

Visual Data Analysis:

real users, real data,
right methods

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data
becomes ubiquitous

visualization & data analysis

real users/real data:

technique angle: characterize how proposed visualization and data analysis techniques perform under real circumstances

problem angle: understand real needs, problems and practices & provide visual and computational solutions

right methods:

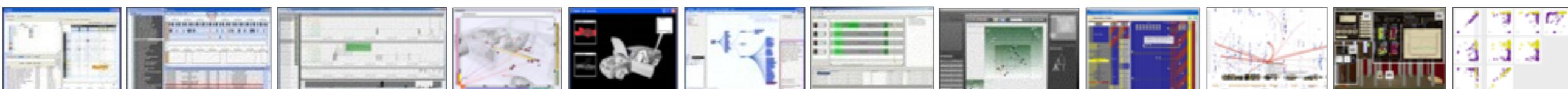
innovate and refine research methods for visual data analysis

real users/real data:

Studies on high-dimensional data analysis techniques



Applied visualization projects (9 BMW, 3 others)



real users/real data:

Studies on high-dimensional data analysis techniques

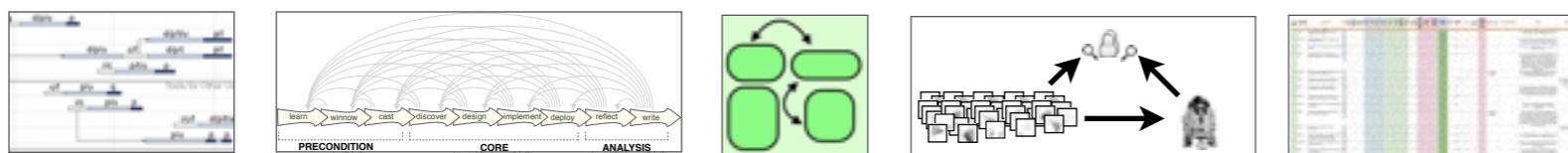


Applied visualization projects (9 BMW, 3 others)



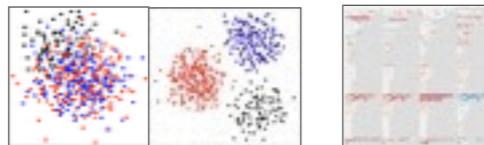
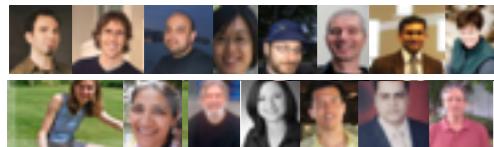
right methods:

Novel and refined research methods/methodologies



real users/real data:

Studies on high-dimensional data analysis techniques

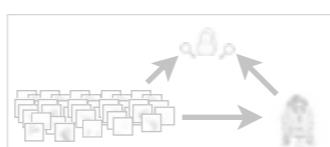
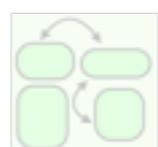
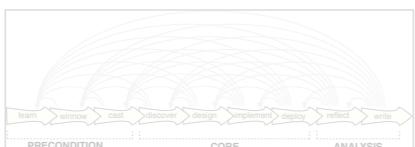


Applied visualization projects (9 BMW, 3 others)



right methods:

Novel and refined research methods/methodologies



**studies on high-
dimensional data analysis
techniques**

high-dimensional data



	length	weight	speed	hp	...
Car 1					
Car 2					
Car 3					
...					

highdim

dimension reduction (DR)



	length	weight	speed	hp	...
Car 1					
Car 2					
Car 3					
...					

highdim



e.g., using
PCA

	sporty	handling
Car 1		
Car 2		
Car 3		
...		

lowdim

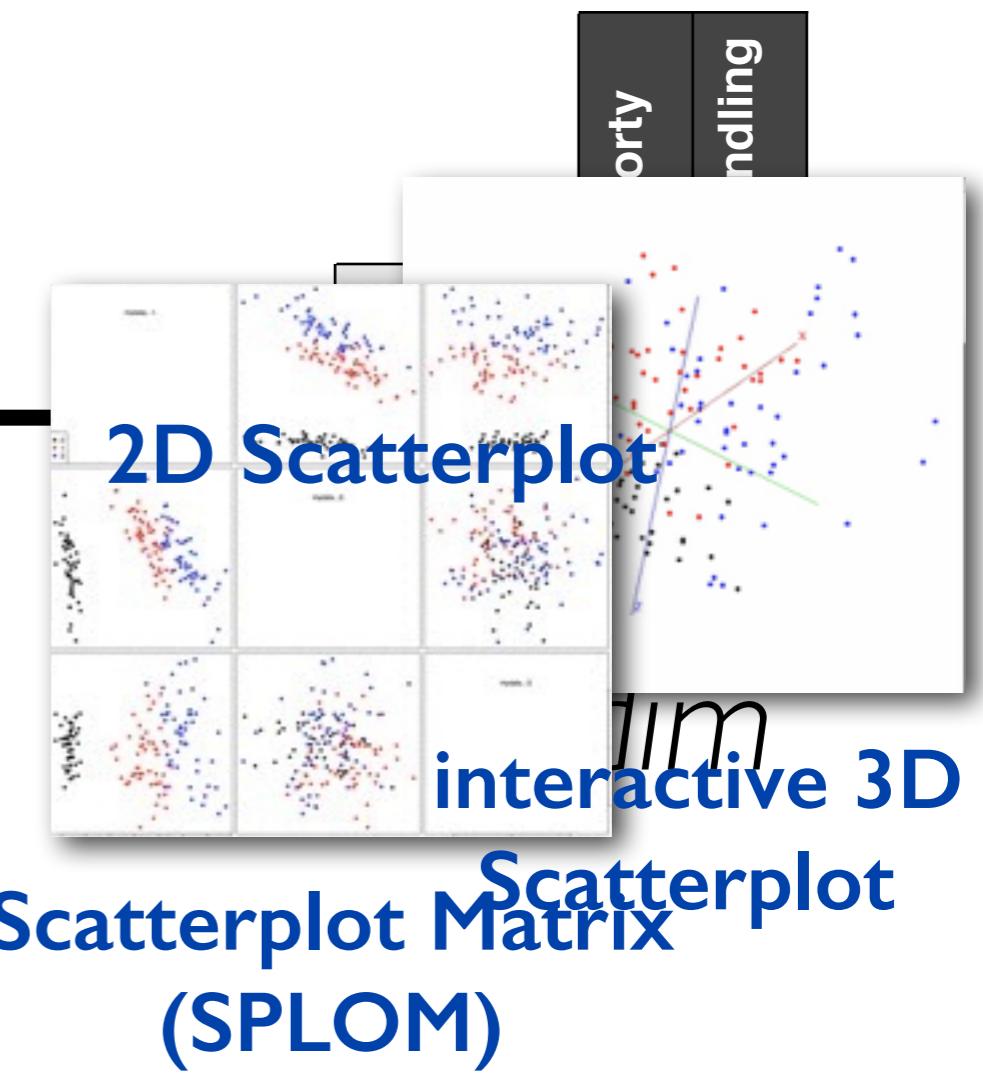
visualizing DR data



	length	weight	speed	hp	...
Car 1					
Car 2					
Car 3					
...					

highdim

DR

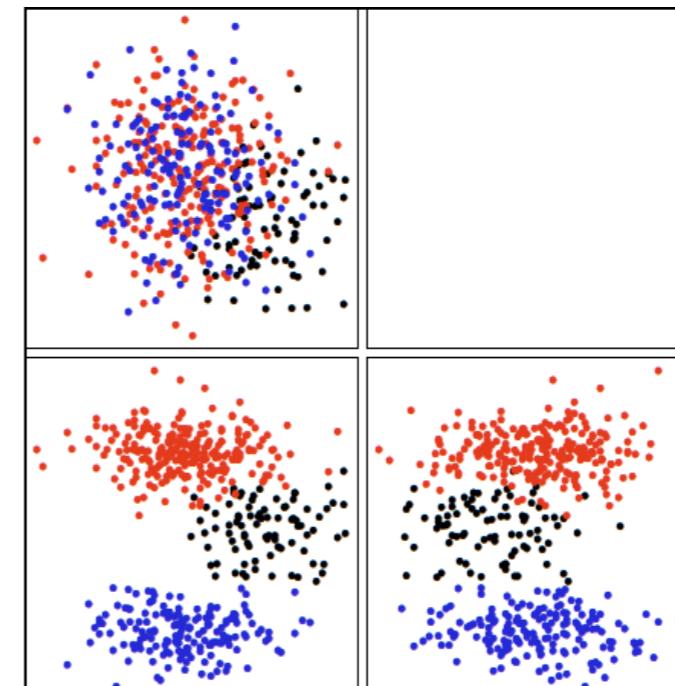
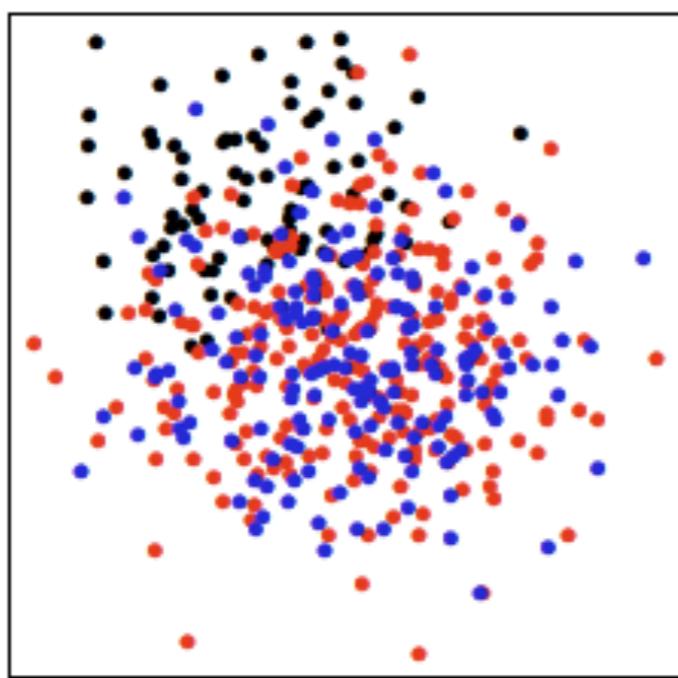


2D vs. 3D vs. SPLOM

Which visual encoding technique
to use for visualizing DR data?

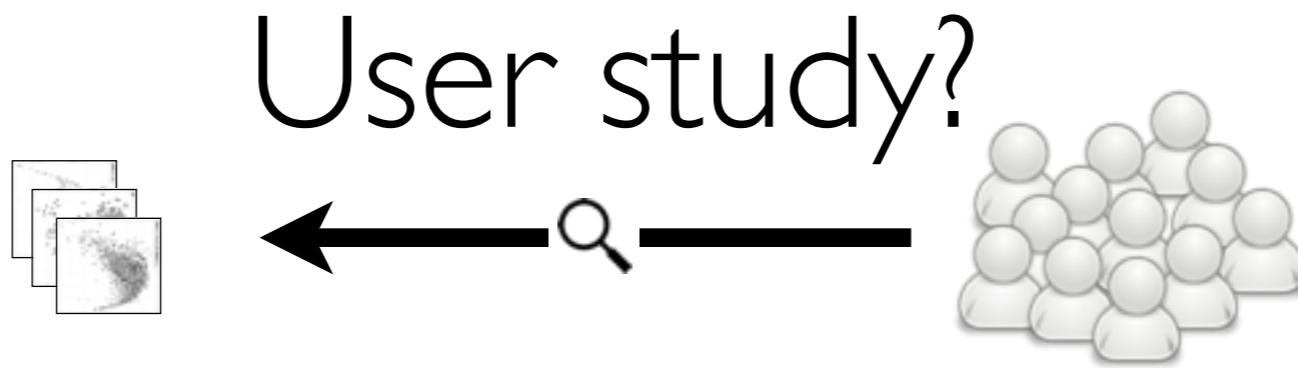
2D vs. 3D vs. SPLOM

The one that gives nicer cluster separability!



2D vs. 3D vs. SPLOM

How to study?



Pilot study - No!

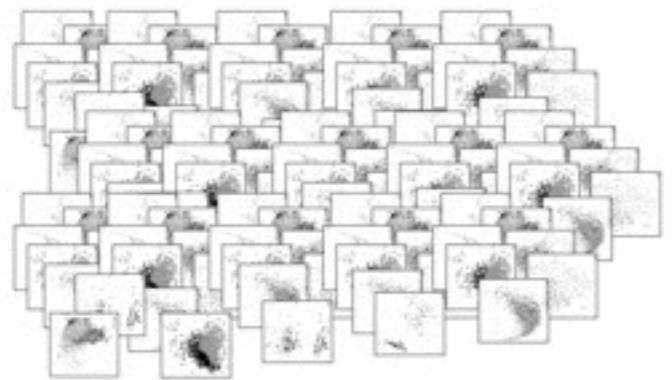
Data characteristics outweigh subtle user differences!

2D vs. 3D vs. SPLOM

How to study?

816 Plots

(75 x datasets,
4 x DR,
3 x visual encoding)

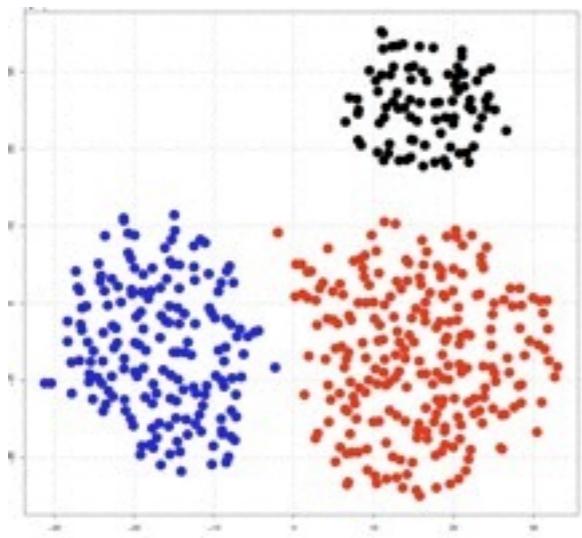


Data study!

