About **Visualization in Bergen**.no and **Interactive Visual Analysis**

Helwig Hauser University of Bergen

In the Following

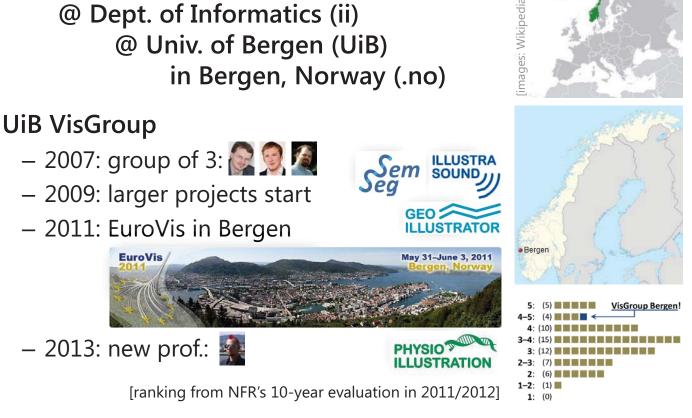
- 1. Briefly about visualization in Bergen, Norway
- 2. Interactive Visual Analysis (IVA)
- 3. High-dimensional Data IVA





ii.UiB.no/vis

HH: prof. in visualization (vis) @ Dept. of Informatics (ii) @ Univ. of Bergen (UiB) in Bergen, Norway (.no)



ii.UiB.no/vis Research

> Application-oriented basic research in visualization:

- 1. Researched visualization methodology (how to visualize)
 - > Interactive Visual Analysis, nD data (H. Hauser et al.)
 - > Visual Knowledge Discovery, 3D data (St. Bruckner et al.)
 - > **Illustrative Visualization** (I. Viola et al.)
- 2. Applications at which this research is oriented (for whom)
 - Medical Visualization (partner in MedViz Bergen, etc.)
- **GeoSciences / Oil & Gas** (e.g., financed by Statoil's Akademiaavtale)
- Biology / Bioinformatics (with CBU@ii et al.)
 - Sem > Fluid Dynamics (in collab. with FFI.no, for ex.)
 - > Engineering (visual analysis of simulation data)

paper distribution 2010-2012

Flow proble GeoSciences, oil & gas Biology

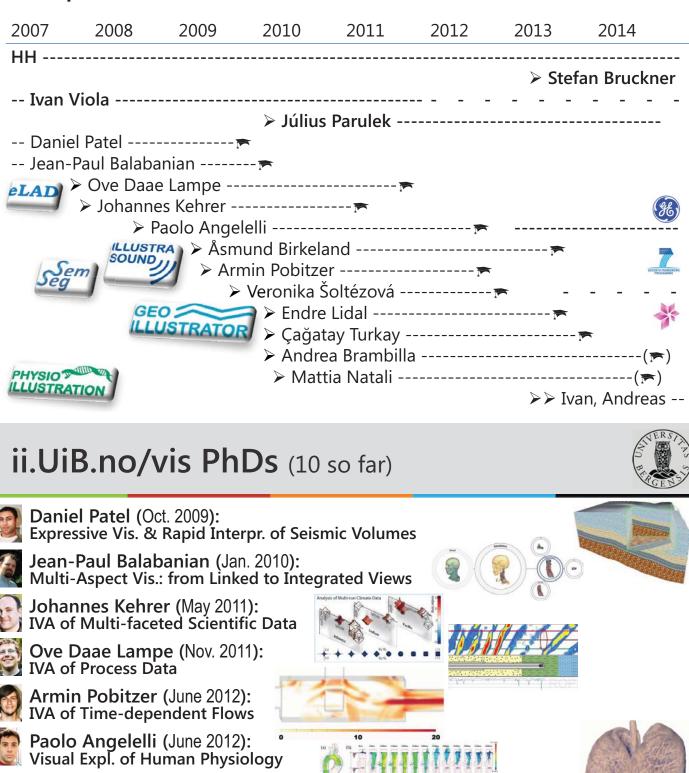
Climatology Marine problem

Scientific data (in general) Abstract data (in general) High-dimensional probler Simulation data

ii.UiB.no/vis Team



Two profs. (HH, StBr) and PostDocs, PhD studs., et al.





Veronika Šoltészová (Oct. 2012): Perception-Augmenting Illumination Åsmund Birkeland (May 2013):

Ultrasonic Vessel Vis.: From Extraction to Perception

Endre Lidal (May 2013): Sketch-based Storytelling for Cognitive Problem Solving



Çağatay Turkay (Nov. 2013): Interactive Visual Analysis of High-dimensional Data

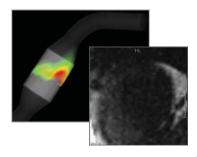
Interactive Visual Analysis (IVA)



- Given data too much and/or too complex to be shown at once:
- IVA is an interactive visualization approach to facilitate
 - the exploration and/or the analysis of data (not necessarily the presentation of data), including
 - hypothesis generation & evaluation, sense making,
 - knowledge crystallization, etc.
 - according to the user's interest/task, for ex., by interactive feature extraction,
 - navigating between overview and details, e.g., to enable interactive information drill-down [Shneiderman]
- through an iterative & interactive visual dialog

Interactive Visual Analysis \leftrightarrow Visual Analytics

- IVA ("interactive visual analysis") since 2000
- Tightly related to visual analytics, of course, e.g., integrating computational & interactive data analysis
- A particular methodology with specific components (CMV, linking & brushing, F+C vis., etc.)
- General enough to work in many application fields, but not primarily the VA fields (national security, etc.), in particular "scientific data" fields...



Integrating Interaction & Computation



2006

Maniyar & Nabney,

[Williams & Munzner, 2004]

- Goal: to combine the best of two worlds [Keim et al.]:
 - data exploration/analysis by the user, based on interactive visualization
 - and data analysis by the computer, based on statistics, machine learning, etc.
- State of the art / levels of integration:
 - mostly no integration, still
 - some vis. of results of computations
 - also: making comp. semi-interactive (here called "inner integration")
 - rare: tight integration
- Outer integration (here!): bundling interaction & computation in a loop

Target Data Model: "Scientific Data"

- Characterized by a combination of
 - independent variables, like space and/or time (cf. domain)
 - and dependent variables, like pressure, temp., etc. (cf. range)
- So we can think of this type of data as given as d(x) with x ↔ domain and d ↔ range examples:
 - CT data $d(\mathbf{x})$ with $\mathbf{x} \in \mathbb{R}^3$ and $d \in \mathbb{R}$
 - unstead 2D flow $\mathbf{v}(\mathbf{x},t)$ with $\mathbf{x} \in \mathbb{R}^2$, $t \in \mathbb{R}$, and $\mathbf{v} \in \mathbb{R}^2$

 $\mathbf{d}(\mathbf{x},t)$ with $\mathbf{x} \in \mathbb{R}^3$, $t \in \mathbb{R}$, and $\mathbf{d} \in \mathbb{R}^n$

- num. sim. result
- system sim. q(p) with $p \in \mathbb{R}^n$ and $q \in \mathbb{R}^m$
- Common property:
 - d is (at least to a certain degree) continuous wrt. x



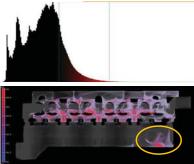
Interactive Visual Analysis of Scientific Data



- Interactive visual analysis (as exemplified in this tutorial) works really well with scientific data, e.g.,
 - results from numerical simulation (spatiotemporal)
 - imaging / measurements (in particular multivariate)
 - sampled models
- When used to study scientific data, IVA employs
 - methods from scientific visualization (vol. rend., ...)
 - methods from statistical graphics (scatterplots, ...), information visualization (parallel coords., etc.)
 - computational tools (statistics, machine learning, ...)
- Applications include
 - engineering, medicine, meteorology/climatology, biology, etc.

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°[±2°])
 - 3. show focus+context vis. in 3D
 - 4. locate relevant feature(s)
- KISS-principle IVA:
 - Iinking & brushing, focus+context visualization, ...

