated)
 - 2002 22 Exabyte
 - 2006 160 Exabyte
 - 2010 almost 1 Zetabyte increase per year (28 trillion e-mails/year, totaling about 6 EB of data)
- Information "stored" by humans
 - est.1 Petabyte in entire life time
 - 80% through vision (space, form, color, texture, ...)
 - through display with 1-100 Megapixels
- **Visualization plays a significant role in dealing with digital data**
- **Interaction and abstraction** are the keys for the visualization of huge data sets

C1: Large Data

- A recurring statement: there's **sooo much data...**
... therefore **visual analytics!**

Daniel Keim, 2009:

Dagstuhl Seminar Talk

Visual Analytics Mantra

„Analyze first,
Show the Important,
Zoom, filter
and analyse,
Details on demand.“



digital data

C1: Large Data – a question mark...

- Christian Chabot (CEO of Tableau), 2008:

People adopt visual analytics primarily to help them see and understand massive data

advice:

Start **small...**

VAST Keynote

Contributor ID	Industry	Recommendaton	Ticker	Close	Volume
1/14/2008	Hardware	Sell	AAPL	50.22	3,485,500
1/11/2008	Hardware	Buy	CSCO	53.25	21,608,000
1/11/2008	Software	Hold	MSFT	54.51	23,372,800

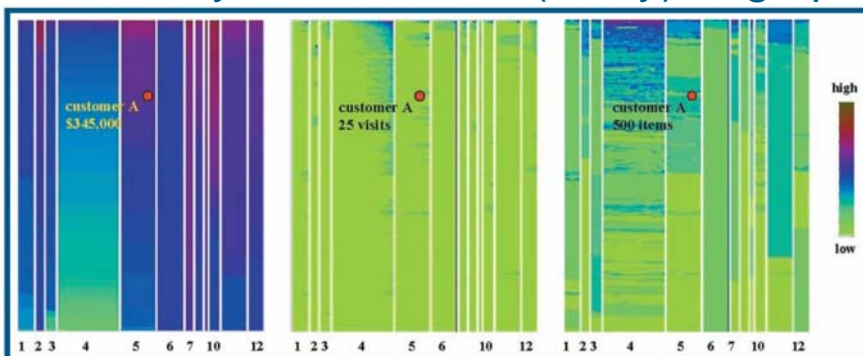
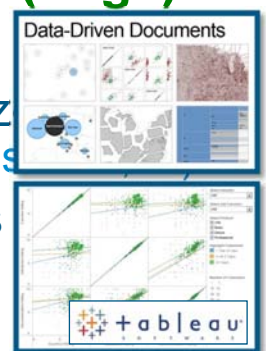
C1: Problem Size – some categorization

- **Small ► moderate ► large ► very large (huge)**
 - no VA needed for (really) small problems
 - lots of solutions do work for moderately sized cases
// e.g., an Excel sheet of data (hundreds, thousands, ...)
 - selected solutions address large problems
// tens to hundreds of thousands, etc.
 - very few focus on (really) huge problems

■ Important difference between large and huge cases!

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Information Visualization (2002) 1, 23–24
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www.palgravejournals.com/iv

Pixel bar charts: a visualization technique for very large multi-attribute data sets†

Daniel A. Keim^{1,3,4}
Ming C. Hao¹
Umesh Dayal¹
Meichun Hsu^{1,2}

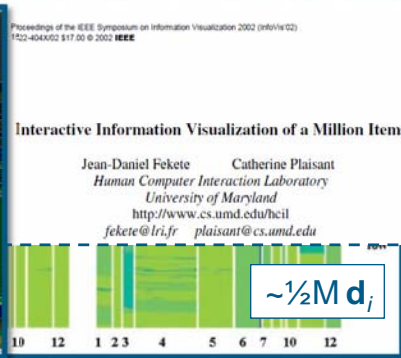
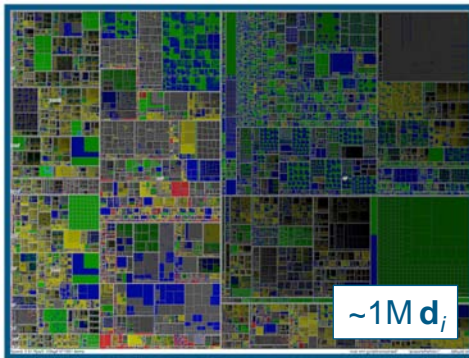
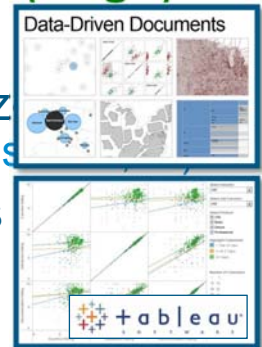
¹ Hewlett-Packard Research Labs, Palo Alto, California, U.S.A.; ² CommerceOne, Pleasanton, California, U.S.A.; ³ AT&T Research Labs, Florham Park, NJ, U.S.A.; ⁴ University of Konstanz, Germany.

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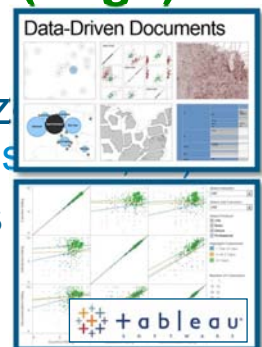
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but still no billions, no Petabyte VA, etc.