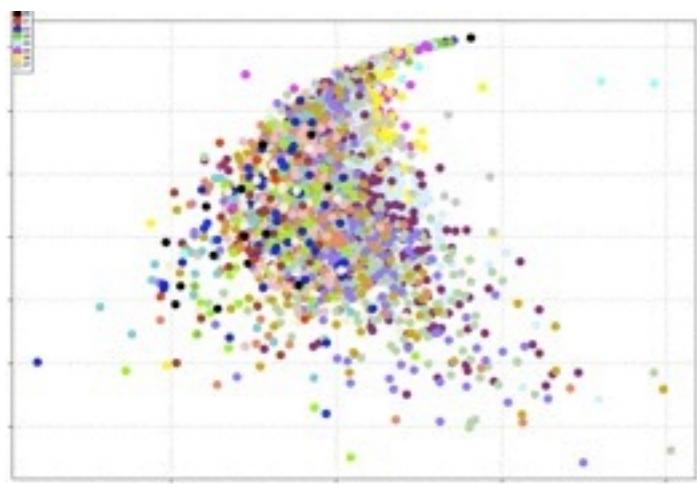


Automatic Judgements

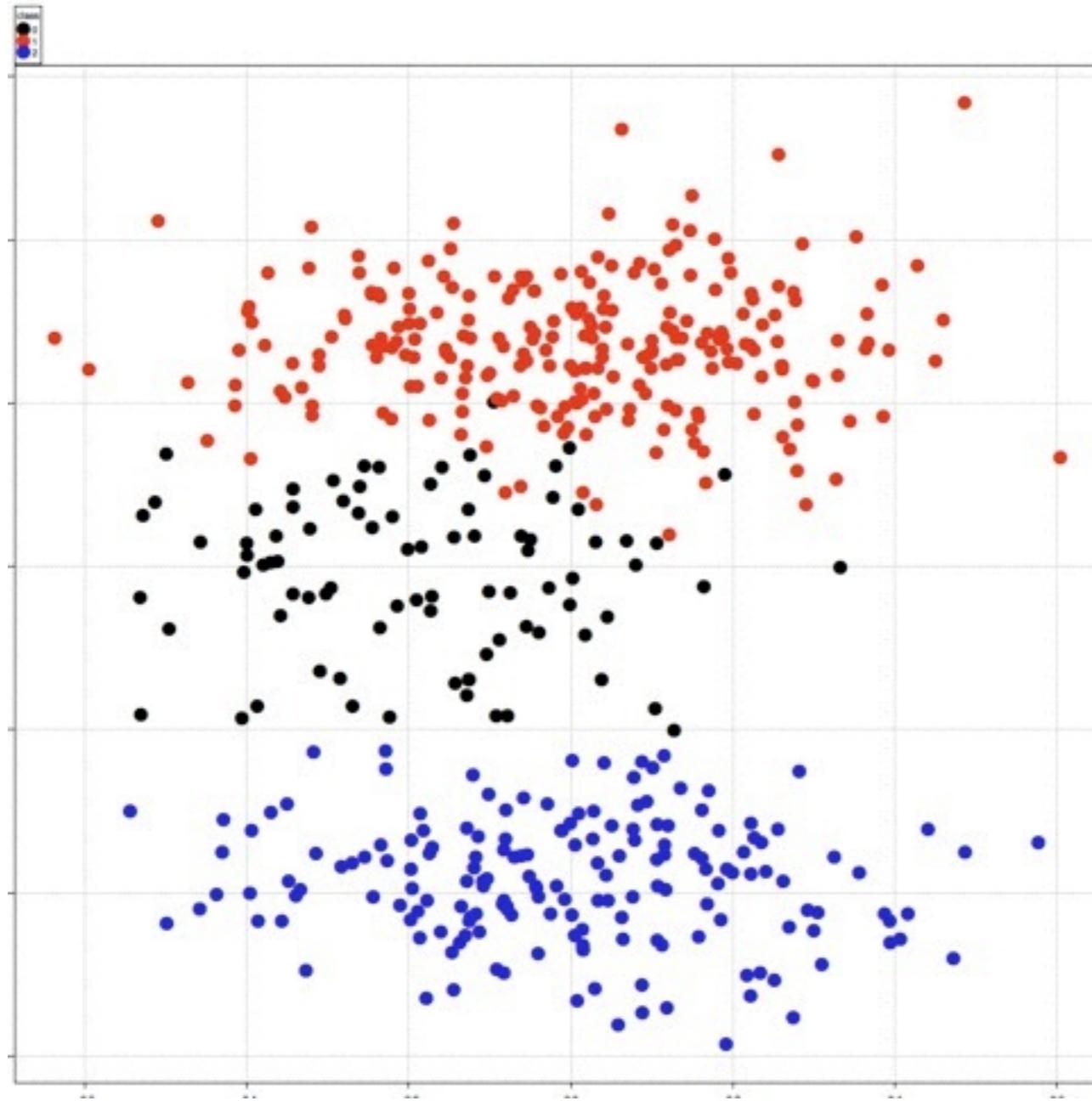
with state of the art separation measures

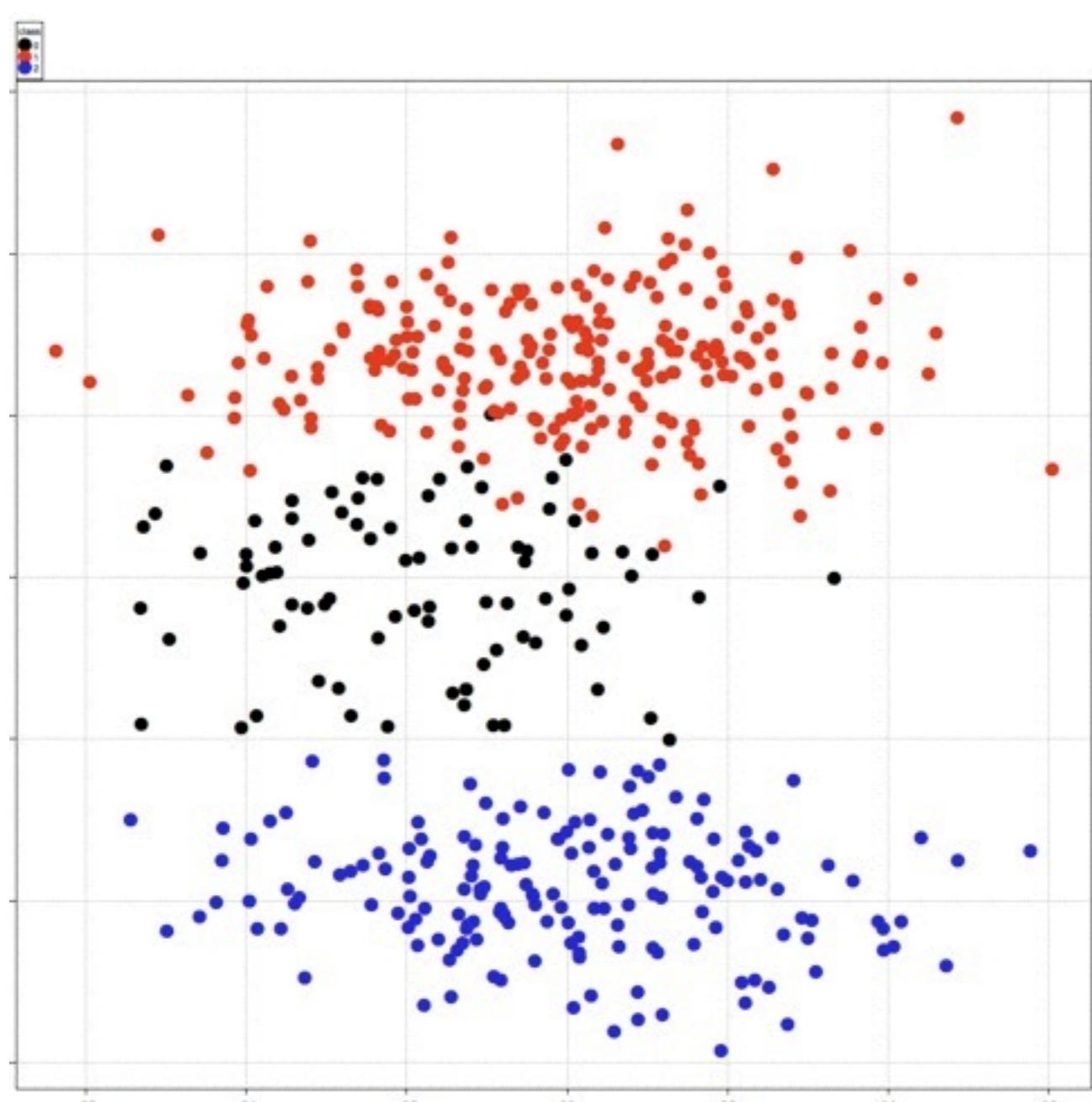


100 (good)