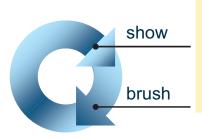


Show & Brush

Tightest IVA loop

show data (explicitly represented information)

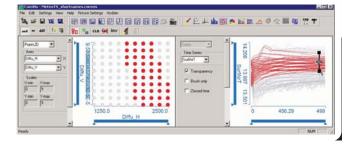
one brush (on one view, can work on >1 dims.)



A typical (start into an) IVA session of this kind:

(basic IVA)

- bring up multiple views
 at least one for x, t
 - at least one for d_i
- I see (something)!
- brush this "something"
- Iinked F+C visualization
- first insight!



Show & Brush

Tightest IVA loop

- show data (explicitly represented information)
- one brush (on one view, can work on >1 dims.)

Requires:

- <u>multiple views</u> (≥2)
- interactive brushing capabilities on views (brushes should be editable)
- focus+context visualization
- linking between views

Allows for different IVA patterns (wrt. domain & range)

(basic IVA)



A typical (start into an) IVA session of this kind:

- bring up multiple views
 - at least one for x, t
 at least one for d_i
- I see (something)!
- brush this "something"
- Iinked F+C visualization
- first insight!

... requires...

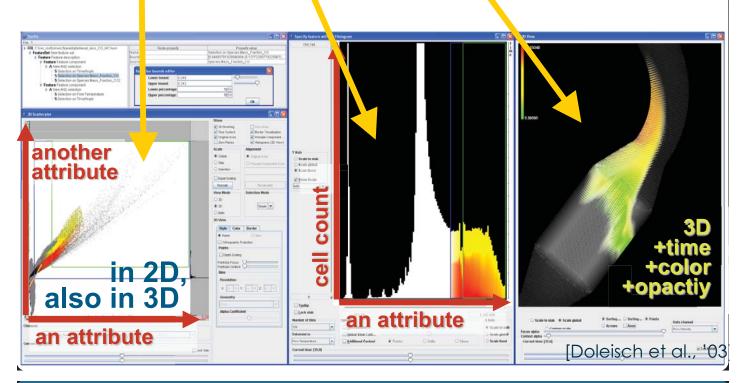
.. is realized via ...

.. leads to... <u>degree of interest</u>

IVA: Multiple Views

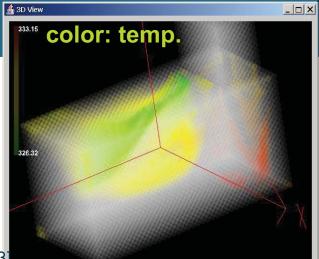


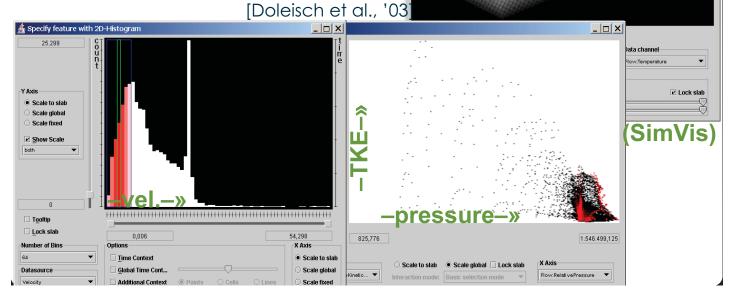
One dataset, but multiple views
Scatterplots, histogram, 3D(4D) view, etc.



Interactive Brushing

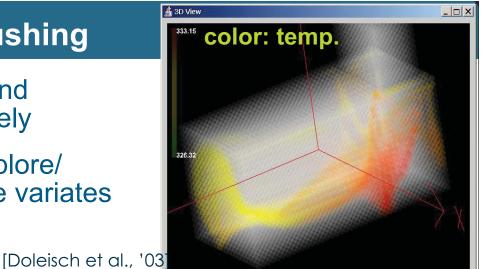
- Move/alter/extend brush interactively
- Interactively explore/ analyze multiple variates

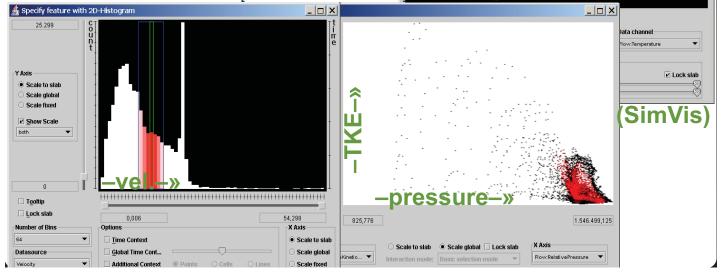




Interactive Brushing

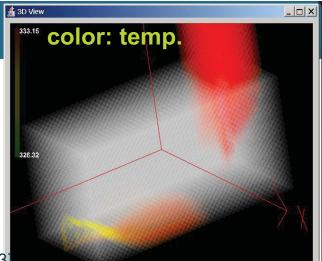
- Move/alter/extend brush interactively
- Interactively explore/ analyze multiple variates

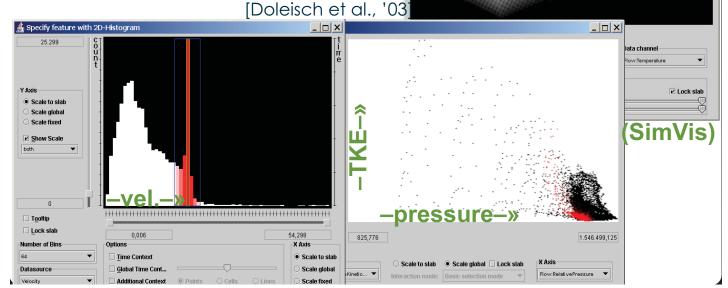




Interactive Brushing

- Move/alter/extend brush interactively
- Interactively explore/ analyze multiple variates



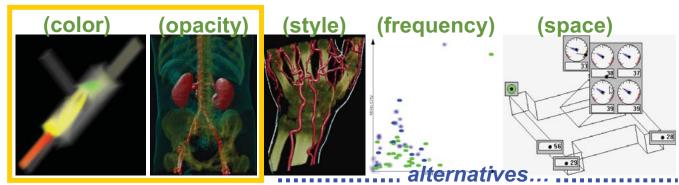


IVA: Focus+Context Visualization



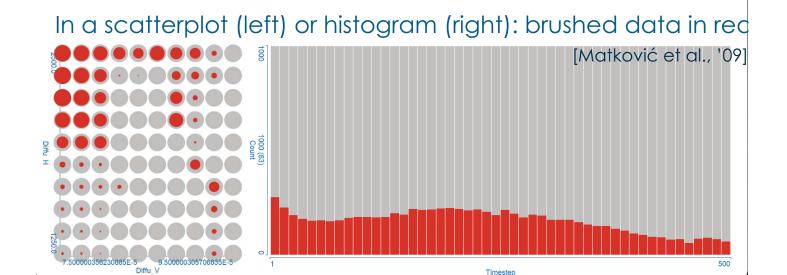
[Mackinlay et al. 1991]

- Traditionally space distortion
 - more space for data of interest
 - rest as context for orientation
- Generalized F+C visualization
 - emphasize data in focus (color,opacity, ...)
 - differentiated use of visualization resources

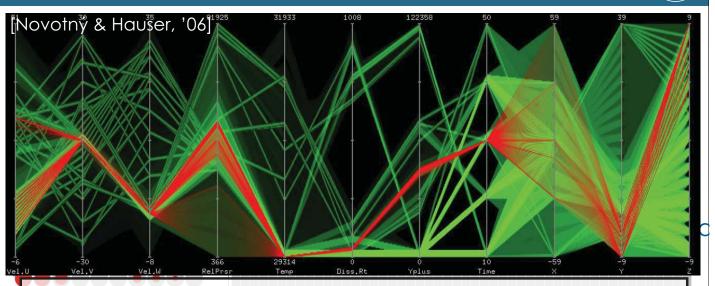


F+C Visualization in IVA Views

- Colored vs. gray-scale visualization
- Opaque vs. semi-transparent visualization