- Important difference between large and huge cases!

* Next C2: Visualization Richness...

C2: Visualization



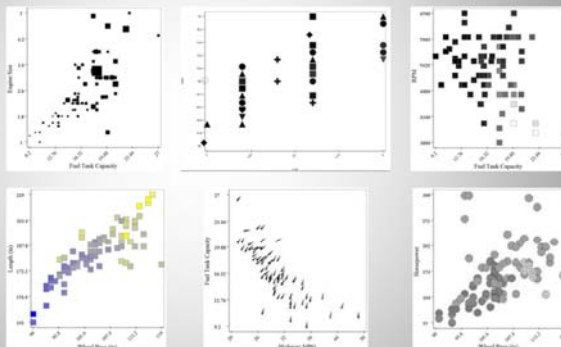
- The **perceptual** and **cognitive power** of users should not be left unutilized!
- Matt Ward, 2010:

EuroVis
Keynote

1. In the Beginning there were Mappings

Data values control the **visual variables** of points, lines, areas, surfaces, and volumes.

- Position
- Size
- Shape
- Value
- Color
- Orientation
- Texture
- Motion



J. Bertin, *Semiology of Graphics: Diagrams, Networks, Maps*. University of Wisconsin Press, Madison (1983).

C2: Visualization

■ The show

■ Mat

EuroVis Keynote

1. In
Data
lines

- Position
- Size
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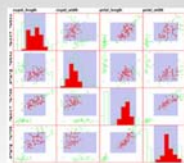
J. Bertin
Madison

Dealing with Dimensions

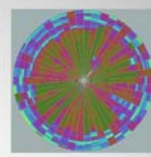
• Many categorizations of dimension organization (see below paper for an early one)

• My categories:

- **Subsetting**
(e.g., SPLOMs, dense pixels)
- **Reorganization**
(e.g., parallel coords, glyphs)
- **Embedding**
(dimensional stacking, stacked bar charts, trellis displays)
- **Reduction**
(PCA, MDS, RadViz)



Scatterplot matrix - XmdvTool



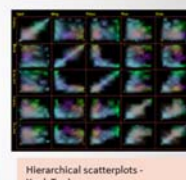
Dense pixel / circle segments - Keim



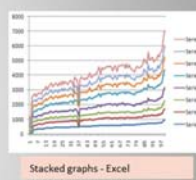
TableLens - Inxight



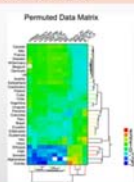
Survey Plot - DataLab



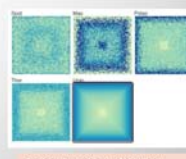
Hierarchical scatterplots - XmdvTool



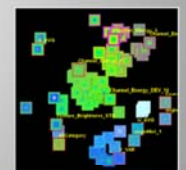
Stacked graphs - Excel



Heat Map - Wilkinson



Dense pixel/spiral - XmdvTool



Value and Relation Display - Yang

P. Wong and R. D. Bergeron, "30 years Scientific Visualization: Overviews, Methodologies, and Techniques, edited by Nielson, Hagen, and Mueller (1994). pp. 3-33.

EuroVis 2010, Bordeaux, France

C2: Visualization

■ The show

■ Mat

EuroVis Keynote

1. In
Data
lines

- Position
- Size
- Shape
- Value
- Color
- Orientation
- Texture
- Motion

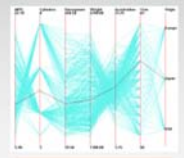
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Dealing with Dimensions

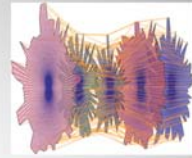
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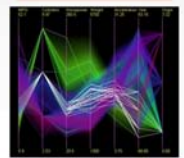
Parallel Coords - XmdvTool



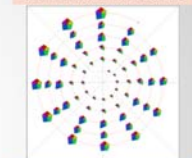
3D Parallel Coordinates - Carpendale



Chernoff Faces - Wikipedia



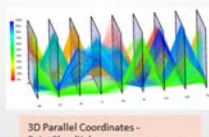
Hierarchical Parallel Coordinates - XmdvTool



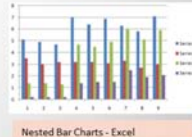
SpiralGlyphics - Lipchak and Ward



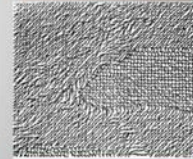
Painterly Glyphs - Healey



3D Parallel Coordinates - PointCloudXplore



Nested Bar Charts - Excel



Stick-figure icons - Pickett and Grinstein

P. Wong and R. D. Bergeron, "30 years of multidimensional multivariate visualization." in Scientific Visualization: Overviews, Methodologies, and Techniques, edited by Nielson, Hagen, and Mueller (1994). pp. 3-33.