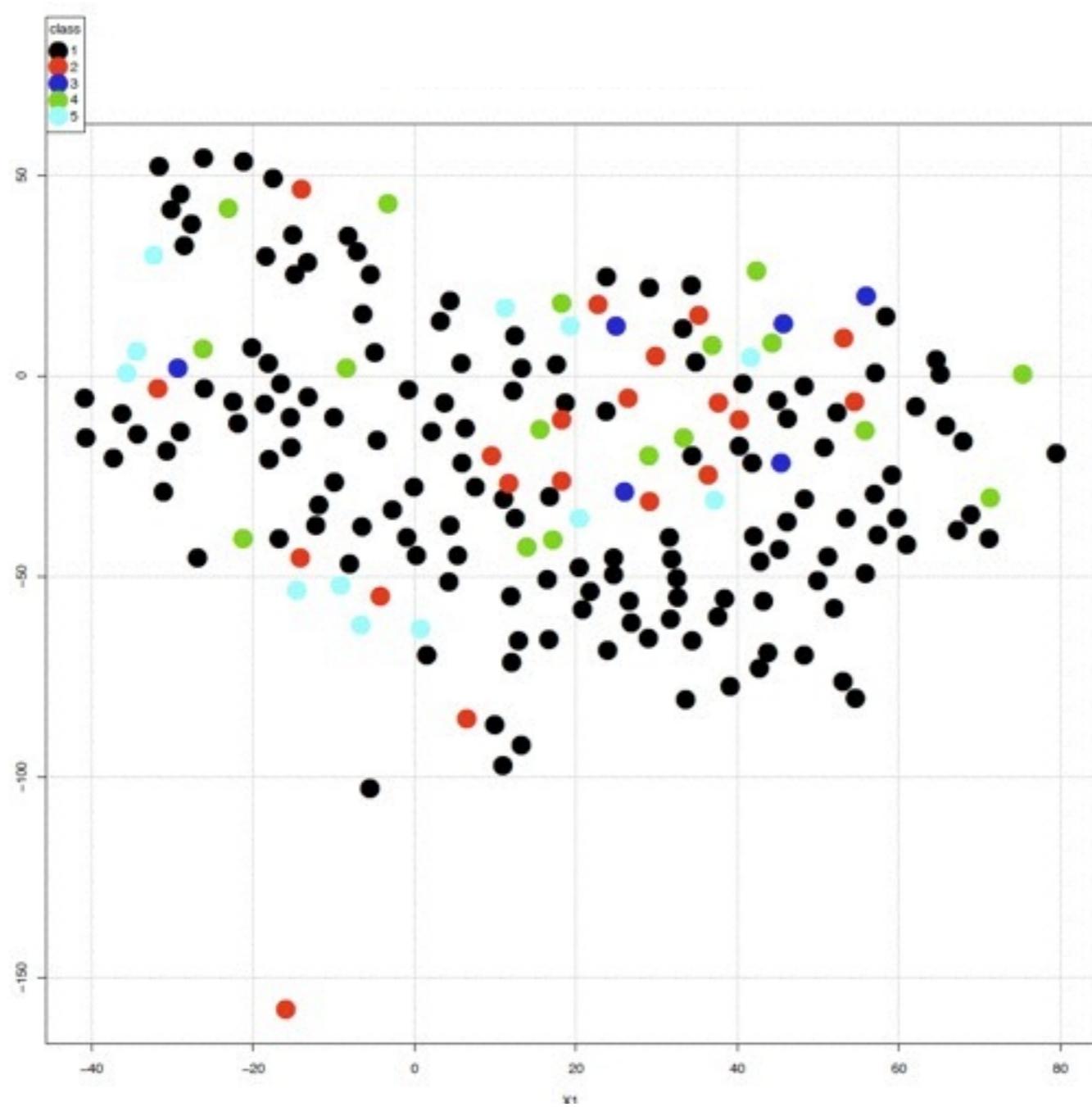


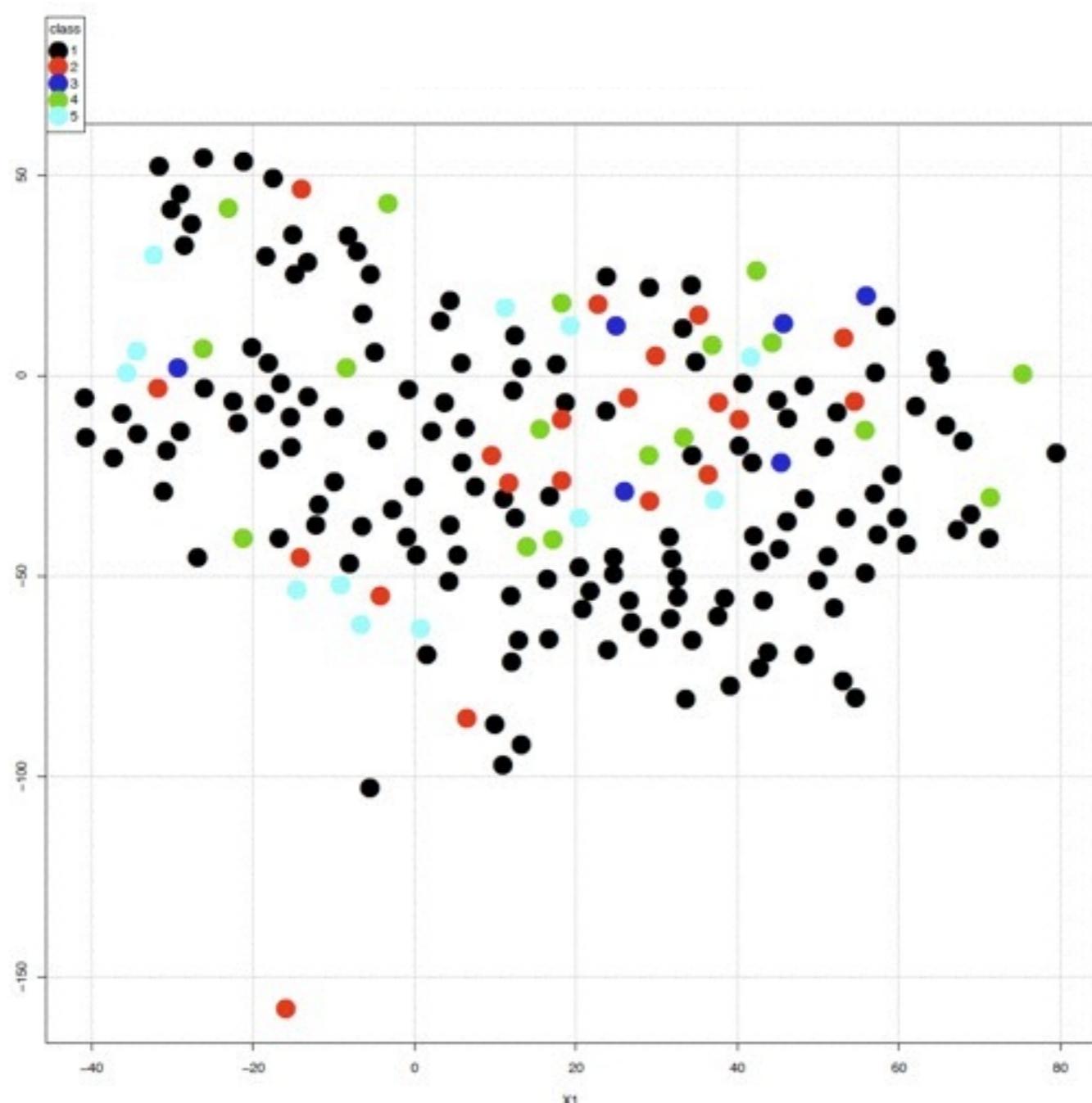
0 (bad)



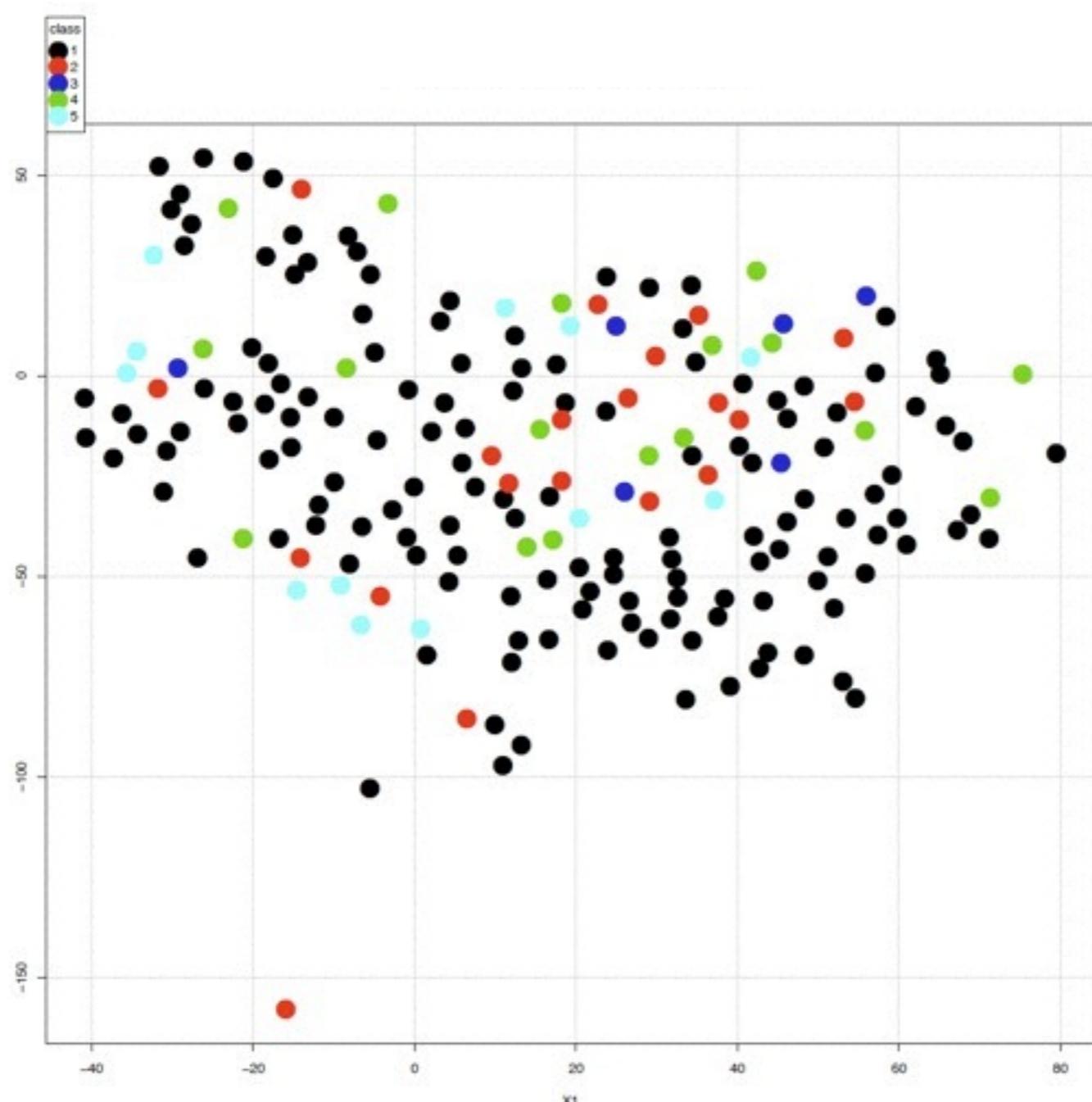


97





82



82



No! Huh?



Many discrepancies
automatic vs. human

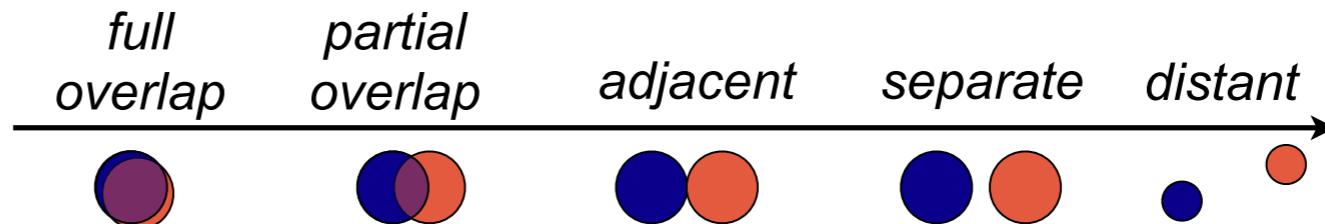
questions



How reliable are current separation measures on a diverse group of datasets?



What factors matter in human cluster perception?



A Taxonomy of Visual Cluster Separation Factors

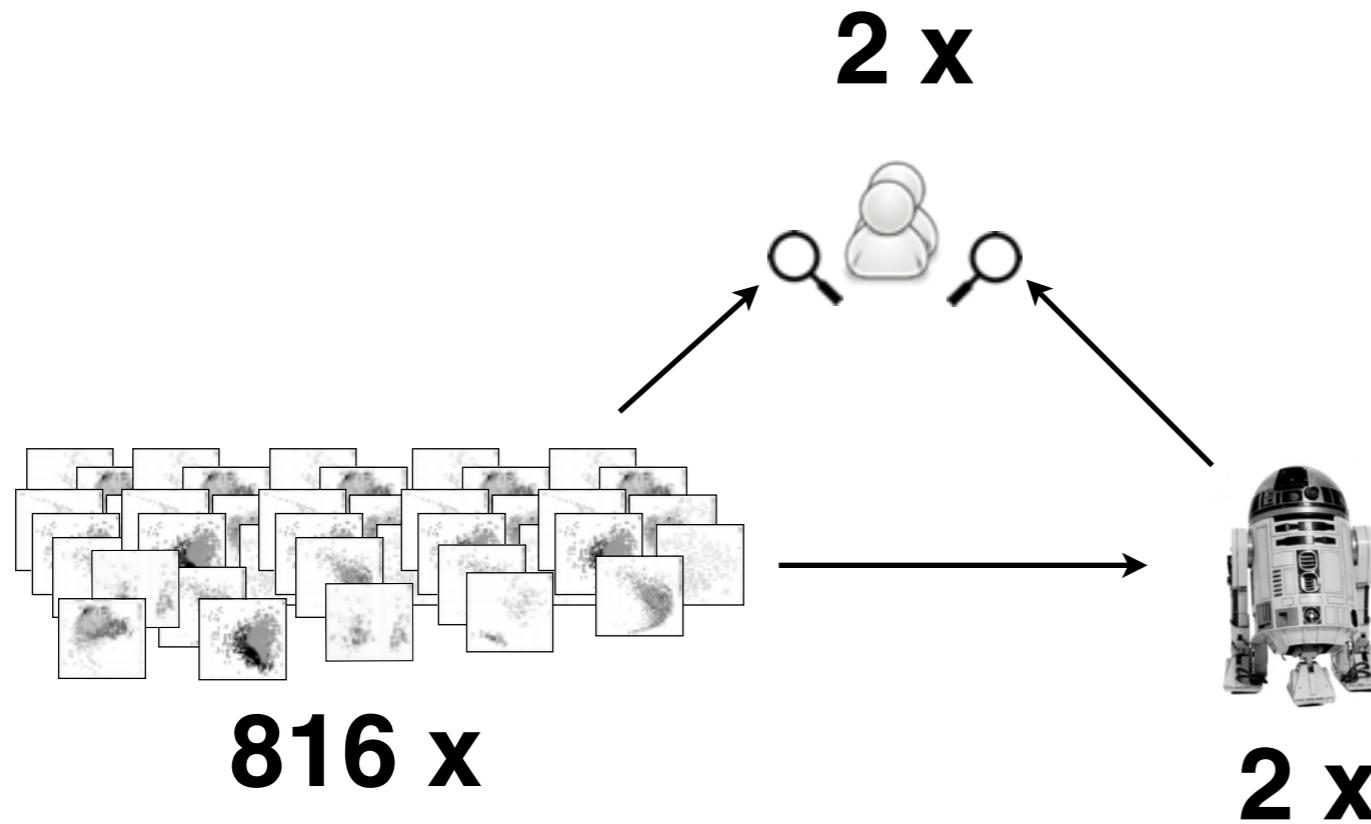
[EuroVis 2012]

M. Sedlmair, A. Tatu, T. Munzner, M. Tory

<http://www.cs.ubc.ca/nest/imager/tr/2012/VisClusterSep/>



qualitative data study



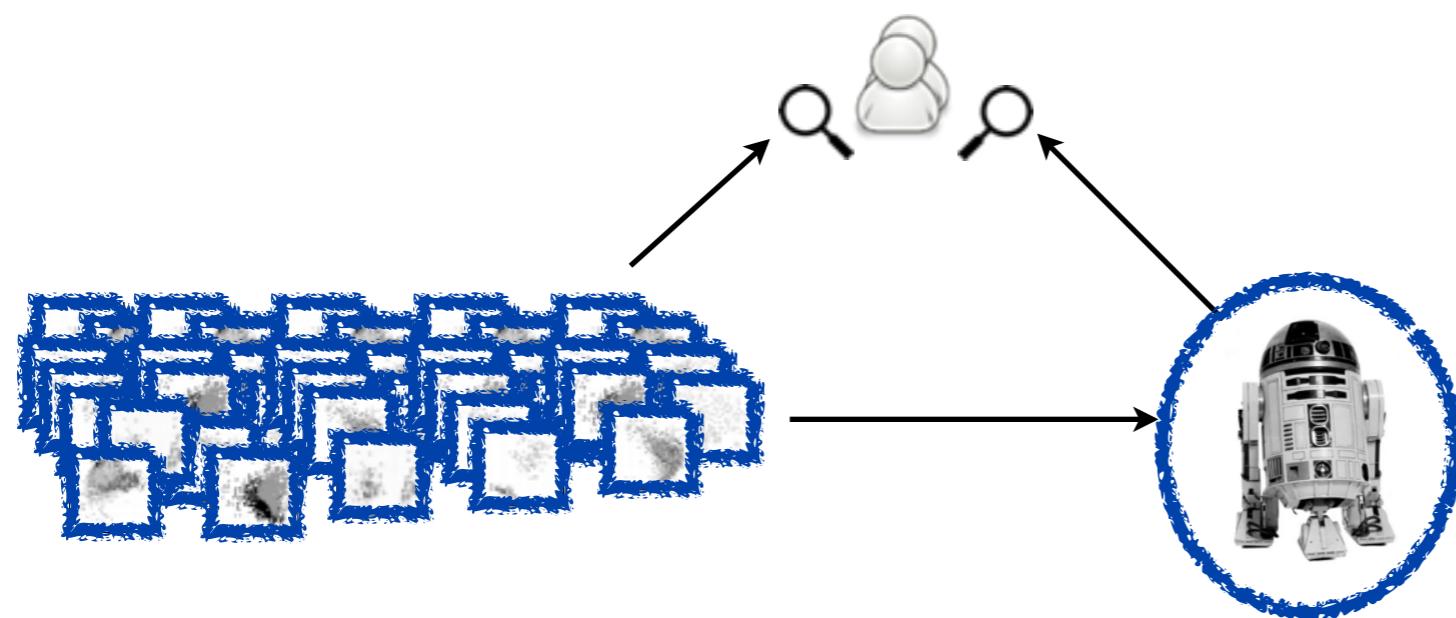
approach out of social science: open and axial coding*

* Charmaz, K. Constructing Grounded Theory: A Practical Guide through Qualitative Analysis. 2006.