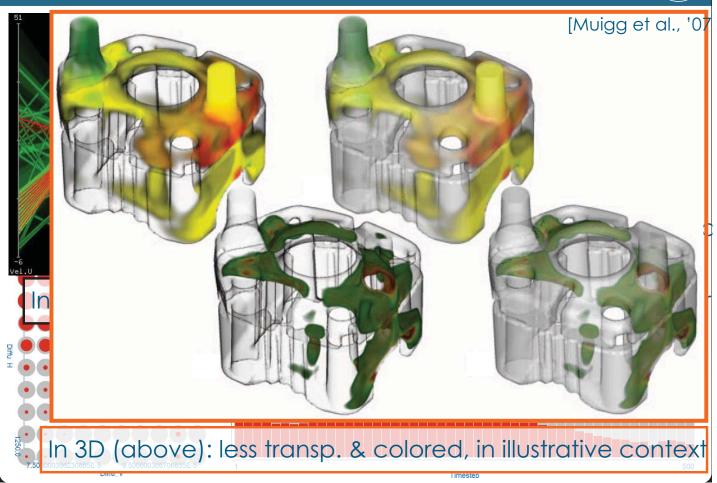
F+C Visualization in IVA Views

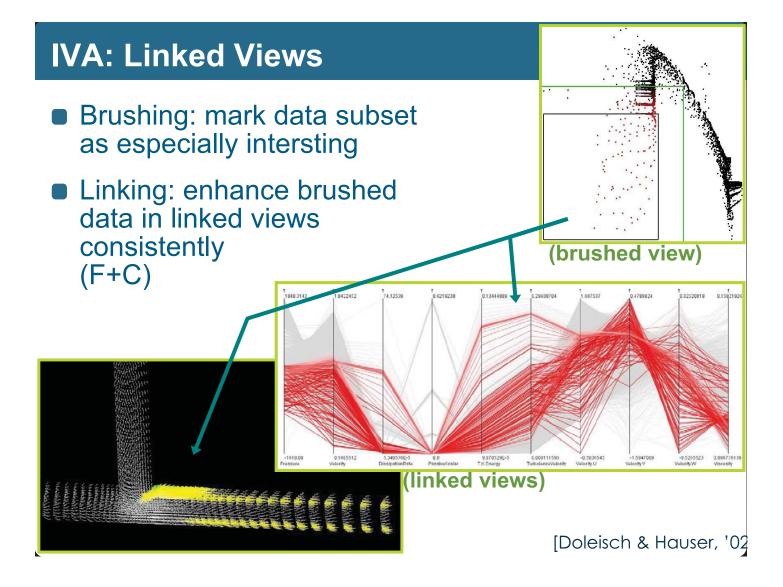


In parallel coordinates (above): brushed data in red & over

Timestep

F+C Visualization in IVA Views

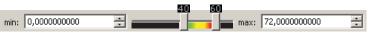




IVA: Degree of Interest (DOI)



- doi(.): data items tr_i (table rows) \rightarrow degree of interest $doi(tr_i) \in [0,1]$
 - $doi(tr_i) = 0 \Rightarrow tr_i$ not interesting ($tr_i \in \text{context}$)
 - $doi(tr_i) = 1 \Rightarrow tr_i \ 100\%$ interesting $(tr_i \in focus)$
- Specification
 - explicit, e.g., through direct selection
 - implicit, e.g., through a range slider



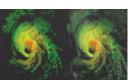
- Fractional DOI values: $0 \le doi(tr_i) \le 1$
 - several levels (0, low, med., …)
 - a continuous measure of interest
 - a probabilistic definition of interest

x	y	d 1	d2	doi
0	0	17 ,20	-0,22	0,00
1	0	12,10	0,10	0,00
2	0	7,70	0,45	0,00
3	0	2,10	0,90	0,00
0	1	24,10	0,02	0,00
1	1	21,90	0,36	0,00
2	1	15,50	0,87	0,74
3	1	11,10	1,20	1,00
0	2	27,20	0,12	0,00
1	2	24,10	0,66	0,18
2	2	17,30	1,35	1,00
3	2	12,10	2,20	0,60
0	3	35,50	0,67	0,00
1	3	30,90	1,30	0,00
2	3	24,50	2,10	0,10
3	3	20,80	2,90	0,00

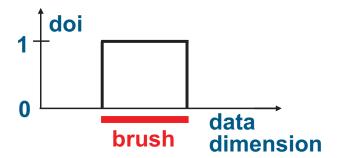
(cont'd on next slid

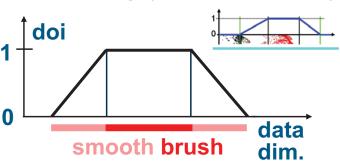
IVA: Smooth Brushing \rightarrow **Fractional DOI**

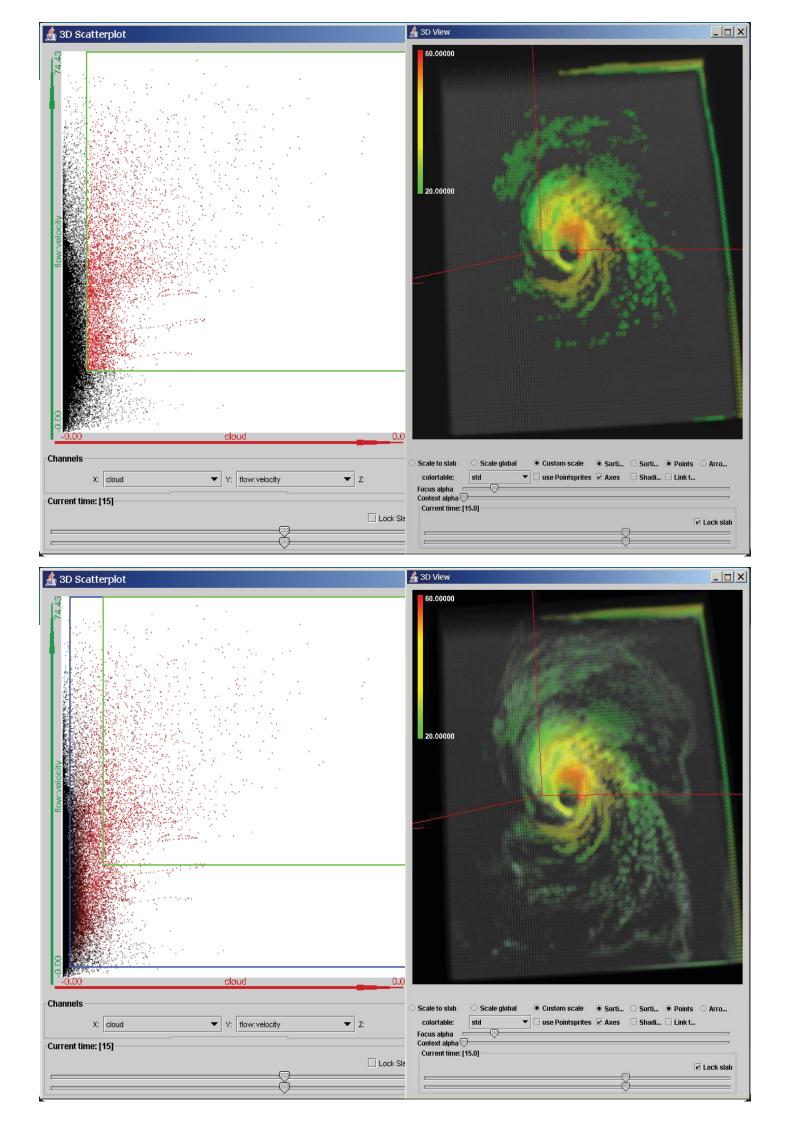
- Fractional DOI values esp. useful wrt. scientific data: (quasi-)continuous nature of data ↔ smooth borders
- Goes well with gradual focus+context vis. techniques (coloring, semitransparency)