EuroVis 2010, Bordeaux, France

C2: Visualization

- The show

- Mat

EuroVis Keynote

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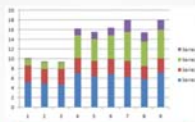
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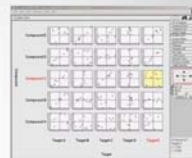
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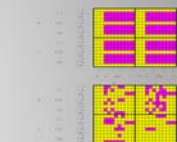
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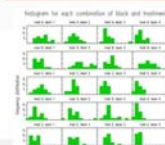
Stacked Bar Charts - Excel



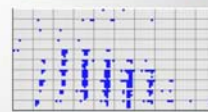
Trellis Display - ChartSpace



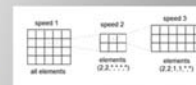
General Logic Diagram - SGI



Trellis Display - GenStat



Dimensional Stacking - XmdvTool



P. Wong and R. D. Bergeron, "30 years of multidimensional multivariate visualization." in Scientific Visualization: Overviews, Methodologies, and Techniques, edited by Nielson, Hagen, and Mueller (1994). pp. 3-33.

EuroVis 2010, Bordeaux, France

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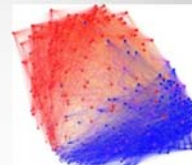
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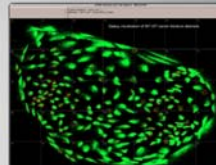
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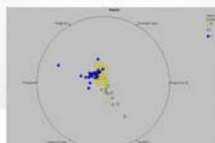
Star Glyphs with PCA - XmdvTool



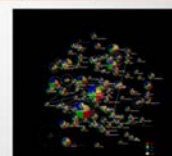
Graph with MDS layout - GUESS



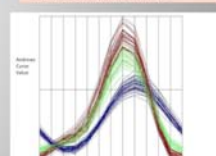
Galaxy Visualization - IN-SPIRE



RadViz - Hoffman et al.



Web Traffic Log - Heard



Andrews Curves - UMASS Lowell

P. Wong and R. D. Bergeron, "30 years of multidimensional multivariate visualization." in Scientific Visualization: Overviews, Methodologies, and Techniques, edited by Nielson, Hagen, and Mueller (1994). pp. 3-33.

EuroVis 2010, Bordeaux, France

C2: Visualization – more...

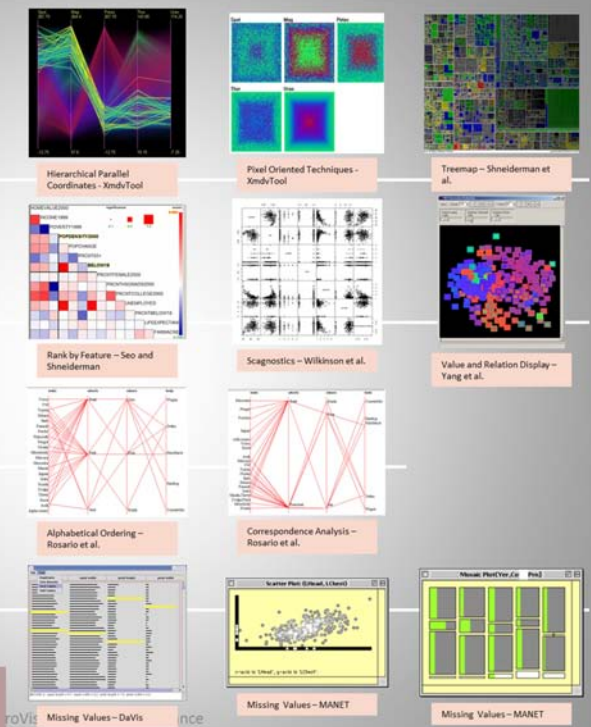
Also from Matt Ward's talk:

EuroVis 2010 Keynote

Other Challenges in Mappings

- Too many records
- Too many variables
- Non-numeric fields
- Missing values
- Streaming data

Many partial solutions; all have limitations.



C2: Visualization – more...

Also from Matt Ward's talk:

EuroVis 2010 Keynote

Other Challenges in Mappings

- Too
- Too
- Non

And Then There are Relations

And What About Data Properties?

... like data uncertainty

- Missing values
- Streaming data

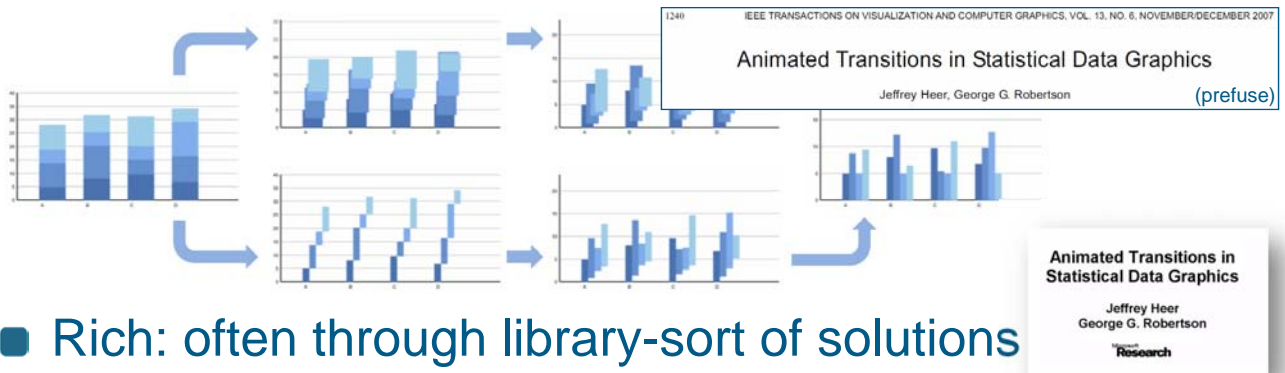
Many partial solutions; all have limitations.