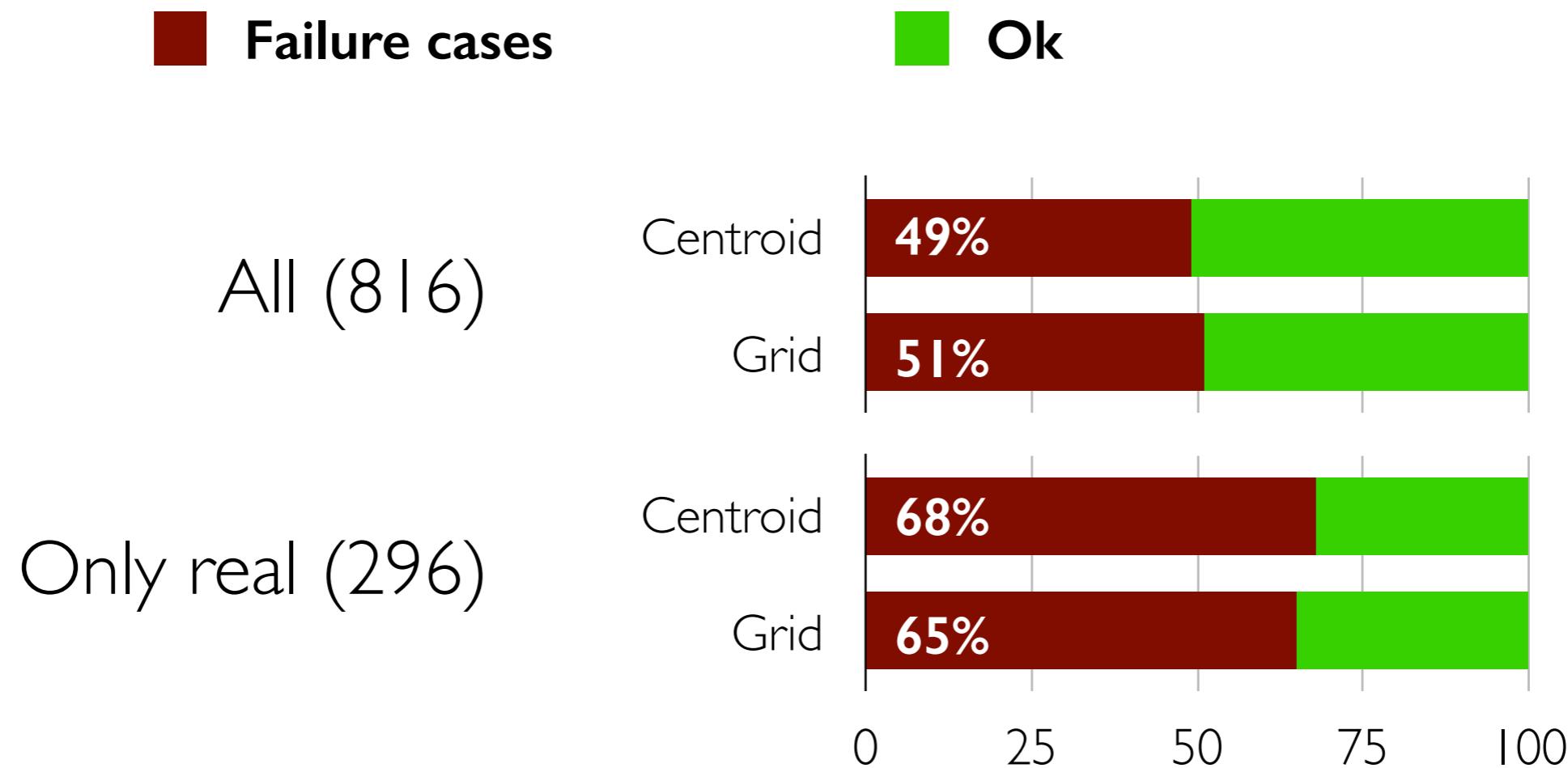
* Furniss, D., Blandford, A., Curzon, P. and Mary, Q. (2011). Confessions from a grounded theory PhD: experiences and lessons learnt. Proc. ACM CHI 2011, p 113-122.

data analysis (part I):

Evaluating the measures

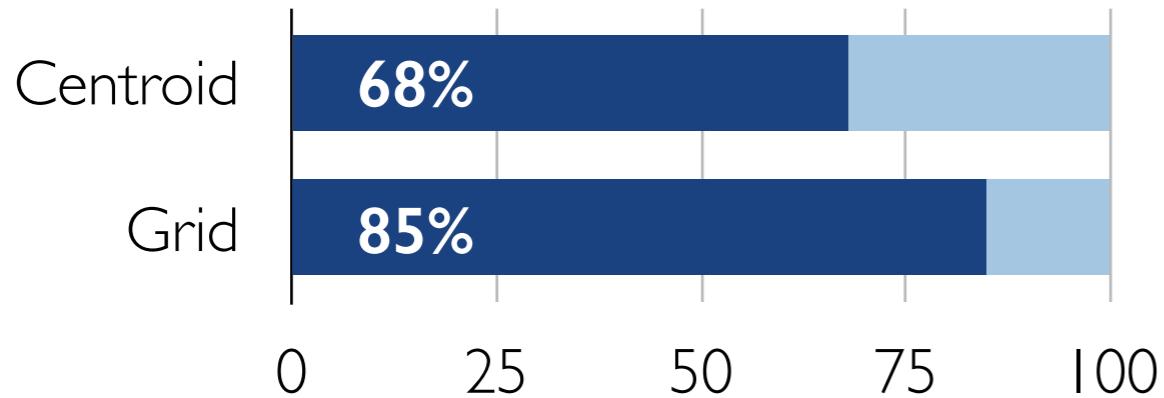


high-level results



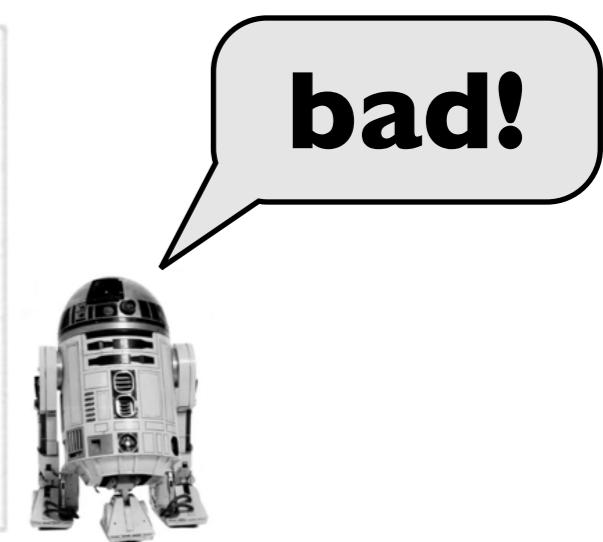
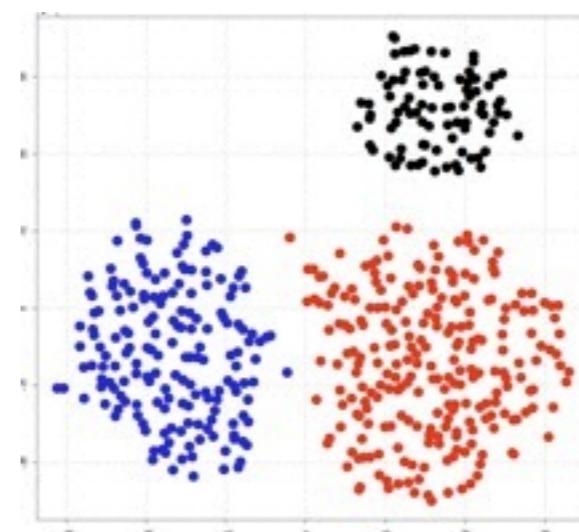
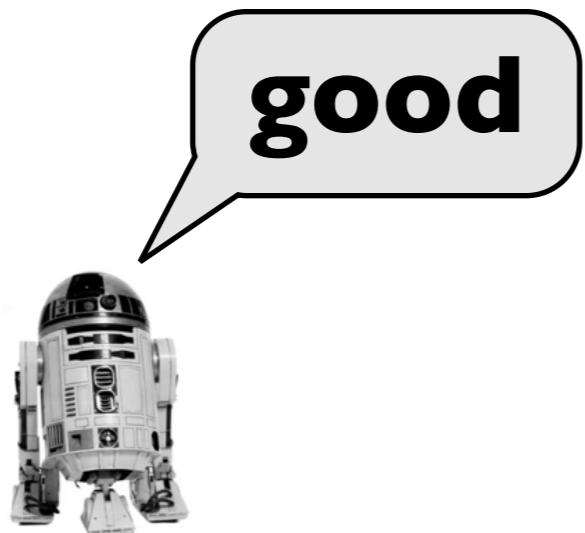
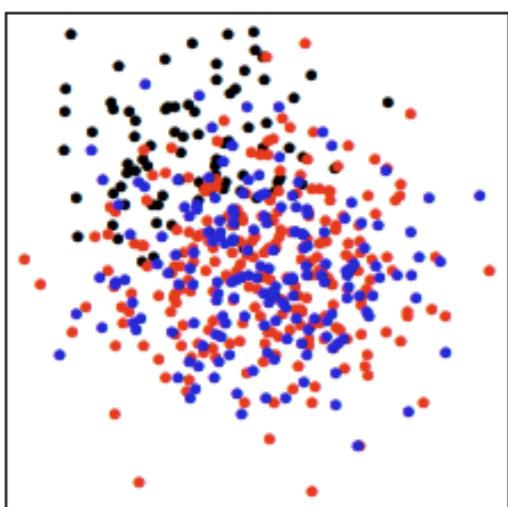
false positives / false negatives

All failure cases:



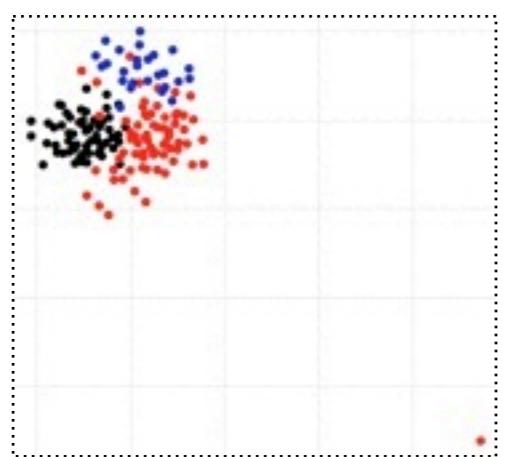
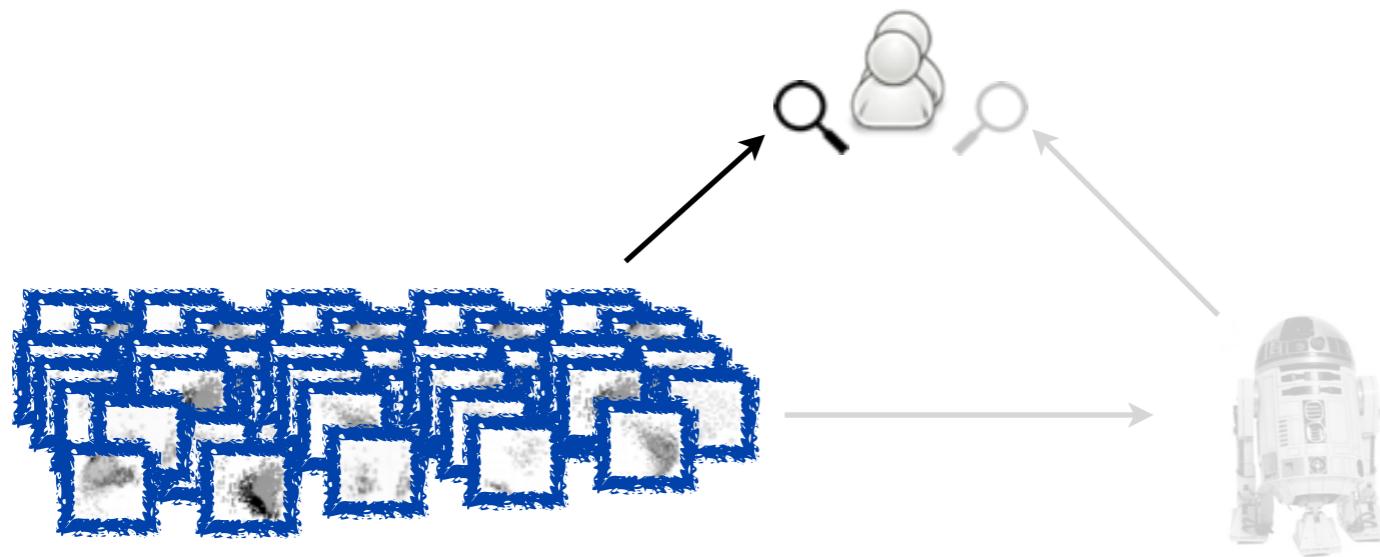
■ false positives

■ false negatives

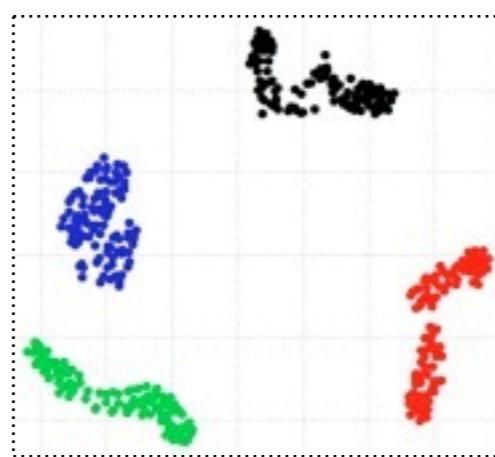


data analysis (part 2):