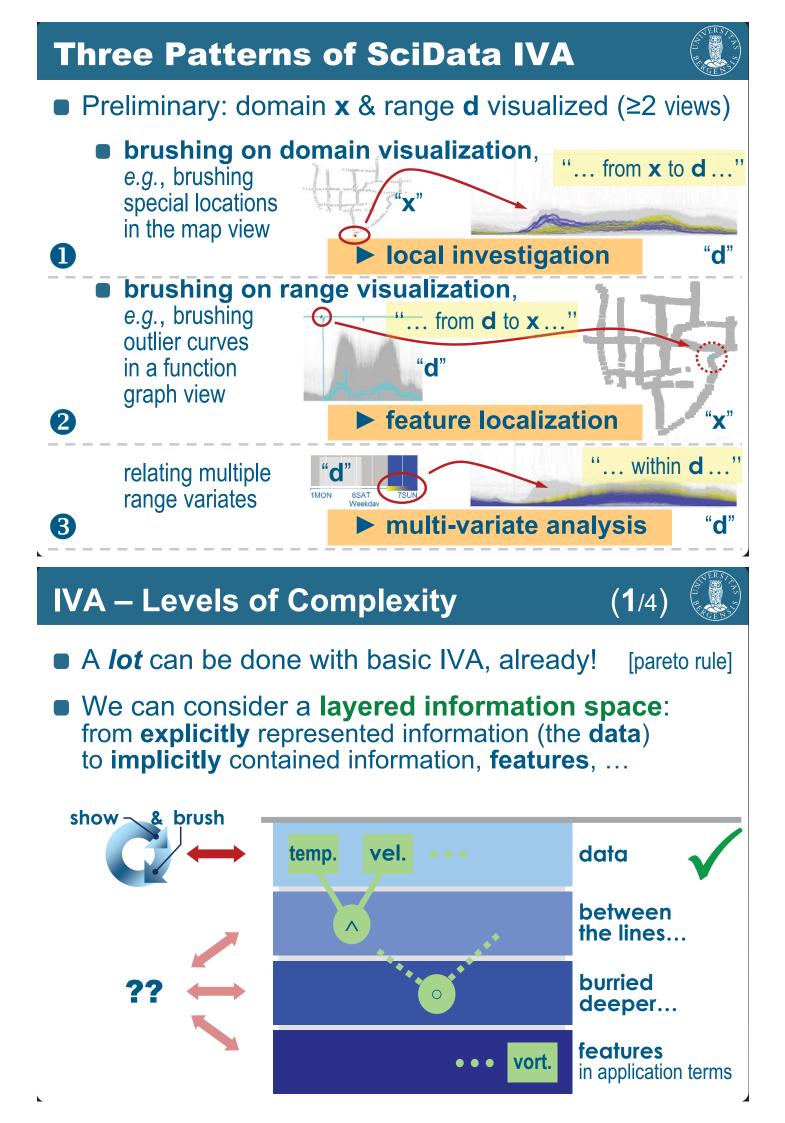


- Specification: smooth brushing
 [Doleisch & Hauser, 2002]
 - "inner" range: all 100% interesting (DOI values of 1)
 - between "inner" & "outer" range: fractional DOI values
 - outside "outer" range: not interesting (DOI values of 0)









IVA – Levels of Complexity

- A lot can be done with basic IVA, already! [pare rule
- For more advanced exploration/analysis tasks, we extend it (in seveal steps):
 - IVA, level 2: logical combinations of brushes, e.g., utilizing the feature definition language [Doleisch et al., 2003]

(2/4)

(2/4)

arity

scription

- IVA, I. 3: attribute derivation; advanced brushing, with interactive formula editor; *e.g.*, similarity brushing
- IVA, I4: application-specific feature extraction, e.g., based on vortex extraction methods for flow analysis
- Level 2: like advanced verbal feature description
 - ex.: "hot flow, also **slow**, near **boundary**" (cooling j.)
 - brushes comb. with logical operators (AND, OR, SUB)
 - in a tree, or iteratively ((((b₀ op₁ b₁) op₂ b₂) op₃ b₃) ...)

IVA – Levels of Complexity



ne with basic IVA, already! [pare rule nced exploration/analysis tasks, seveal steps):

IVA, level 2: logical combinations of brushes, e.g., utilizing the feature definition language [Deleich et al., 2003]

IVA, I. 3: attribute derivation, addition, addition,

IVA, I4: application-specific feat based on vortex extraction method

Level 2: like advanced ver views & sels.

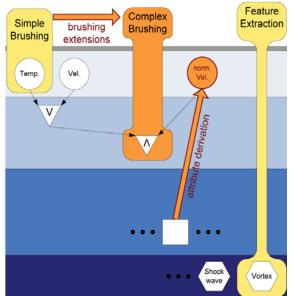
- ex.: "hot flow, also slow, near boundary" (cooling j.)
- brushes comb. with logical operators (AND, OR, SUB)
- in a tree, or iteratively ((($(b_0 op_1 b_1) op_2 b_2) op_3 b_3$) ...)

IVA – Levels of Complexity

- A lot can be done with basic IVA, already! [pare rule
- For more advanced exploration/analysis tasks, we extend it (in seveal steps):
 - IVA, level 2: logical combinations of brushes is a utilizing the feature definition language [Dileisch et a 2007]
 - IVA, I. 3: attribute derivation; advanced brushing, with interactive formula editor; e.g., similarity brushing
 - IVA, I4: application-specific feature extraction, e.g., based on vortex extraction methods for flow analysis
- Level 3: using general info extraction mechanisms, two (partially complementary) approaches:
 - 1. derive additional attribute(s), then show & brush
 - 2. use an advanced brush to select "hidden" relations

IVA – Levels of Complexity

- A lot can be done with basic I
- For more advanced explorat we extend it (in seveal steps):
 - IVA, level 2: logical combin utilizing the *feature definitior*
 - IVA, I. 3: attribute derivatio with interactive formula editc
 - IVA, I4: application-specific based on vortex extraction n



(3/4)

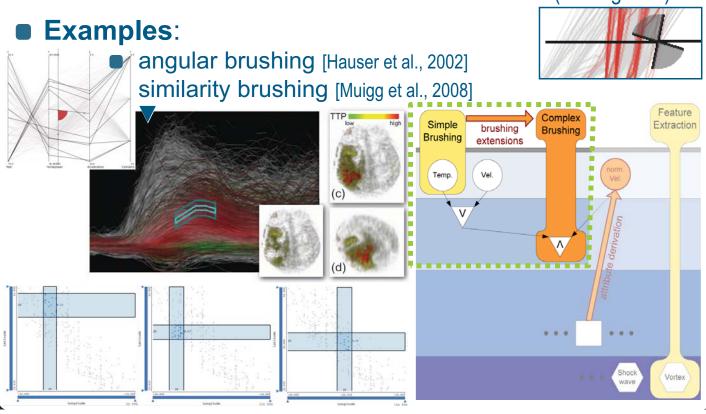
(3/4)

- Level 3: using general info extraction mechanisms, two (partially complementary) approaches:
 - 1. derive additional attribute(s), then show & brush
 - 2. use an advanced brush to select "hidden" relations

IVA (level 3): Advanced Brushing

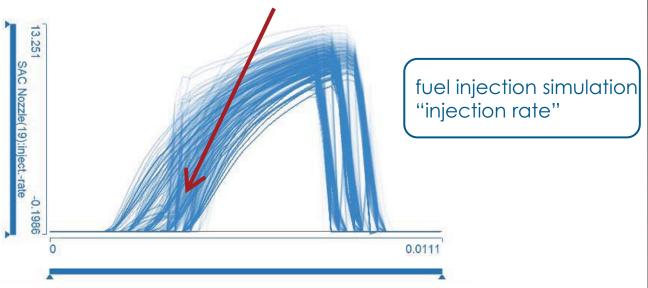


Std. brush: brush 1:1 what you see Adv. brush: executes additional function ("intelligent"?)