C2: Visualization Richness

■ None / primitive ► advanced ► rich

- none or at least some primitive vis (bar charts, etc.) are the minimum – state-of-the-art, in particular outside visualization
- advanced: state-of-the-art wrt. visualization, in particular **selected** advanced visualization
- rich: an extensive spectrum of available vis. – there is a choice of various advanced vis. techniques



- Rich: often through library-sort of solutions

After Mapping Comes Interaction

Visualization without interaction
is like a sports car with no engine!

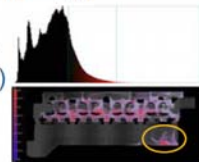
Nice to look at,
but not good for much! 😊

C3: Interaction

- Making VA a **loop**, an **interactive visual dialog**, like
 - show & brush
 - ...

The Iterative Process of IVA

- Loop / bundling of *two complementary parts*:
 - **visualization** – show to the user!
Something new, or something due to interaction.
 - **interaction** – tell the computer!
What is interesting? What to show next?
- Basic example (**show – brush – show – ...**),
cooling jacket context:
 1. show a histogram of temperatures
 2. brush high temperatures ($>90^\circ[\pm 2^\circ]$)
 3. show focus+context vis. in 3D
 4. locate relevant feature(s)
- **KISS-principle IVA**:
 - linking & brushing, focus+context visualization, ...



C3: Interaction

- Making VA a **loop**, an **interactive visual dialog**, like
 - show & brush
 - ...

HH, EuroVA 2012 Keynote

Interactive Analysis – levels of complexity

A lot can be done with KISS-principle IVA! [pareto rule] (level 1)

For more advanced exploration/analysis tasks, we extend it (in several steps):

- IVA, level 2: **logical combinations of brushes**, e.g., utilizing the *feature definition language* [Doleisch et al., 2003]
- IVA, l. 3: **attribute derivation; advanced brushing**, with interactive formula editor; e.g., similarity brushing
- IVA, l4: **application-specific feature extraction**, e.g., based on vortex extraction methods for flow analysis

The Iterative Process of IVA

complementary parts:
to the user!
nothing due to interaction.
computer!
what to show next?

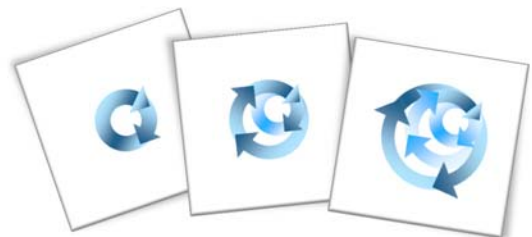
brush – show – ...),

temperatures
ures (>90°[±2°])
vis. in 3D
re(s)

ocus+context visualization, ...

C3: Interaction

- Making VA a **loop**, an **interactive visual dialog**, like
 - show & brush
 - ...
- A really important question is: **how fast is one such loop?**



- Jean-Daniel Fekete, 2012:

Response Times

- 0.1 sec - animation, visual continuity, sliders
- 1 sec - system response, conversation break
- 10 sec - cognitive response

Stuart K. Card, George G. Robertson, Jock D. Mackinlay. The information visualizer, an information workspace. *Proc. CHI '91*, 181-186, 1991.

- Beyond 20 sec, users wait and loose attention
 - Forget their goals and plans
 - **Progress bar needed!**

TABLE 3. HUMAN TIME CONSTANTS FOR TUNING COGNITIVE CO-PROCESSOR

TIME CONSTANT	VALUE	REFERENCES
Perceptual processing	.1 s	[5]
Immediate response	1 s	[21]
Unit task	10 s	[5,21]

THE INFORMATION VISUALIZER, AN INFORMATION WORKSPACE

Stuart K. Card, George G. Robertson, Jock D. Mackinlay

Xerox Palo Alto Research Center
Palo Alto, California 94304
(415) 494-4362, Card.PARC@Xerox.COM

CHI '91

Dagstuhl Seminar Talk

C3: Interaction

Jean-Daniel Fekete, 2012:

Dagstuhl Seminar Talk

Interaction / Cognition

- Main issue: **managing short-term memory** efficiently
 - 7 items ± 2
 - Needed to maintain planning, hypotheses
- Typing/language use several items
 - **Scripting / SQL interfere with exploration**
- Other issue: avoid distracting, understanding is cognitively demanding!