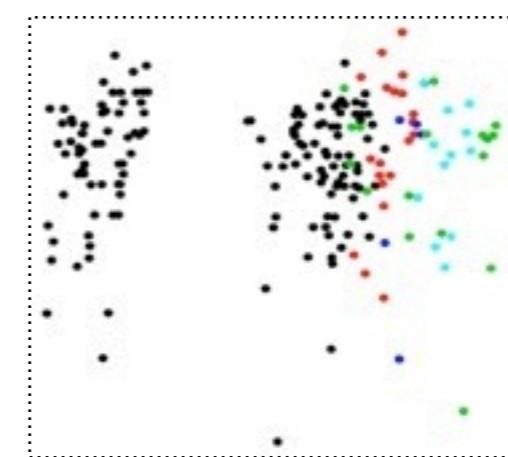
Qualitative analysis of cluster separation factors



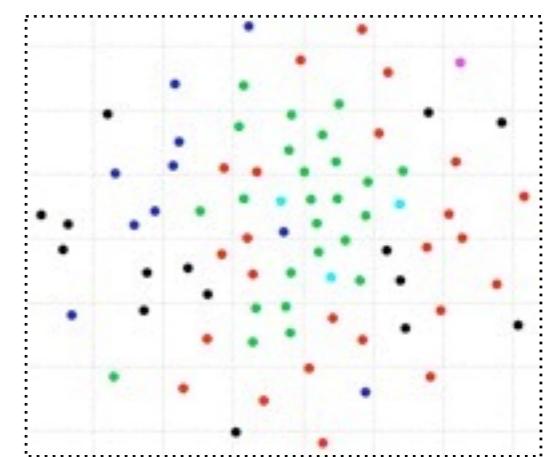
outlier



shape

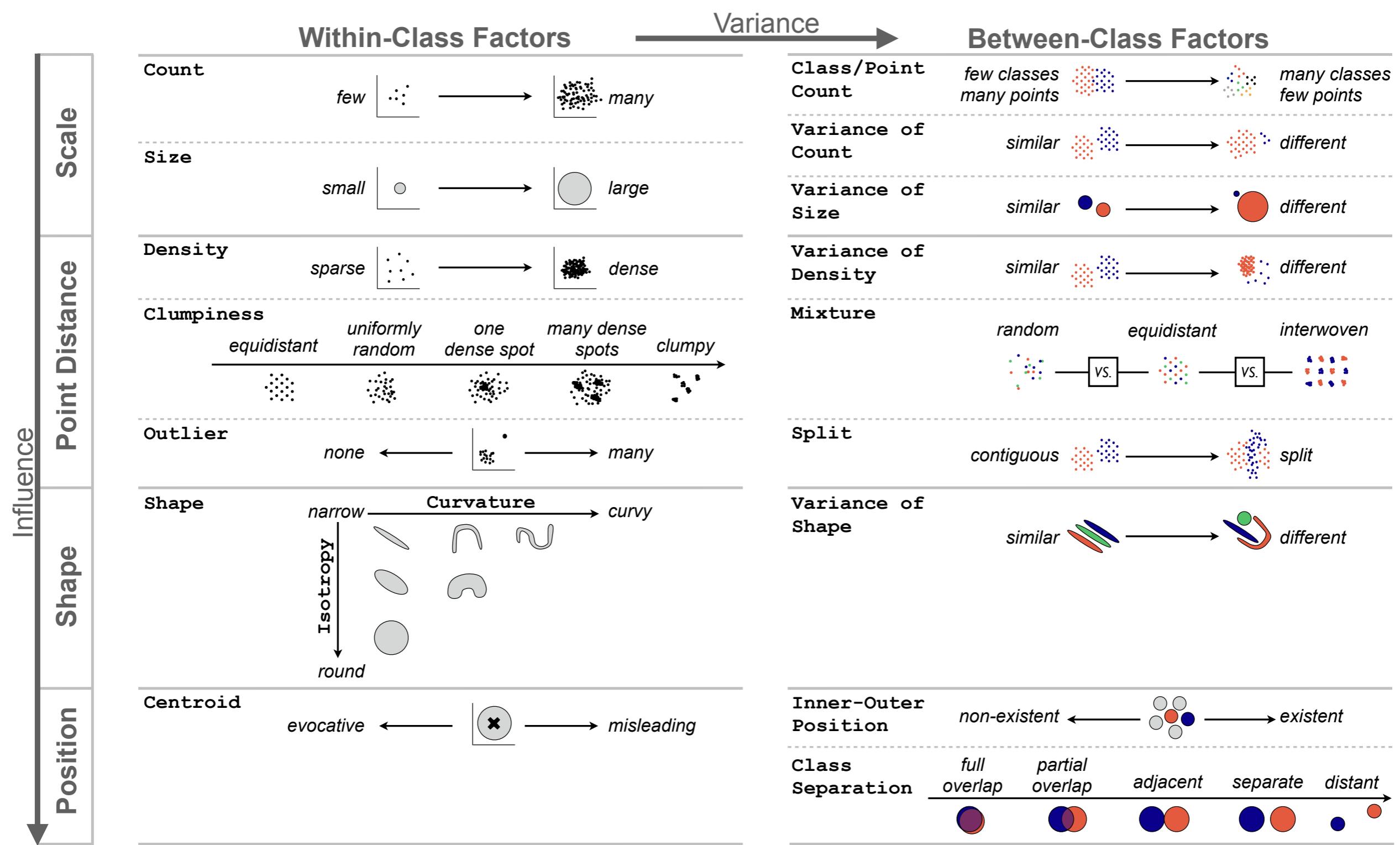


split

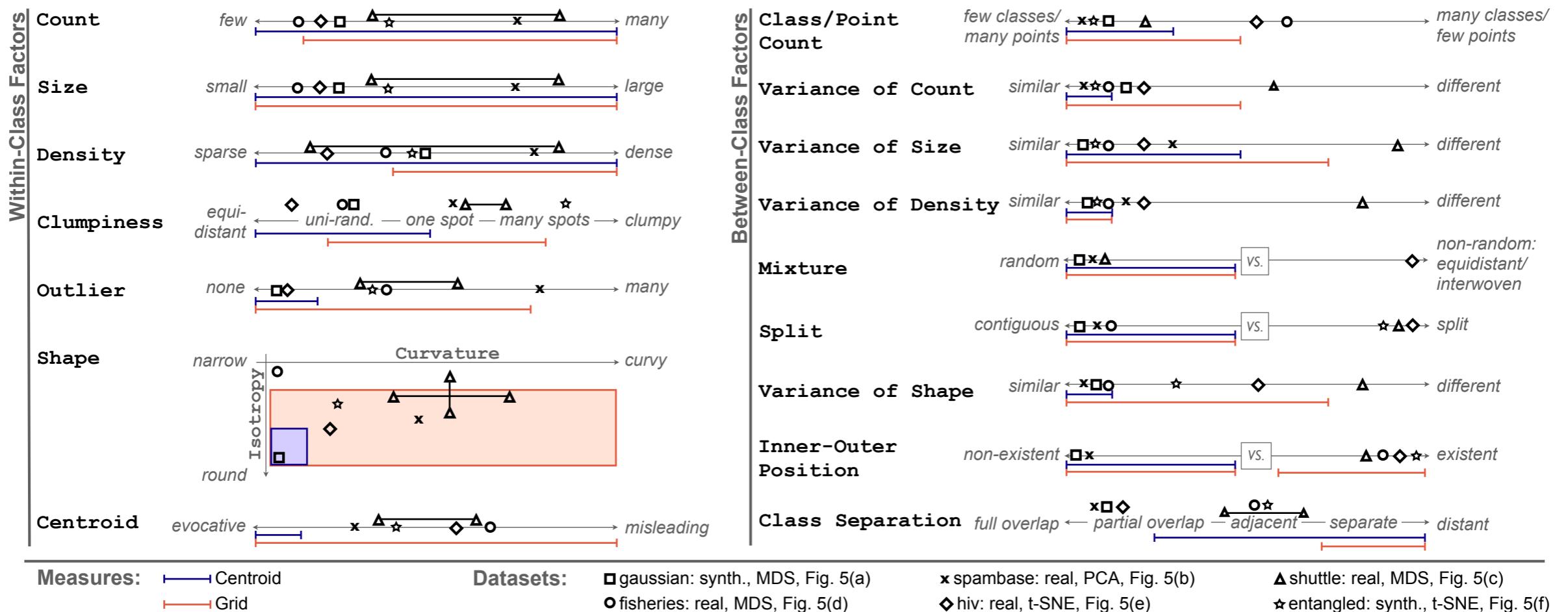


equidistant
points

A taxonomy of visual cluster separation factors



Use taxonomy to analyze why measures failed

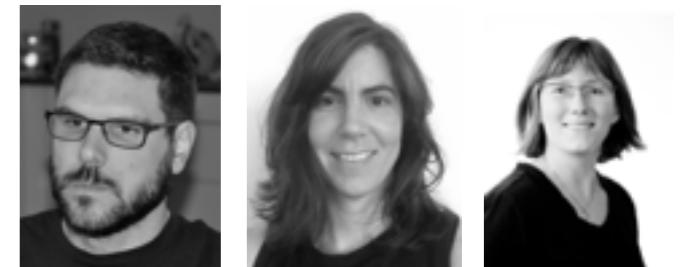


Empirical Guidance on Scatterplot and Dimension Reduction Technique Choices

[InfoVis 2013]

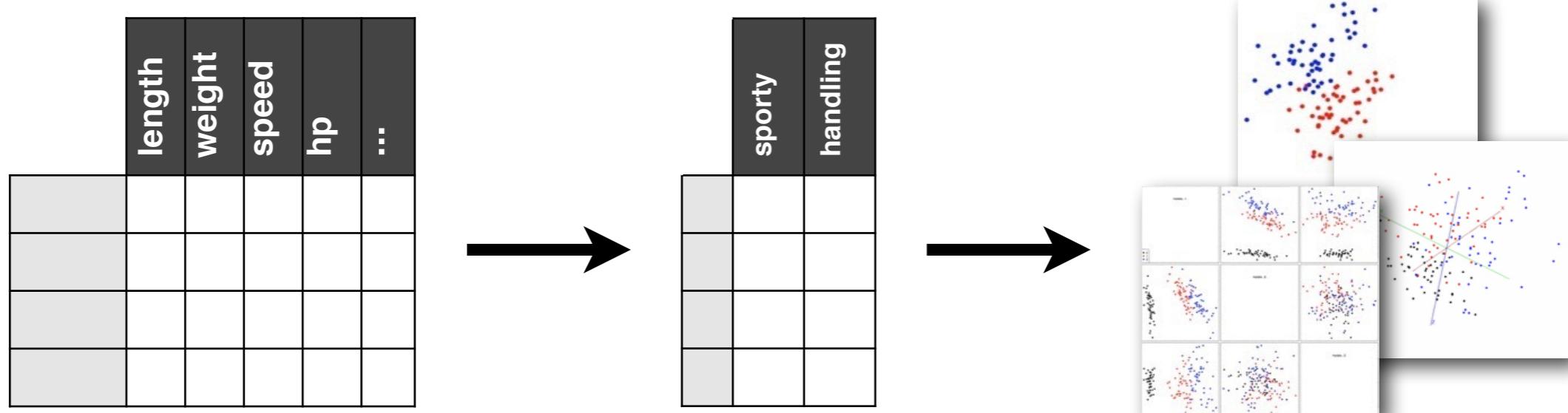
M. Sedlmair, T. Munzner, M. Tory

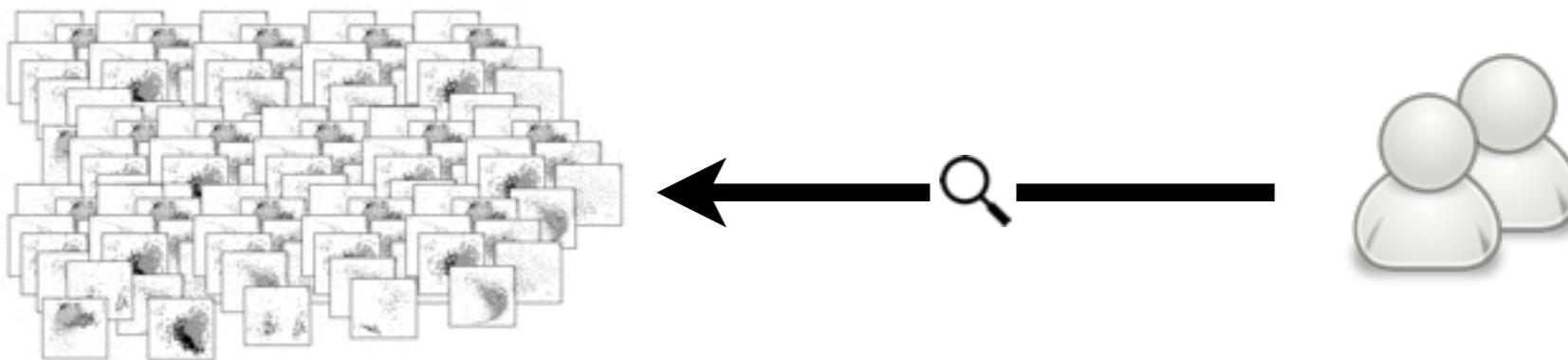
<http://www.cs.ubc.ca/labs/imager/tr/2013/ScatterplotEval/>



2D vs. 3D vs. SPLOM

Which visual encoding technique
to use for visualizing DR data?