3rd level IVA, adv. brushing example

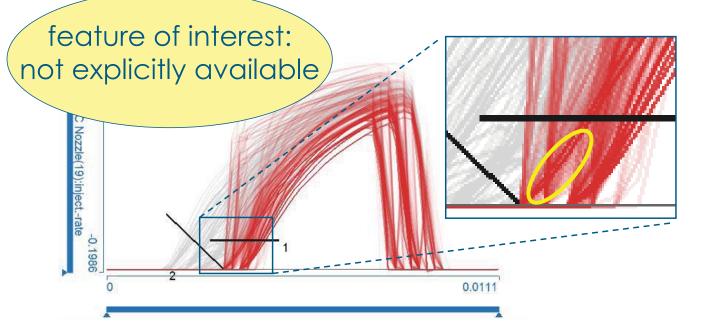
- Considering a visualization of a family of function graphs:
 - select the steeply rising graphs



3rd level IVA, adv. brushing example



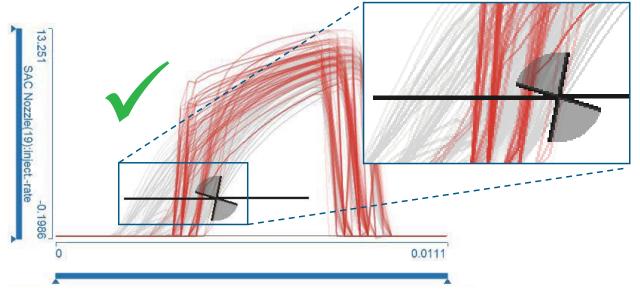
- A simple line brush is not enough
- Combining line brushes does not work, either



example prepared by Konyha, Zolt

3rd level IVA, adv. brushing example

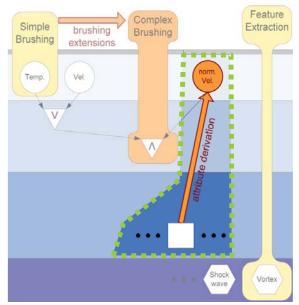
- The angular line brush (a specialized brush) selects the intended function graphs
 - that it intersects, and
 - the angle is in a given threshold



IVA (level 3): Attribute Derivation



- Principle (in the context of iterative IVA):
 - see some data feature Φ of interest in a visualization
 - identify a mechanism T to describe Φ
 - execute (interactively!) an attribute derivation step to represent Φ explicitly (as new, synthetic attribute[s] d_{φ}) Simple brushing Complex Brushing
 - **brush** d_{φ} to get Φ
- **Tools** T to describe Φ from:
 - numerical mathematics
 - statistics, data mining
 - etc.
 - scientific computing
- IVA w/ T ↔ visual computing



Attribute Derivation ↔ User Task / example

- The tools T, available in an IVA system, must reflect/match the analytical steps of the user:
- Example:
 first vis.:
 so?
 ah!
 → let's normalize y and then brush (a)

 Image: Solution of the selection:

What user wishes to reflect?



- Many generic wishes users interest in:
 - something relative (instead of some absolute values), example: show me the top-15%
 - change (instead of current values), ex.: show me regions with increasing temperature
 - some non-local property, ex.: show me regions with high average temperature
 - statistical properties, ex.: show me outliers
 - ratios/differences. ex.: show me population per area, difference from trend
 - etc.
- Common characteristic here:
 - questions/tools generic, not application-dependent!

How to reflect these user wishes?

- Many generic wishes users interest in:
 - something relative (instead of some absolute values). example: show me the top-1=> use, e.g., normalization
 - change (instead of current values) ex.: show me regions with inc a derivative estimation
 - some non-local property, ex.: show me regions with $hig \Rightarrow$ numerical integration
 - statistical properties, ex.: show me outliers
- \Rightarrow descriptive statistics
- ratios/differences. ex.: show me population per area, difference \Rightarrow calculus ⇒ data mining (fast enough?)
- etc.
- Common characteristic here:
 - questions/tools generic, not application-dependent!

Some useful tools for 3rd-level IVA



(1)

Sec. 1

- From analysis, calculus, num. math:
 - linear filtering (convolve the data with some linear filter on demand, e.g., to smooth, for derivative estimation, etc.)
 - calculus (use an interactive formula editor for computing simple relations between data attributes; +, -, ·, /, etc.)
 - gradient estimation, numerical integration (e.g., wrt. space and/or time)
 ⇒ example
 - fitting/resampling via interpolation/approximation
- From statistics, data mining:
 - descriptive statistics (compute the statistical moments, also robust, measures of outlyingness, detrending, etc.)
 - embedding (project into a lower-dim. space, ⇒ example
 e.g., with PCA for a subset of the attribs., etc.)
 ⇒ example
- Important: executed on demand, after prev. vis.

3rd-level IVA – Sample Iterations

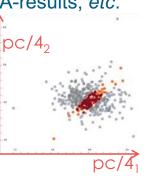
The Iterative Process of 3rd-level IVA:

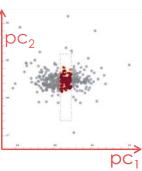
- Example 1:
 - you look at some *temp. distribution over some region*
 - you are interested in raising temperatures, but not temperature fluctuations
 - you use a **temporal derivate estimator**, for ex., central differences $t_{change} = (t_{future} - t_{past}) / len(future - past)$
 - you plot t_{change}, e.g., in a histogram and brush whatever change you are interested in
 - maybe you see some frequency amplification due to derivation, so you go back and
 - use an appropriate smoothing filter to remove high frequencies from the temp. data, leading to a derived new $\tau = t_{smooth}$ data attribute
 - selecting from a **histogram** of τ_{change} (computed like above) is then less sensitive to temperature fluctuations

3rd-level IVA – Sample Iterations

• The Iterative Process of 3rd-level IVA:

- Example exploiting PCA:
 - you bring up a scatterplot of d₁ vs. d₂: (from an ECG dataset [Frank, Asuncion; 2010])
 - obviously, d₁ and d₂ are correlated, fridada our interest: the data center wrt. the main trend <-</p>
 - we ask for a (local) **PCA** of d_1 and d_2 :
 - then we brush the data center
 - we get the wished selection
 - from here further steps are possible..., incl. study of other PCA-results, etc.



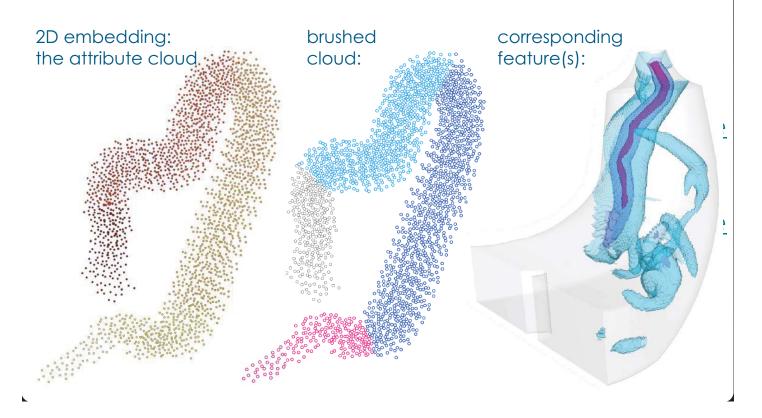


(2/2

[IEEE Vis, 2008]

Brushing of Attribute Clouds for the Visualization of Multivariate Data

Heike Jänicke, Michael Böttinger, and Gerik Scheuermann, Member, IEEE



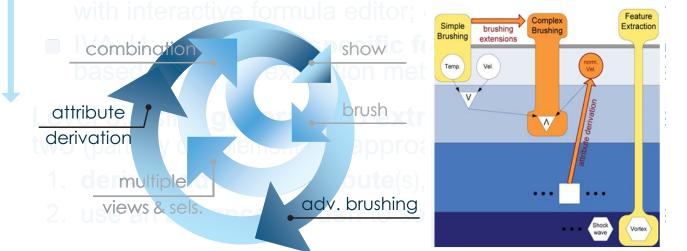
IVA – Levels of Complexity

- A lot can be done with basic IVA, already! [pare]
- For more advanced exploration/analysis tasks, we extend it (in seveal steps):
 - IVA, level 2: logical combinations of brushes is a utilizing the feature definition language [Dieisch et al. 200]
 - IVA, I. 3: attribute derivation; advanced brushing,

(4/4)

(4/4)

rule



IVA – Levels of Complexity

- A lot can be done with basic IVA, already! [pare rule
- For more advanced exploration/analysis tasks, we extend it (in seveal steps):
 - IVA, level 2: logical combinations of brughes utilizing the feature definition language [Direisch et and one)
 - IVA, I. 3: attribute derivation; advanced brushing, with interactive formula editor; e.g., similarity in the
 - IVA, I4: application-specific feature extraction based on vortex extraction methods for flow a any
- Level 4: application-specific procedures
 - tailored solutions (for a specific problem)
 - "deep" information drill-down
 - etc.