C3: Interaction

Jean-Daniel Fekete, 2012:

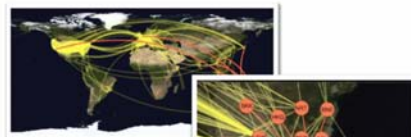
Dagstuhl Seminar Talk

Examples of Interaction

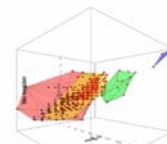
- **View-level**
 - Topology-Aware Navigation in Large Networks
- **Visual-form level**
 - ScatterDice, GraphDice
- **Data level**
 - Dynamic Queries, Brushing Histograms
- **Machine Learning Level**

Topology-Aware Navigation in Large Networks

T. Moscovich, F. Chevalier, N. Henry Riche, E. Pietriga, J.-D. Fekete, ACM CHI 09



Visual Form Interaction: ScatterDice



Brushing Histograms

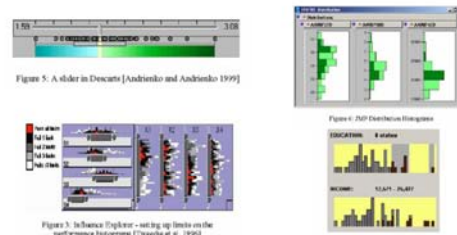


Figure 5: A slider in Decartes [Andrienko and Andrienko 1999]

Figure 6: 2D Brushing Histograms

Figure 7: Influence Explorer - setting up limits on the performance histogram [Tweede et al. 1996]

Figure 8: Brushing Histograms

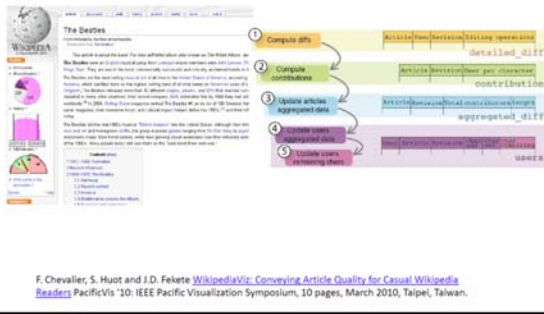
Qing Li and Chris North. 2003. Empirical comparison of dynamic query sliders and brushing histograms. In *Proceedings of the Ninth annual IEEE conference on Information Visualization (INFOVIS'03)*, Tamara Munzner and Stephen North (Eds.), IEEE Computer Society, Washington, DC, USA, 147-153.

C3: Interaction

Jean-Daniel Fekete, 2012:

Dagstuhl Seminar Talk

WikipediaViz: Pre-computed data (continuously)

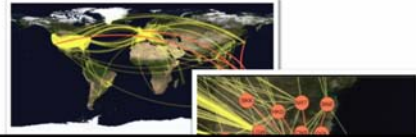


F. Chevalier, S. Huot and J.D. Fekete [WikipediaViz: Conveying Article Quality for Casual Wikipedia Readers](#) PacificVis '10: IEEE Pacific Visualization Symposium, 10 pages, March 2010, Taipei, Taiwan.

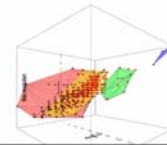
- Machine Learning Level

Topology-Aware Navigation in Large Networks

T. Moscovich, F. Chevalier, N. Henry Riche, E. Pietriga, J.-D. Fekete, ACM CHI 09



Visual Form Interaction: ScatterDice



Brushing Histograms

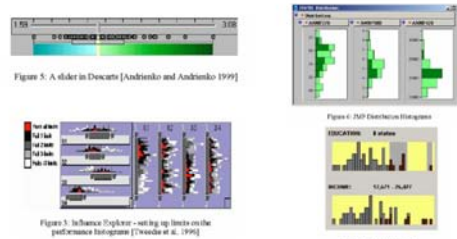


Figure 5: A slider in Dacarta [Anstienko and Anstienko 1999]

Figure 6: ZIP Election Histograms

Figure 7: Influence Explorer - setting up sliders on the performance histograms [Woodruff et al. 1996]

Qing Li and Chris North. 2003. Empirical comparison of dynamic query sliders and brushing histograms. In *Proceedings of the Ninth annual IEEE conference on Information visualization (INFOVIS'03)*, Tamara Munzner and Stephen North (Eds.), IEEE Computer Society, Washington, DC, USA, 147-153.

C3: Interaction Pace



Separate ► unit task ► immediate ► continuous

- separate: offline processing
- unit task [Card et al., '91]: $\approx 10s$ – before attention breaks!
- immediate: $\approx 1s$ – maintains an interplay, a conversation
- continuous: $\approx 0.1s$ – smooth in the eye (perception)

The perceptual processing time constant. The Cognitive Co-processor is based on a continuously-running scheduler loop and double-buffered graphics. In order to maintain the illusion of animation in the world, the screen must be repainted at least every .1 sec [5]. The Cognitive Co-processor therefore has a *Governor* mechanism that monitors the basic cycle time. **When the cycle time becomes too high, cooperating rendering processes reduce the quality of rendering (e.g., leaving off most of the text during motion) so that the cycle speed is increased.**

The unit task time constant. Finally, we seek to make it possible for the user to complete some elementary task act within 10 sec (say, 5–30 sec) [5,21], about the pacing of a point and click editor. Information agents may require considerable time to complete some complicated request, but the user, in this paradigm, always stays active. He or she can begin the next request as soon as sufficient information has developed from the last or even in parallel with it.

The immediate response time constant. A person can make an unprepared response to some stimulus within about a second [21]. If there is more than a second, then either the listening party makes a backchannel response to indicate that he is listening (e.g., "uh-huh") or the speaking party makes a response (e.g., "uh...") to indicate he is still thinking of the next speech. These serve to keep the parties of the interaction informed that they are still engaged in an interaction. In the Cognitive Co-processor, we attempt to have agents provide status feedback at intervals no longer than this constant. **Immediate response animations (e.g., swinging the branches of a 3D tree into view) are designed to take about a second.** If the time were much shorter, then the user would lose object constancy and would have to reorient himself. If they were much longer, then the user would get bored waiting for the response.