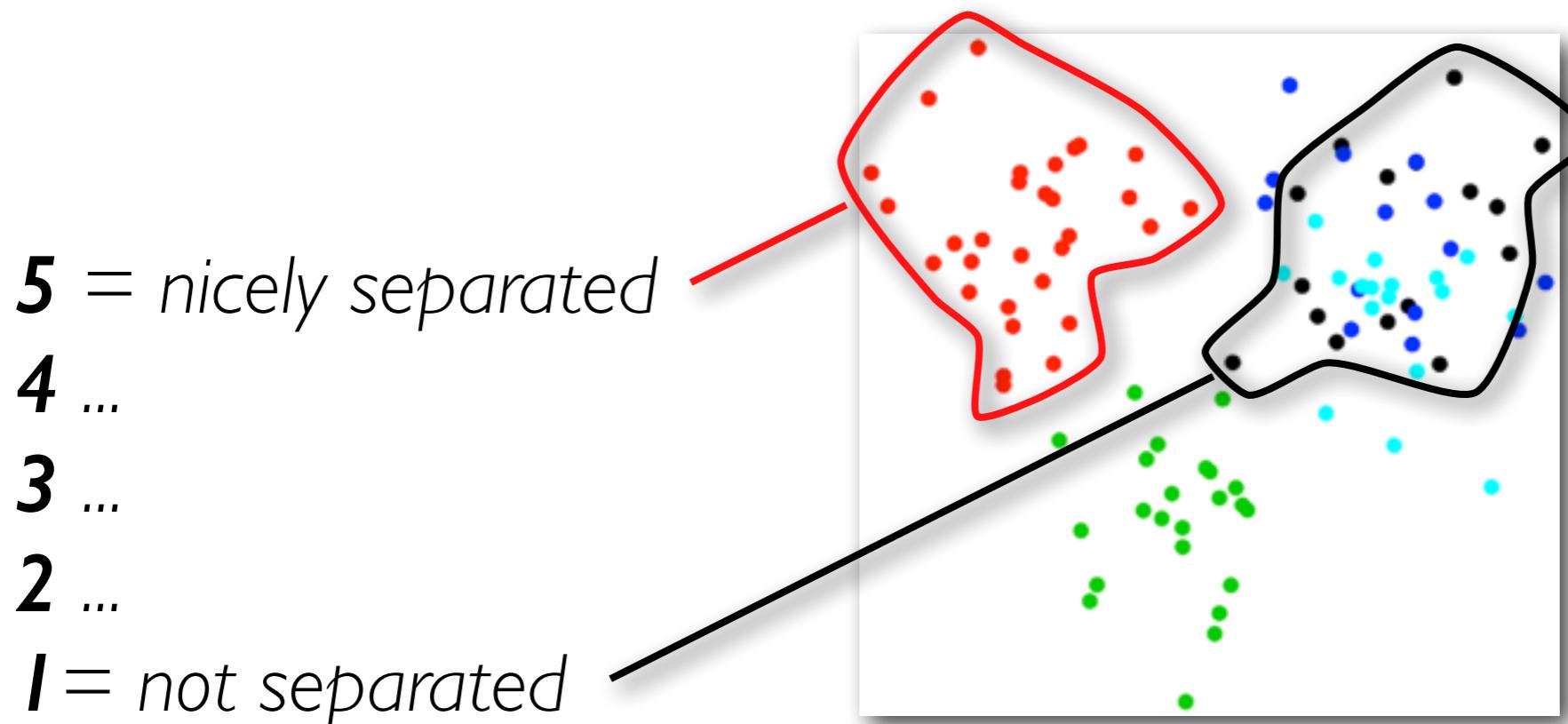


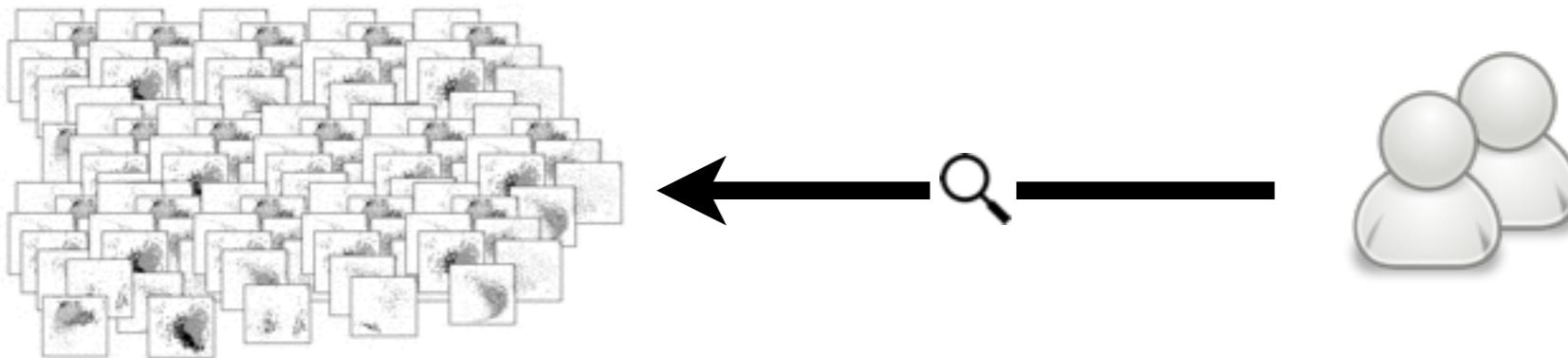


data study with 2 coders

inspect all 816 plots

quantitatively judge all 5460 clusters:





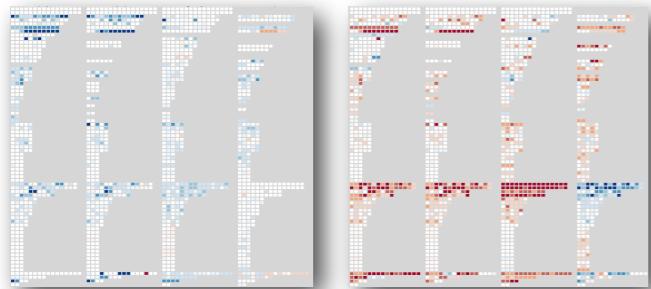
judging reliability

high inter-coder reliability (Krippendorff's alpha = 0.86)

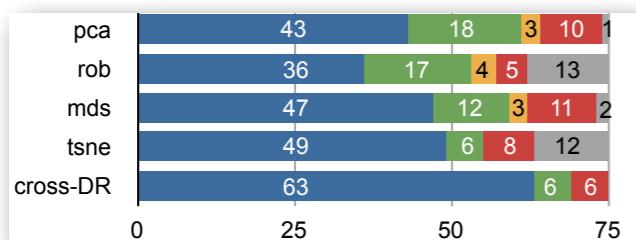


“The Krippendorff’s alpha coefficient is a statistical measure of the extent of agreement among coders” [Gwet, 2011]

data analysis



- Heatmaps approach



- Descriptive statistics

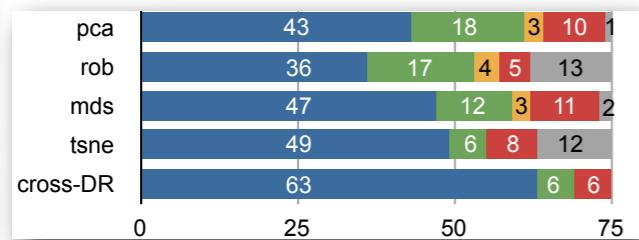
$p < .05$

- Significance tests

data analysis



- Heatmaps approach



- Descriptive statistics

$p < .05$

- Significance tests

* previous work:

cost assumption

- **2D < SPLOM < 3D**
- Based on rich body of previous work*

Drawbacks of 3D

Chalmers: Using a landscape metaphor to represent a corpus of documents [COSIT'93]

Cockburn and McKenzie: An evaluation of cone trees [British Conf. on HCI'00]

Cockburn and McKenzie: Evaluating the effectiveness of spatial memory in 2D and 3D physical and virtual environments [CHI'02]

Newby: Empirical study of a 3D visualization for information retrieval tasks. J. Intelligent Information Systems, 18(1):31–53, 2002.

Tory et al.: Spatialization design: comparing points and landscapes [InfoVis'07]

Tory et al.: Comparing dot and landscape spatializations for visual memory differences [InfoVis'09]

Westerman and Cribbin: Mapping semantic information in virtual space: dimensions, variance and individual differences [IJHCS'00]

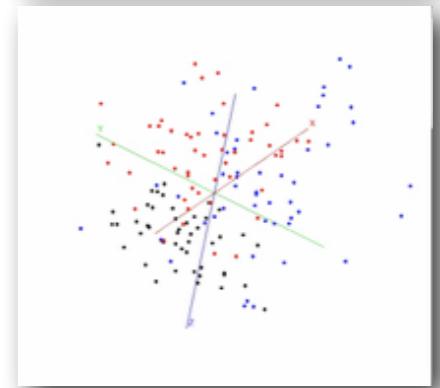
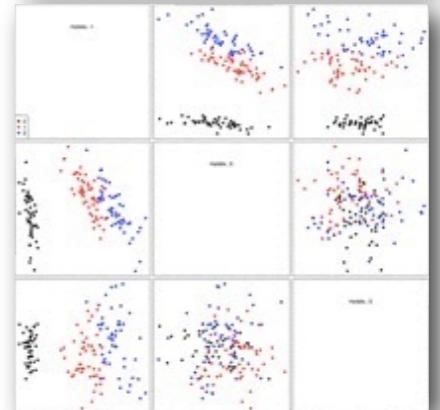
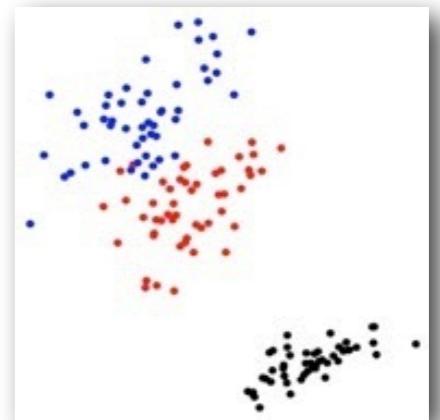
Interaction Costs

Lam: A framework of interaction costs in information visualization [InfoVis'08]

Van Wijk: Views on visualization [TVCG'06]

cost assumption

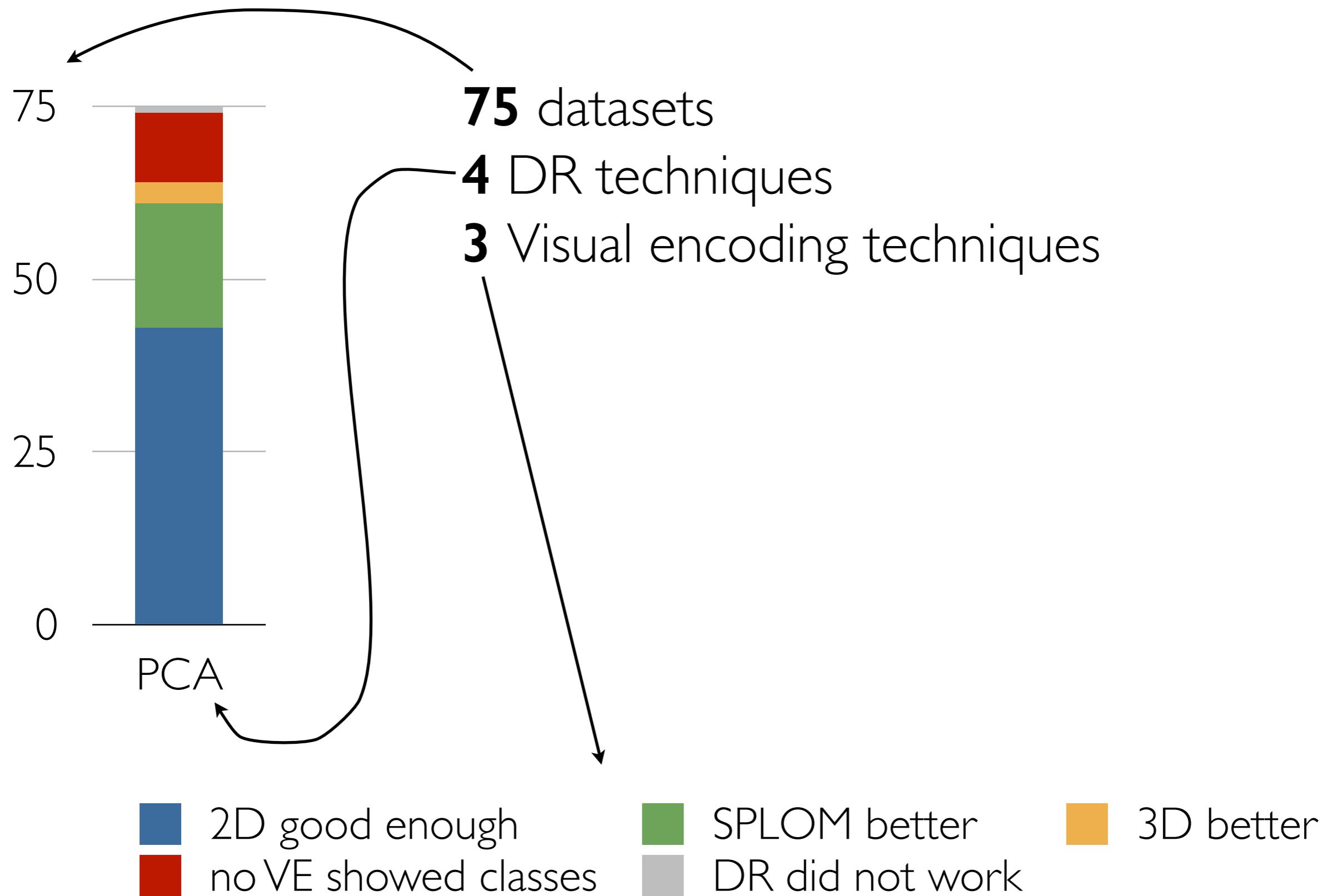
- $2D < SPLOM < 3D$
 - Based on rich body of previous work*
- **Reasons:**
 - 2D (low): static, directly visible
 - SPLOM (medium): switching attention between views
 - 3D (high): interaction to resolve occlusions