Interactive Visual Analysis – delivery

CO

Understanding data wrt. range d

- which distribution has data attribute d_i?
- how do d_i and d_j relate to each other? (multivariate analysis)
- which d_k discriminate data features?

Understanding data wrt. domain x

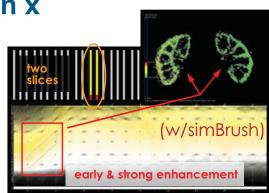
- where are relevant features? (feature localization)
- which values at specific x? (local analysis)
- how are they related to parameters?

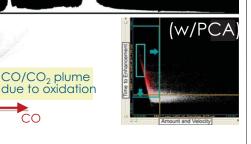
The Iterative Process of IVA...

...is a very useful methodology for data exploration & analysis

- ... is **very general** and can be (has already been) applied to **many different application fields** (in this talk the focus was on scientific data)
- ...meets scientific computing as a complementary methodology (with the important difference that in IVA the user with his/her perception/cognition is in the loop at different frequencies, also many fps)

...is **not yet fully implemented** (we've done something, e.g., in the context of **SimVis**, **ComVis**, *etc*.) – from here: different possible paths, incl. InteractiveVisualMatlab, IVR, *etc*.)





emperature ~570°C - ~1160°C



The **Dual Analysis Framework** for **High-dimensional Data IVA**

Çağatay Turkay, Helwig Hauser University of Bergen

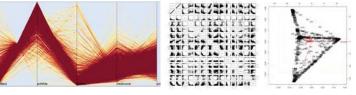


Target: High-dimensional Data



High- vs. multi-dimensional data

- multi-dimensional: >3D, 4D, 6D, 12D, ..., 24D(?)



- high-dimensional: ..., 40D, 80D, 240D, 1200D, ...

- std. tools for multi-dim. data vis. don't work
- lots of statistics, etc., do not work properly, esp. when #dims. > #items

Where?

Biology data (e.g., from genomics/proteomics), astronomy data (e.g., spectral imaging data), survey data (many questions), ...

Understanding *n*D for (really) large *n*



Curse of dimensionality is a problem, when *n* large

- nD distances become meaningless
- with that distances-based project methods
- statistics of wide tables don't work

Hypothesis:

- there is valuable information in the «space of dimensions»
- the «space of dimensions» is **structured**, **heterogeneous**
- it's worthwhile to understand this «space of dimensions» in order to do a better informed IVA of the data items

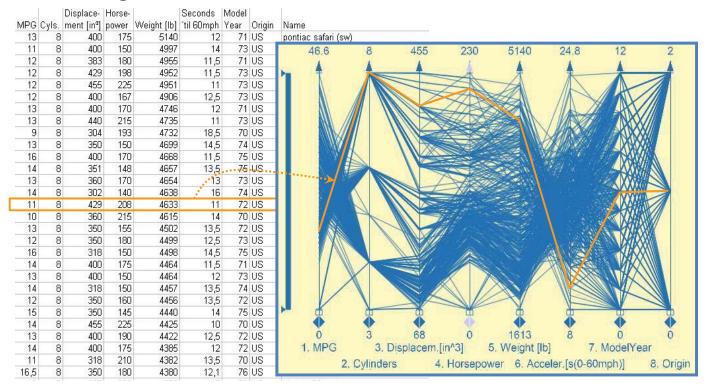
But how to understand this «space of dimensions»?

Can we visualize the dimensions of a dataset?

Traditional Vis = Items Visualization



Almost all of visualization is about visualizing the (multi-dimensional) data items



A new perspective: Dims. Visualization



Alternatively, and esp., when we have so many dims., we could visualize the **data dimensions** themselves!

MDO			Horse-	507. S. L. 10. 1	Seconds			
				Weight [lb]				
13	8	400					US	pontiac safari (sw)
11	8	400	150	4997	14		US	46.6 8 455 230 5140 24.8 12 2
12		383	180	4955			US	and the second sec
12	8	429	198		11,5		US	
12 12	8	455	and the second se		11		US	
12	8	400		4906			US	
13	8	400					US	
13 9	8	440	215				US	
	8	304	193				US	
13	8	350	150		14,5		US	
16 14	8	400	170		11,5		US	
	8	351	148		13,5		US	
13	8	360	170				US	
14	8	302	140	4638	16		US	
11	8	429	208			72	US	
10	8	360	215		14	70	US	
13	8	350	155	4502	• 13,5	72	US	
12	8	350	180	4499	12,5	73	US	
16	8	318	150	4498		75	US	
14	8	400	175	4464	11,5	71	US	
13	8	400	150	4464	12	73	US	
14	8	318	150	4457	13,5		US	
12	8	350	160	4456			US	
15	8	350	145	4440			US	
14	8	455	225	4425	10		US	
13	8	400	190	4422	12,5		US	0 3 68 0 1613 8 0 0
14	8	400			12		US	1. MPG 3. Displacem.[in^3] 5. Weight [lb] 7. ModelYear
11	8	318	succession and succes				US	
16,5	8	350	180				US	2. Cylinders 4. Horsepower 6. Acceler.[s(0-60mph)] 8. Origin



Transposing the data table should do it, right? :--)

Not really...

Naïve Approach

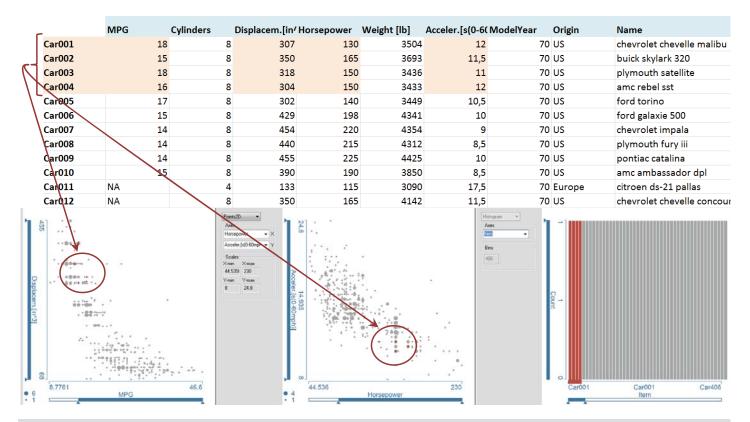


Transposing the data table should do it, right? :--) Not really...

	MPG	Cylinders	Disp	lacem.[in/ Hors	epower	Weight [lb]	Acceler.[s(0-60	ModelYear	Origin	Name
Car001		18	8	307	130	3504	12	70	US	chevrolet chevelle malibu
Car002		15	8	350	165	3693	11,5	70	US	buick skylark 320
Car003		18	8	318	150	3436	11	70	US	plymouth satellite
Car004		16	8	304	150	3433	12	70	US	amc rebel sst
Car005		17	8	302	140	3449	10,5	70	US	ford torino
Car006		15	8	429	198	4341	10	70	US	ford galaxie 500
Car007		14	8	454	220	4354	9	70	US	chevrolet impala
Car008		14	8		215	4312	8,5	70	US	plymouth fury iii
Car009		14	jusi	TOK IIIU	strat	<i>101</i> . 4425	10	70	US	pontiac catalina
Car010		15	200	6 cars,	7 ¹⁹⁰	3850	c dina ⁵	ncio ⁷⁰	US	amc ambassador dpl
Car011	NA		400	o cars,	/ 11	umen	c ange	INSION	Durope	citroen ds-21 pallas
Car012	NA		(no	t a high	-diff	oncian	al data	70 (tot	US	chevrolet chevelle concour
Car013	NA		hio		-01153		aruata	5et:) 70	US	ford torino (sw)
Car014	NA		8	383	175	4166	10,5	70	US	plymouth satellite (sw)
Car015	NA		8	360	175	3850	11	70	US	amc rebel sst (sw)
Car016		15	8	383	170	3563	10	70	US	dodge challenger se
Car017		14	8	340	160	3609	8	70	US	plymouth 'cuda 340
Car018	NA		8	302	140	3353	8	70	US	ford mustang boss 302
Car019		15	8	400	150	3761	9,5	70	US	chevrolet monte carlo
Car020		14	8	455	225	3086	10	70	US	buick estate wagon (sw)
Car021		24	4	113	95	2372	15	70	Japan	toyota corona mark ii