Really important differences on the user side!

* Sure, **C4: Computational Analysis...**

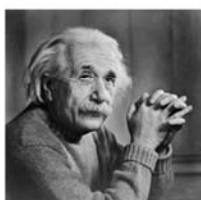
C4: Computational Analysis



- VA is about the **integration** of **interactive visual analysis means** and **computational analysis**

Humans and Computers

*"Computers are incredibly fast, accurate, and stupid;
humans are incredibly slow, inaccurate, and brilliant;
together they are powerful beyond imagination."*

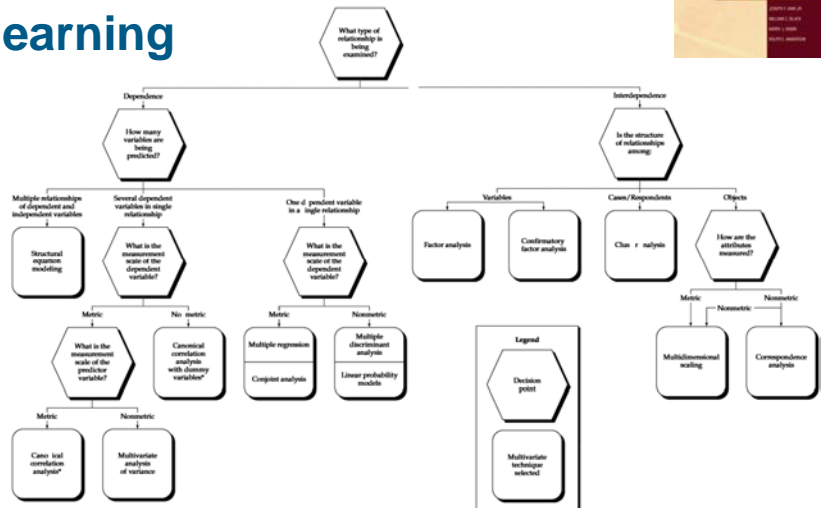
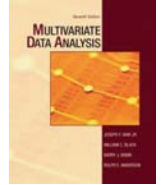


attributed to Albert Einstein

D. Keim, Dagstuhl Seminar Talk, 2012

C4: Computational Analysis

- VA is about the **integration of interactive visual analysis means and computational analysis**
- So then: computational analysis...
 - from **statistics**
 - from **data mining**
 - from **machine learning**
 - from ...



C4: Computational Analysis

- None** ► **selected** ► **rich**
 - vis.-and-only-vis. solutions do not offer comp. analysis

HH, Dagstuhl Seminar, 2012

Integrated Methods

- Clustering
 - k-means
 - hierarchical clustering me
 - etc.
- Projections (embeddings), e.g.,
 - PCA
 - MDS
 - etc. (SOM)
- Classification, regression
 - decision trees
 - SVM
 - etc. (gen. alg.)
- Etc.

Some Examples


- Integration of clustering
 - [Fua..., '99]
 - [v. Wijk..., '99]
 - [Sukharev..., 2009]
- Integration of projection/embedding
 - [Oeltze..., 2007]
 - [Andrienko..., 2009]
 - [Sun..., 2010]
- Integration of classification/learning
 - [v. d. Elzen..., '11]
 - [Fuchs..., 2009]


* Last, here, **C5: Comprehensiveness...**

C5: Comprehensiveness




- How **specialized** is the VA solution?
Does it cover **heterogenous** aspects?
Is the VA solution **open**?
- Chris Weaver, 2011:

What is Improve? 

It's a desktop application for **interactively building and browsing visualizations.** 

It's different because of how richly interactive its visualizations can be,

and how multiple views of data allow analysts to express complex queries using only simple interactions.

Rich interaction can afford more useful visual analysis tools. 

19

C5: Comprehensiveness

- How **specialized** is the VA solution?
Does it cover **heterogenous** aspects?
Is the VA solution **open**?

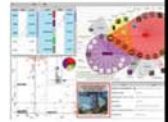
What Does Improve Try To Do?

- Support **live design of visual tools** as an integral and essential part of the data exploration and analysis process, by
 - accessing and querying data
 - visually encoding data
 - creating, coordinating, and laying out views
 - coupling view interactions with data transformations**
- Aim for "improvisational visualization" by combining
 - a full information visualization toolkit (similar to the InfoVis Toolkit and prefuse)
 - an architecture and language for coordinating queries across multiple views
 - an integrated user interface for building and browsing visual tools on-the-fly

Improvise?



for interactively visualizations.



because of how visualizations can be,

multiple views of data allow to express complex queries using only simple interactions.

tools.



C5: Comprehensiveness

- How **specialized** is the VA solution?