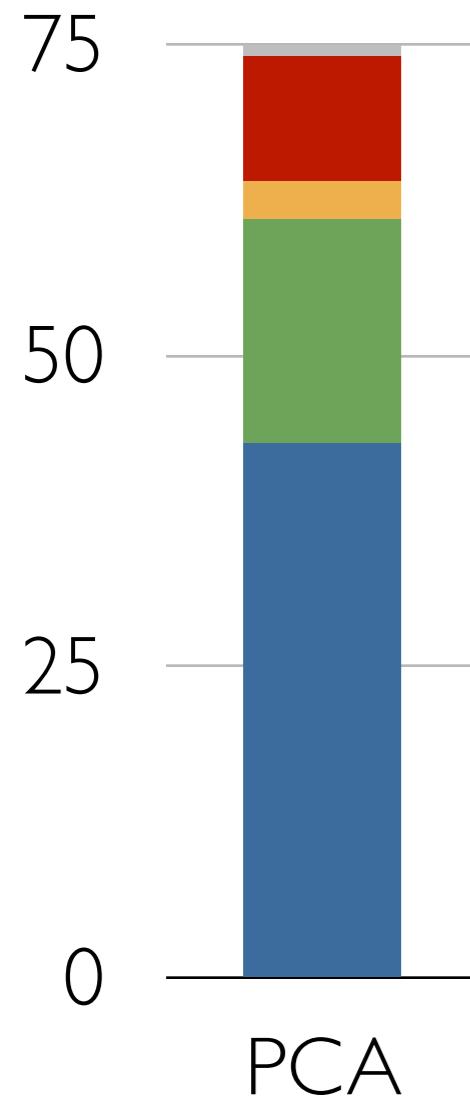
cost assumption

- Use a higher cost visual encoding **only** if it provides notably better class separation
- Use 2D if “**good enough**”, if not then SPLOM, then 3D

results

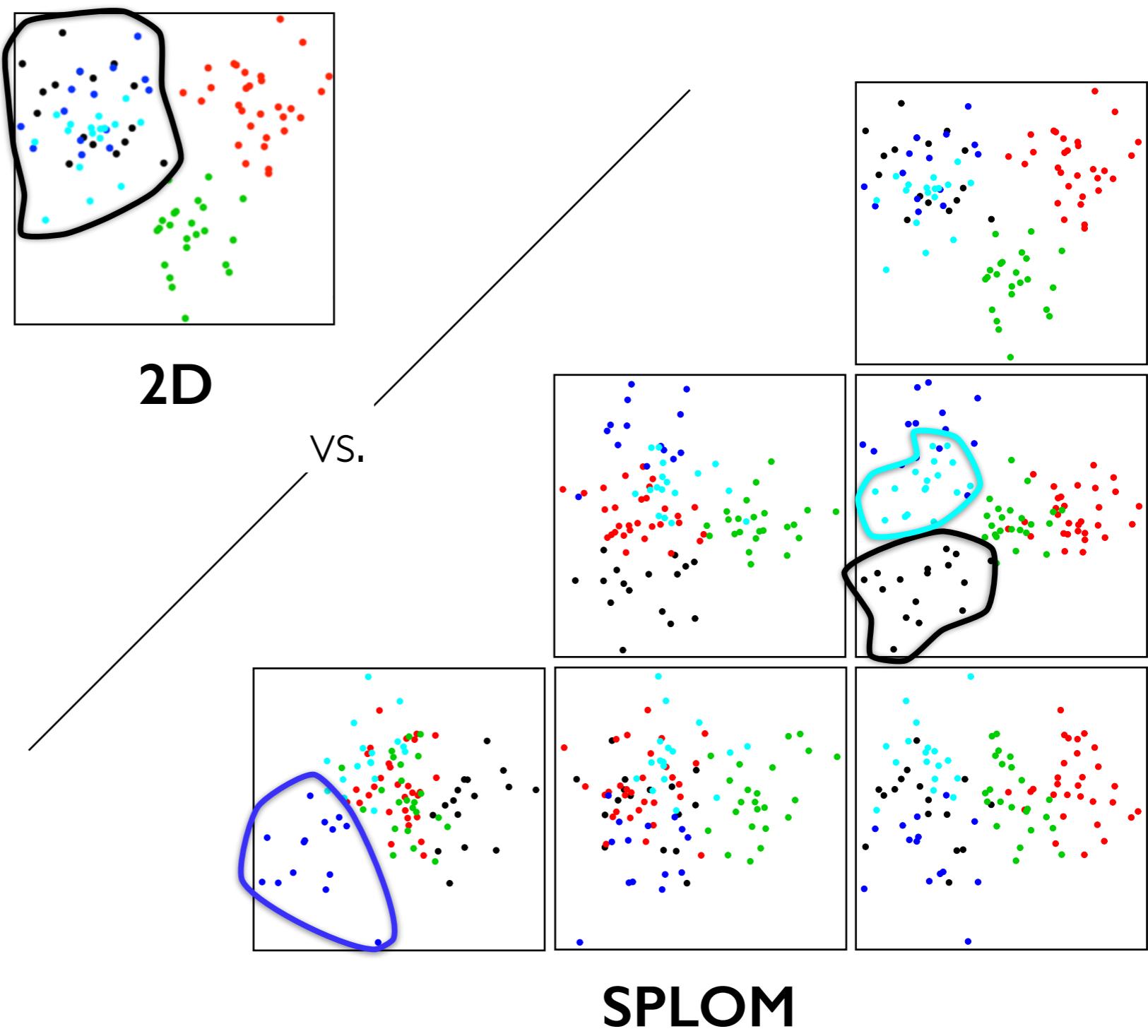
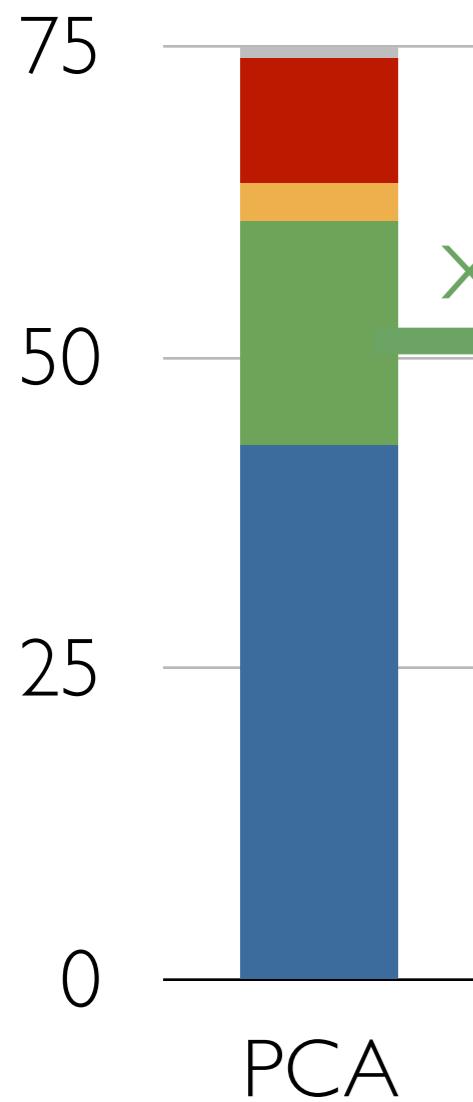


results



“better” = at least one class is
notably more separable

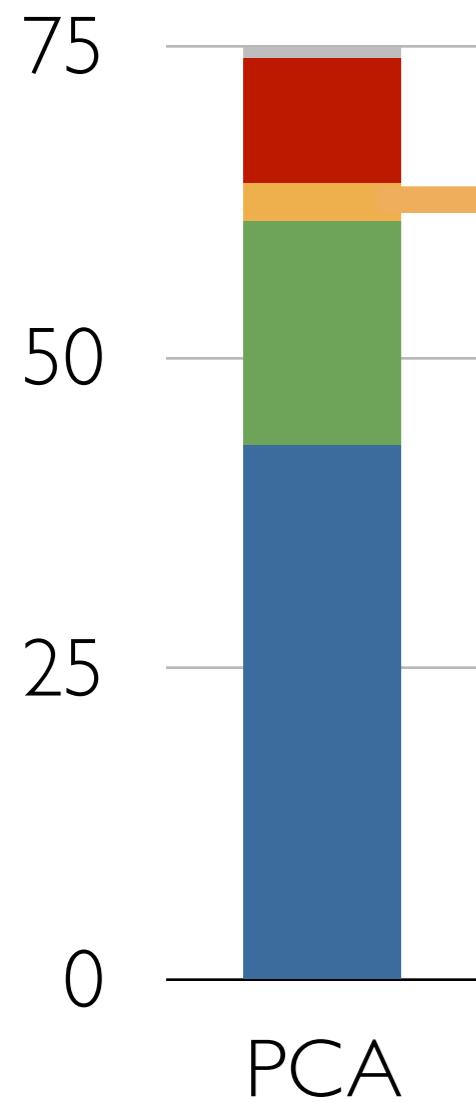
- 2D good enough
- no VE showed classes
- SPLOM better
- 3D better
- DR did not work



█ 2D good enough
█ no VE showed classes

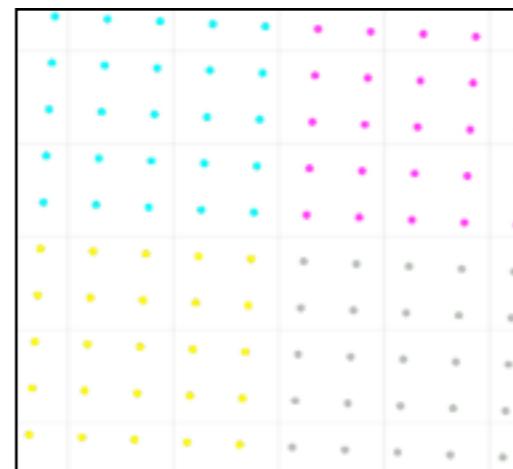
█ SPLOM better
█ DR did not work

█ 3D better



x3

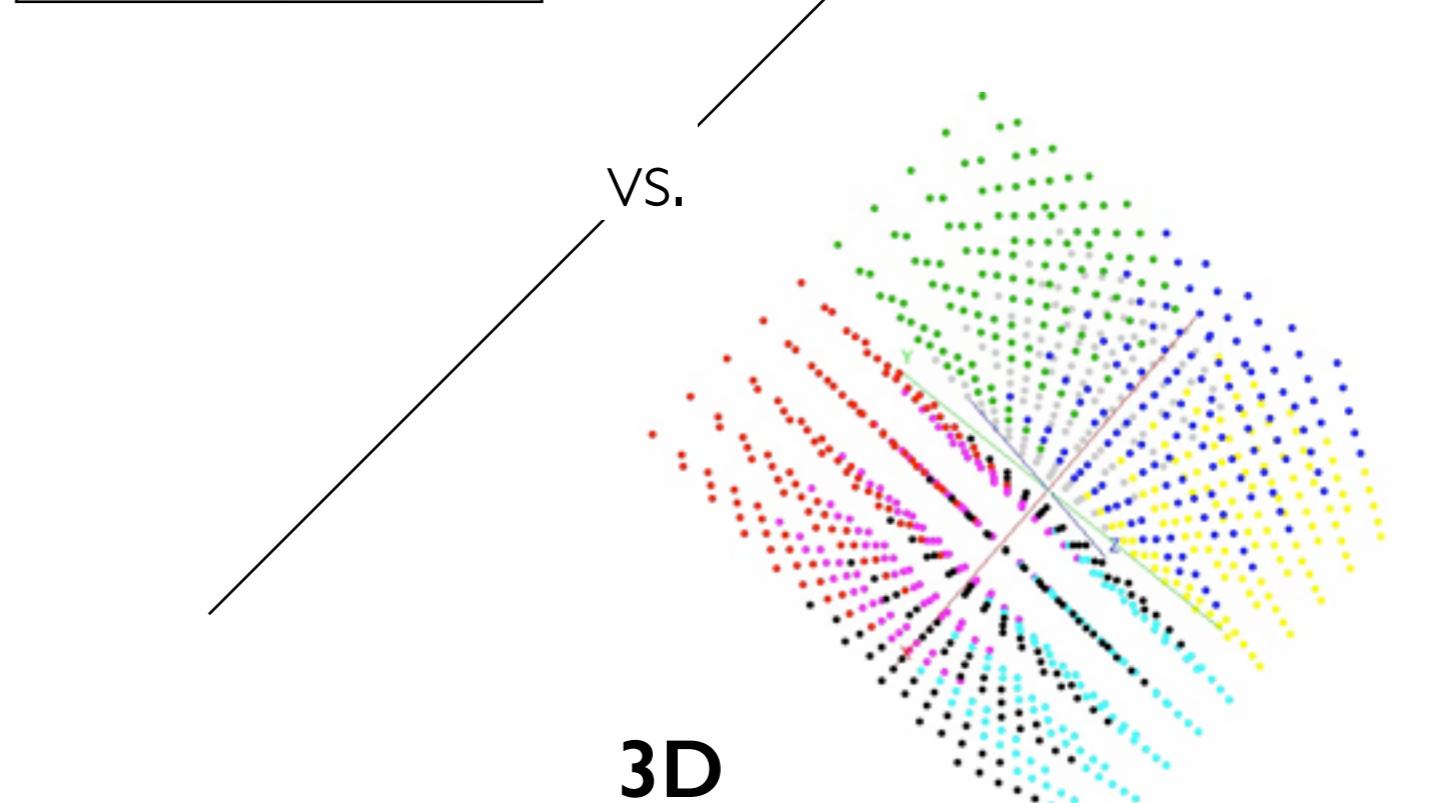
highly artificial
examples **only**



2D

vs.