Visualizing rows (cars) from this table is standard InfoVis:



Naïve Approach



Data transposition makes the dimensions to rows:

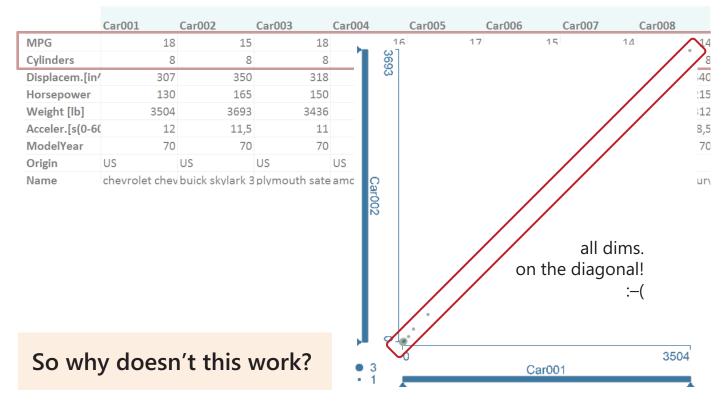
	Car001	Car002	Car003	Car004	Car005	Car006	Car007	Car008
MPG	18	15	18	16	17	15	14	14
Cylinders	8	8	8	8	8	8	8	8
Displacem.[in/	307	350	318	304	302	429	454	440
Horsepower	130	165	150	150	140	198	220	215
Weight [lb]	3504	3693	3436	3433	3449	4341	4354	4312
Acceler.[s(0-60	12	11,5	11	12	10,5	10	9	8,5
ModelYear	70	70	70	70	70	70	70	70
Origin	US	US	US	US	US	US	US	US
Name	chevrolet chev	buick skylark 3	plymouth sate	amc rebel sst	ford torino	ford galaxie 50	chevrolet impa	plymouth fury

So what about visualizing this table?

ford galaxie 50 chevrolet impeplymouth fury



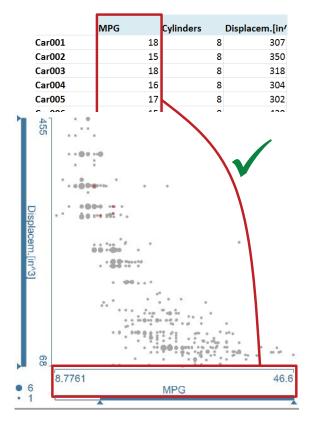
Data transposition makes the dimensions to rows:

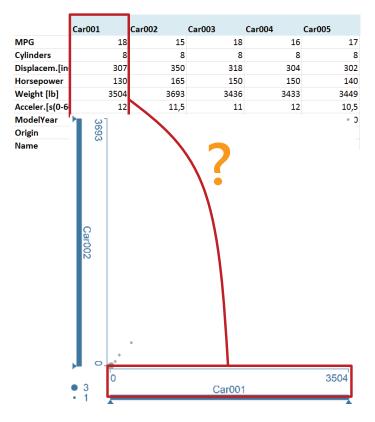


Naïve Approach



No comparable values in the columns after transposition!







What do we do, when we visualize data items?

- per data item \mathbf{p}_i , we map properties/attributes of \mathbf{p}_i to vis.-cues, f.i., x and $y \rightarrow$
- we see, how the \mathbf{p}_i relate to each other wrt. to their props.!

Translating this to visualizing dimensions:

- per data dimension \mathbf{d}_{j} , we map properties/attributes of \mathbf{d}_{j} to vis.-cues, f.i., x and $y \rightarrow$
- we see, how the \mathbf{d}_{i} relate to each other wrt. to their props.!

Expressive properties of dimensions d_j (selection):

- descriptive statistics, like mean and std.-der.
- measures of outlyingness

Dual Analysis Framework

So: constructing the properties table for dims. d;

normalization first, then feature extraction

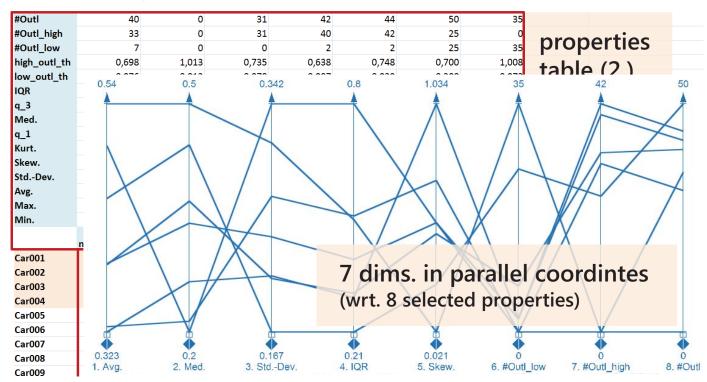
#Outl	40	0	31	42	44	50	35			
#Outl_high	33	0	31	40	42	25	0			
#Outl_low	7	0	0	2	2	25	35	prop	erties e (2.)	
high_outl_th	0,698	1,013	0,735	0,638	0,748	0,700	1,008	وأوامه	(2)	
low_outl_th	0,076	-0,013	-0,078	0,007	0,029	0,200	0,072	table	e (Z.)	
IQR	0,309	0,800	0,510	0,298	0,396	0,210	0,500			
q_3	0,532	1,000	0,605	0,457	0,570	0,548	0,750			
Med.	0,372	0,200	0,214	0,266	0,343	0,446	0,500			
q_1	0,223	0,200	0,095	0,159	0,174	0,338	0,250			
Kurt.	-0,511	-1,411	-0,811	0,541	-0,821	0,373	-1,200			
Skew.	0,457	0,506	0,694	1,034	0,506	0,230	0,021			
StdDev.	0,208	0,342	0,271	0,210	0,240	0,167	0,312			
Avg.	0,39	0,50	0,33	0,32	0,39	0,45	0,54			
Max.	1,00	1,00	1,00	1,00	1,00	1,00	1,00			
Min.	0,00	0,00	0,00	0,00	0,00	0,00	0,00			
		(Culindana) m(Diamla agus [im/l]		/_:_h+ [h])//		la dalVaan) (Dulata	Name	
Car001			Displacem.[in(H					•	chevrolet chevelle	an a lite a
	0,24	1,00	0,62	0,46	0,54	0,24	-,			malibu
Car002	0,16	1,00	0,73	0,65	0,59	0,21	0,00	norm	nalized	
Car003	0,24	1,00	0,65	0,57	0,52	0,18	0,00		prymouthoutomto	
Car004	0,19	1,00	0,61	0,57	0,52	0,24	0,00	data	a (11re)el sst f(11e)no	
Car005	0,21	1,00	0,60	0,51	0,52	0,15	0,00			
Car006	0,16	1,00	0,93	0,83	0,77	0,12	0,00		ford galaxie 500	
Car007	0,13	1,00	1,00	0,95	0,78	0,06	0,00 l		chevrolet impala	
Car008	0,13	1,00	0,96	0,92	0,77	0,03	0,00 l		plymouth fury iii	
Car009	0.13	1.00	1.00	0.97	0.80	0.12	0.00 l	JS	pontiac catalina	





Now we can visualize the dims. d_{I}

- mapping coherent and expressive properties to vis.-cues!



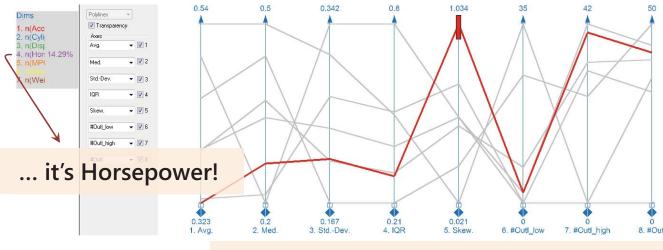
Dual Analysis Framework



Now the dual analysis can start!