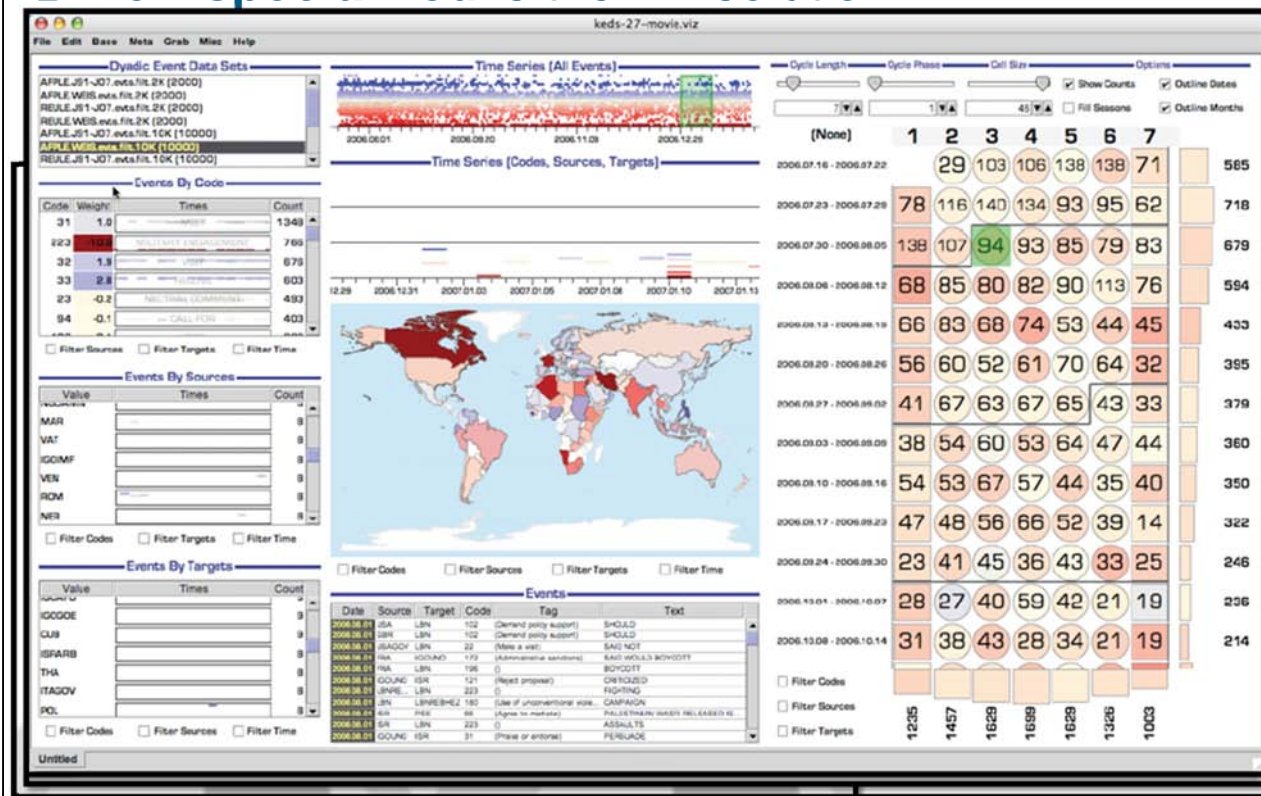
The screenshot displays a complex software interface for data visualization. It features several panels:

- Control Panel:** Lists various control types such as 'Plane View 2D', 'Range Double', and 'Range Doubled'.
- Variables Panel:** Shows a list of variables and their properties, including 'Range Double (2)' and 'Range Doubled (2)'.
- Coordination Graph:** A central diagram showing the relationships between different views and controls, with nodes like 'Range Double', 'Range Doubled', 'Axis', and 'Background'.
- Table View:** A table listing control types, control names, and their values. The table has columns for Control Type, Control Name, Type, and Value.

Control Type	Control Name	Type	Value
OpenParameter	Plane View	Font	Font(Dialog 12 plain)
OpenParameter	Plane View	Variable Binding	LexicalMutation
OpenParameter	Plane View	YRange	Range Double
OpenParameter	Plane View	XRange	Range Double
OpenParameter	Plane View	XPoint	Double
OpenParameter	Plane View	YPoint	Double
OpenParameter	Plane View	XTransform	LexicalMutation
OpenParameter	Plane View	YTransform	LexicalMutation
OpenParameter	Plane View	YAxis	String
OpenParameter	Plane View	XAxis	String

C5: Comprehensiveness

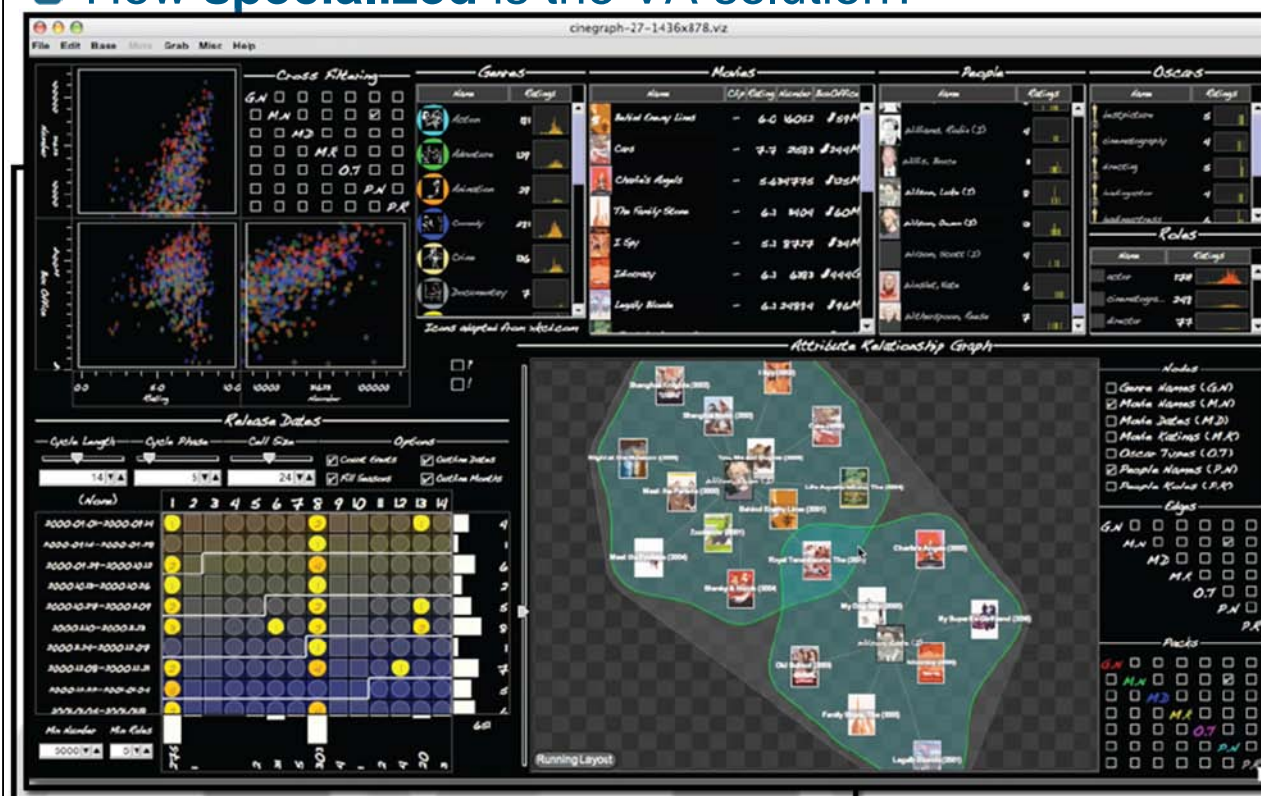
How specialized is the VA solution?



Oklahoma State, CS Colloquium, 2011

C5: Comprehensiveness

How specialized is the VA solution?



Oklahoma State, CS Colloquium, 2011

■ Targeted ► semi-flexible ► open

- targeted: one specific problem context, tailored / optimized solution
- semi-flexible: general wrt. a certain type of problem
- open: broad variety of problems, also broad variety of problem aspects (can treat heterogeneous problems)



Five Characteristics – summary

C1: **problem size**

small ► moderate ► large ► very large (huge)

C2: **visualization richness**

none / primitive ► advanced ► rich

C3: **interaction pace**

separate ► unit task ► immediate ► continuous

C4: **computational analysis**

none ► selected ► rich

C5: **comprehensiveness**

targeted ► semi-flexible ► open



Five Characteristics – summary

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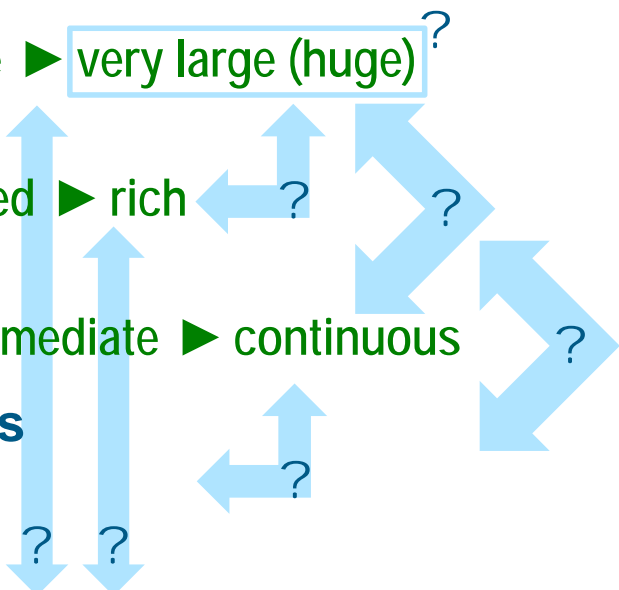
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none ► selected ► rich

C5: **comprehensiveness**

targeted ► semi-flexible ► open



Five Characteristics – summary

C1: **problem size**

small ► moderate ► large ► very large (huge)

► distinguish between large and huge!

C2: **visualization richness**

none / primitive ► advanced ► rich

► different views for different purposes!

C3: **interaction pace**

separate ► unit task ► immediate ► continuous

► respect the *human* time constants!

C4: **computational analysis**

none ► selected ► rich

► huge potential for VA!

C5: **comprehensiveness**

targeted ► semi-flexible ► open

► so many VA cases are, in fact, heterogeneous!

approaches to VA: ► from visualization, adding analysis
► from analysis, adding visualization

Acknowledgements

■ You!

■ Daniel Keim, Thomas Ertl, Christian Chabot,
Matt Ward, Jean-Daniel Fekete, Chris Weaver,

...

■ Çağatay Turkey

■ Questions?
Discussion?