- look up informative properties in the dims.-vis.
- do related items-visualization, accordingly

Example 1: exploring the most skewed dimension



1., selecting max(skew) in dims.-vis. (PC)

Dual Analysis Framework



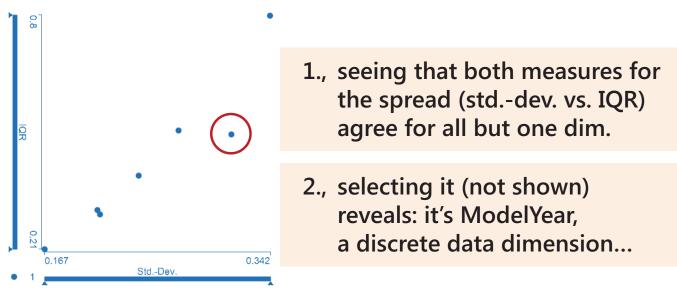
1., selecting max(skew) in dims.-vis. (PC)

Dual Analysis Framework

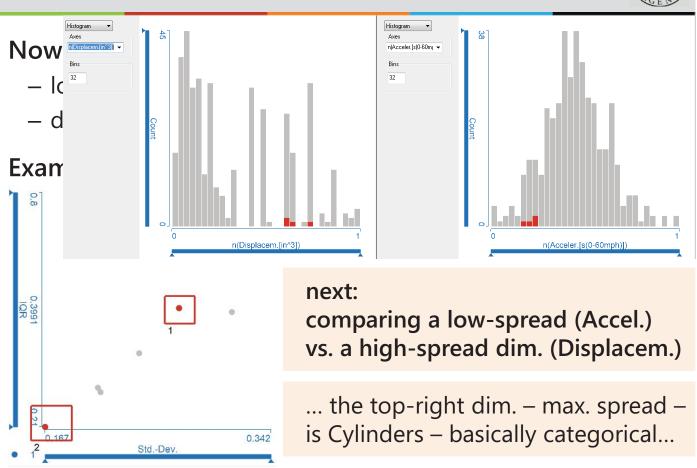
Now the dual analysis can start!

- look up informative properties in the dims.-vis.
- do related items-visualization, accordingly

Example 2: comparing Gaussian & ranking-based stats.



Dual Analysis Framework



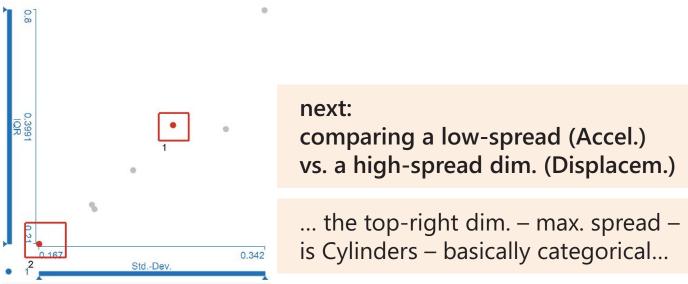
Dual Analysis Framework

TU BRIST

Now the dual analysis can start!

- look up informative properties in the dims.-vis.
- do related items-visualization, accordingly

Example 2: comparing Gaussian & ranking-based stats.



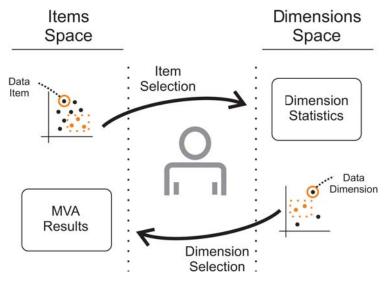


Quickly, we explore the dims. according to their props.

- hundreds or thousands of dims. \rightarrow no problem! :–)
- dozens of properties \rightarrow std. InfoVis is fine!

The Dual Analysis emerges through iteration:

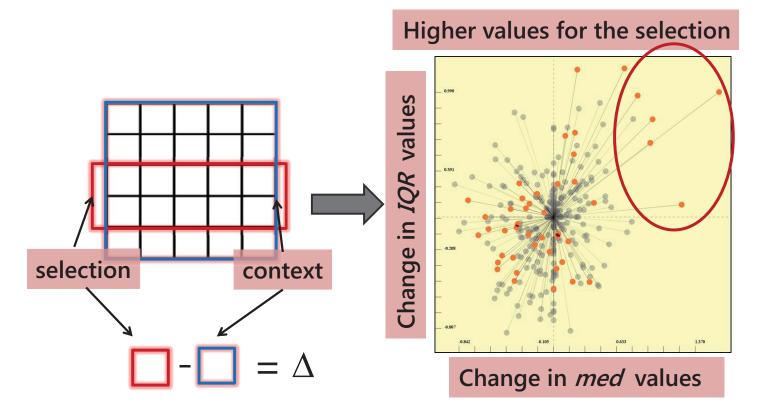
 one key tool: the difference view



Dual Analysis Framework



Working with the difference view





Difference View in action:

Dataset & ×	['medIncome', 'pct2Par']	₽×	[median_1', 'IQR_1']	e ×
1 ▲ ⊡ Dataset ⊕ ⊕ ExtraDimension ⊕ Grignal ⊕ Stats_Original ⊕ ⊕ Stats_Transformed □ □ DimensionType ⊕ □ - stdev_1 □ □ - stdev_1 □ □ - stdev_1 □ □ - untoisp_1 − □ - stdev_1 □ □ - undewlakeCount_1 − − roportoonOfOutliers_1 − − skew(AtD_1) − − start(MAD_1) ♥ Animated Brush Setup Mode ♥ Setup Mode: <td></td> <td></td> <td>_ 1.667 </td> <td></td>			_ 1.667 	
Use histogram bins for animation	8866 47119 85372	2 123625	-1.667 -0.556	0.556 1.667
Loop animations	dataTable			<u> </u> &×
Smooth Mouse Interaction	Dimensions			<u> </u>
Animation Length: 10 sec.	1 pop_unitSd			
IU sec.	2 perHoush_unitSd			
Non-linear Animations:	3 pctBlack unitScl			
Animation Frequency: 10 Hz 💌				
1	4 pctWhite_unitSd			
	P autolog college			•

Dual Analysis Framework

More in the thesis / papers of Çağatay Turkay et al.

C. Turkay, P. Filzmoser, and H. Hauser. Brushing Dimensions-A Dual Visual Analysis Model for High-Dimensional Data. *IEEE Transactions on Visualization and Computer Graphics*, 17(12):2591–2599, 2011.

C. Turkay, A. Lundervold, A.J. Lundervold, and H. Hauser. Representative Factor Generation for the Interactive Visual Analysis of High-Dimensional Data. *IEEE Transactions on Visualization and Computer Graphics*, 18(12):2621–2630, 2012.

C. Turkay, P. Angelelli, P. Filzmoser, and H. Hauser. Outlier Dimensions – Outlier Aware Analysis of High-dimensional Data. In submission to: *IEEE Transactions on Visualization and Computer Graphics*, 2013.

C. Turkay and H. Hauser. Optimizing Processes in Visual Analytics to Meet the Three Human Time Constants. In submission to: *Computers and Graphics*, 2013.

C. Turkay, A. Lundervold, A.J. Lundervold, and H. Hauser. (Hypothesis Generation by Interactive Visual Exploration of Heterogeneous Medical Data. Human-Computer Interaction and Knowledge Discovery in Complex, Unstructured, Big Data. Lecture Notes in Computer Science, Volume 7947:1–12, 2013.

C. Turkay, A. Lex, M. Streit, H.P. Pfister, and H. Hauser. Characterizing Cancer Subtypes using the Dual Analysis Approach in Caleydo. In submission to: *IEEE Computer Graphics and Applications*, 2013.

C. Turkay, J. Parulek, N. Reuter, and H. Hauser. Interactive Visual Analysis of Temporal Cluster Structures. *Computer Graphics Forum*, 30(3):711–720, 2011.

Integrating Computational Tools in Interactive and Visual Methods for Enhancing High-dimensional Data and Cluster Analysis

CAGATAY TURKAY



Dissertation for the degree of Philosophiae Doctor (PhD)

Supervised by Helwig Hauser Co-supervised by Peter Filmos Institute for Informatics University of Bergen Norway Norway