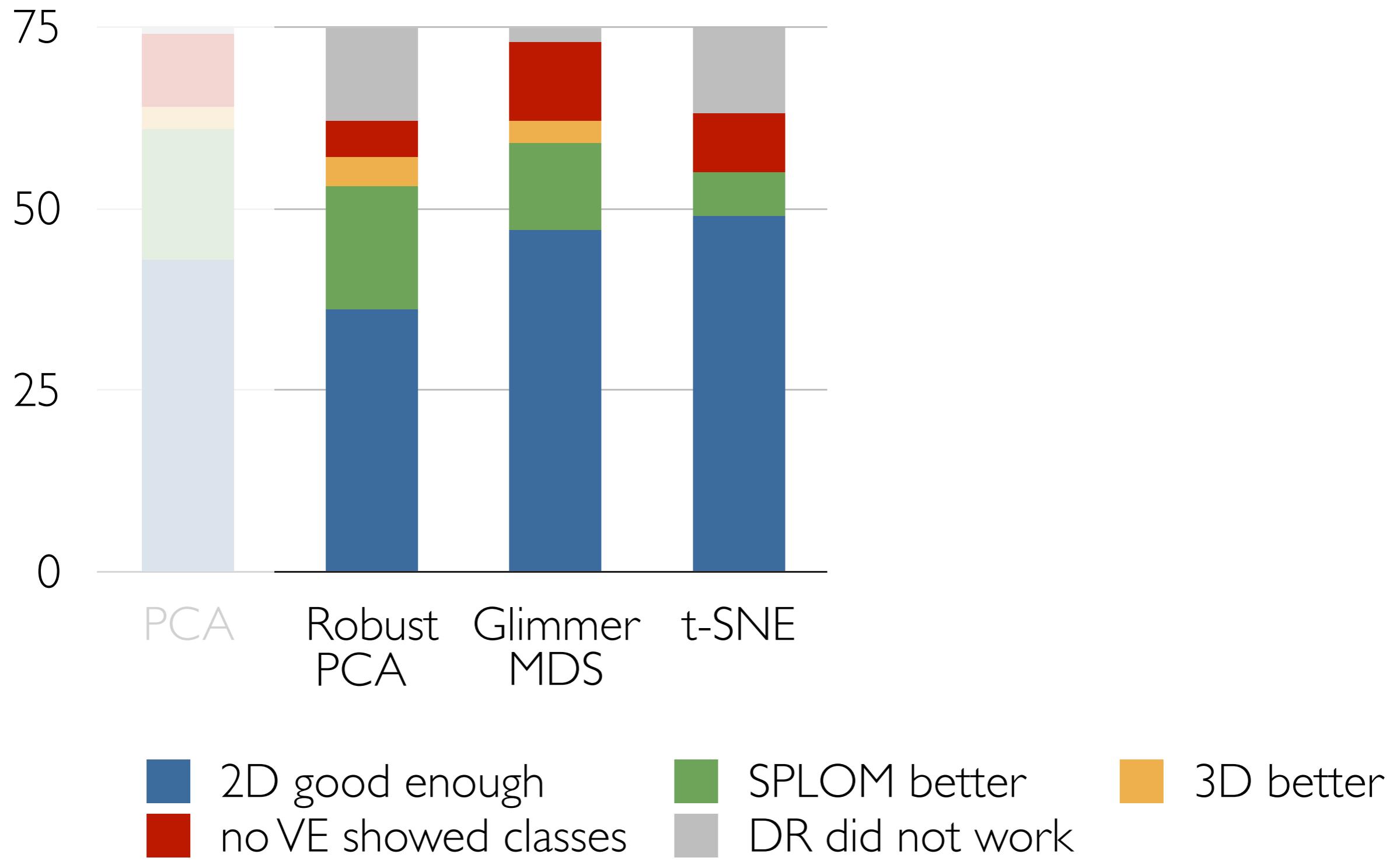
3D



█ 2D good enough
█ no VE showed classes

█ SPLOM better
█ DR did not work

█ 3D better





implications

Use 2D: 2D often good enough

Change DR: if not, change DR technique

Then SPLOM: SPLOM occasionally helps

No 3D: 3D rarely helps and often hurts

real users/real data:

Studies on high-dimensional data analysis techniques

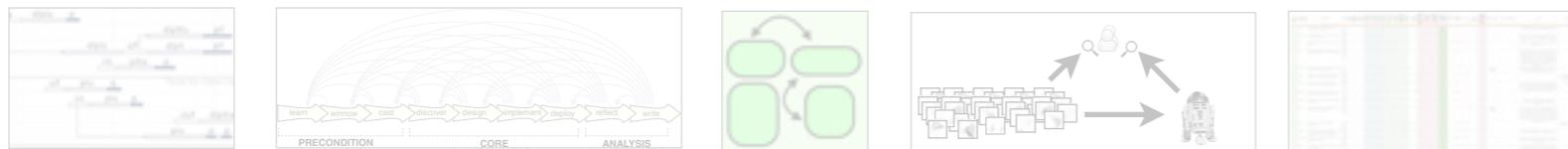


Applied visualization projects (9 BMW, 3 others)



right methods:

Novel and refined research methods/methodologies

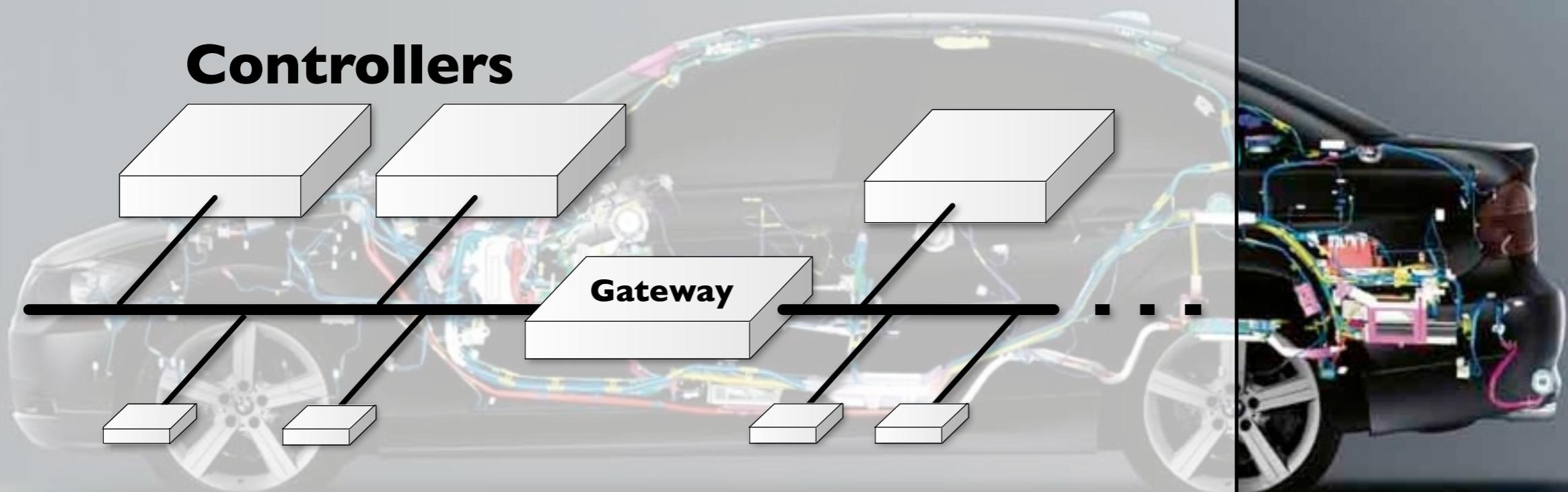


Applied Visualization Projects: Automotive Engineers

more and more electronics...



... enabled by in-car communication networks



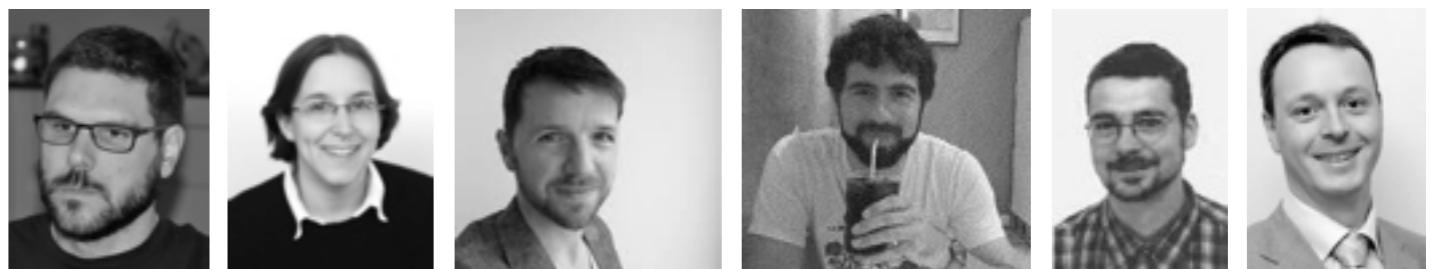
~70 Controllers / Car

Cardiogram: Visual Analytics for Automotive Engineers

[CHI 2011]

M. Sedlmair, P. Isenberg, D. Baur, M. Mauerer, C. Pigorsch, A. Butz

<http://homepage.univie.ac.at/michael.sedlmair/papers/sedlmair2011chi.pdf>

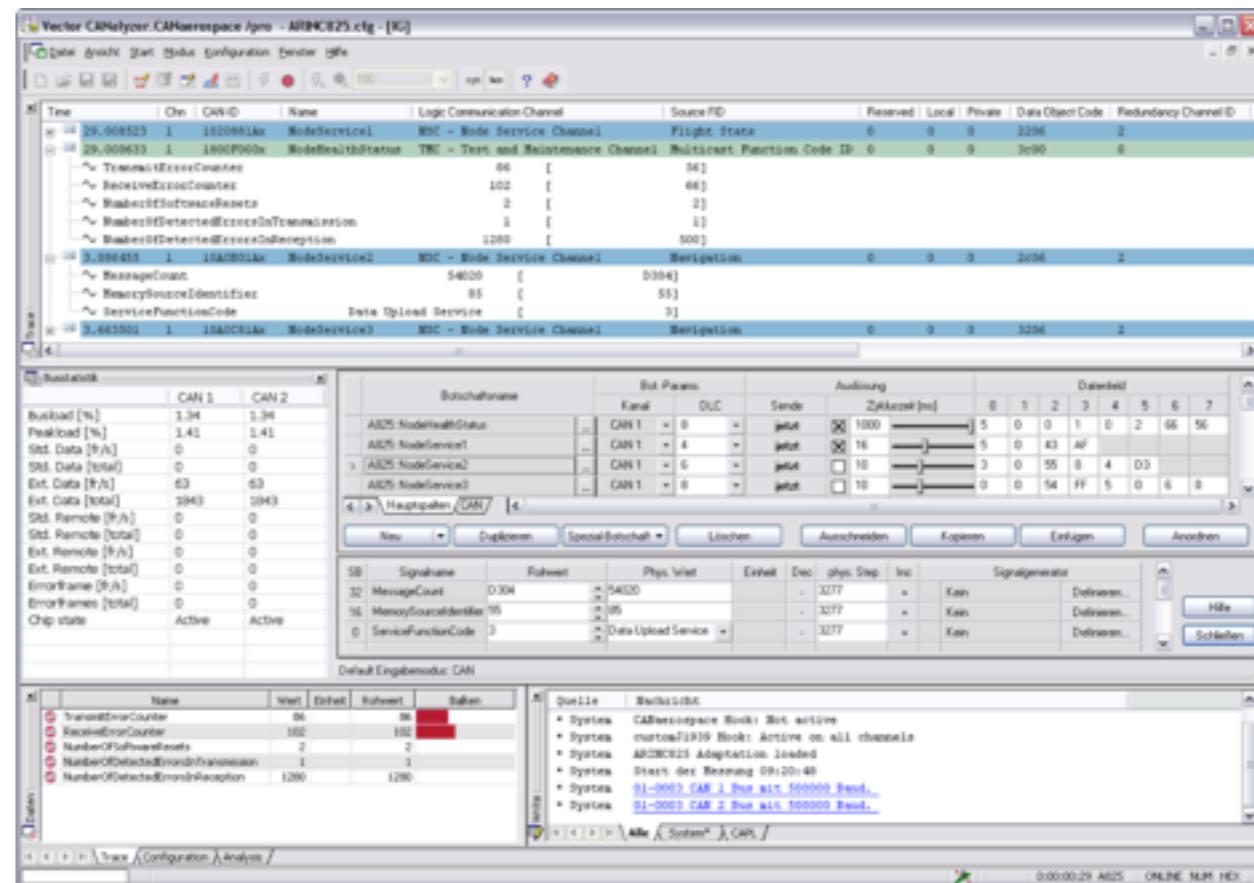


problem characterization



task: finding errors
process: test drives
data: recorded traces (15k messages/sec)
current practices: mainly textual lists

75836...	F...	55	Rx	16	5a 77 f8 27 00 20 00 20 20 0f 00 0...	
75836...	F...	56	Rx	16	ee 7e f8 27 00 20 00 20 20 0f 00 0...	
75836...	F...	57	Rx	16	ed 77 10 20 00 20 00 20 20 0f 00 0...	
75836...	F...	58	Rx	16	5e f8 1f 00 02 20 ff 21 22 22 07 f...	
75851...	F...	5a	Rx	16	33 08 77 22 75 d2 6f e2 70 f2 03 0...	
75851...	I	1a1	V_VEH	Rx	5 c1 f7 00 00 8a	
~ V_VEH_COG		0 km/h		[0]	
~ ST_ECU_V_VEH		Signal ungültig		[f]	
~ QU_V_VEH_COG		Signalwert ist gültig, Zustand/3		[a]	
~ DVCO_VEH		Fahrzeug steht		[0]	
~ CRC_V_VEH		193		[c1]	
~ ALIV_V_VEH		7		[7]	
75851...	F...	5c	Rx	8	00 00 00 00 ff ff 00 10	
75851...	I	1c4	Rx	6	00 00 00 00 ff ff	
75851...	F...	12f	Rx	72	00 00 00 00 00 00 ff 59 87 21 4c 0...	
75851...	I	1c5	Rx	6	02 00 04 00 ff ff	
75836...	F...	1	Rx	16	10 7d 18 28 00 20 00 20 20 0f 00 0...	
75836...	F...	2	Rx	16	ca 76 f9 27 00 20 00 20 20 0f 00 0...	
75836...	F...	3	Rx	16	6a 7d fa 27 00 20 00 20 20 0f 00 0...	
75836...	F...	4	Rx	16	a3 76 0e 28 00 20 00 20 20 0f 00 0...	
75836...	F...	5	Rx	16	2c f7 1f 00 02 20 ff 21 22 22 07 f...	
75851...	F...	7	Rx	16	6d f9 76 12 75 d2 6f f2 70 f2 01 1...	
75851...	F...	12	Rx	0		
75851...	I	301	AVL_STEA_DV	Rx	7 51 15 f8 7f ff 7f 11	
75851...	I	301	AVL_STEA_DV	Rx	7 51 15 f8 7f ff 7f 11	
75851...	I	4	137	Rx	2 fd 00	
75851...	I	3	d9	ANG_ACPD	Rx	8 9b 99 00 c0 00 e0 7f f0
75848...	I	299		Rx	5 9e ff ff ff ff	
75851...	F...	21		Rx	0	
75851...	I	4	a5	TORQ_CRSH_1	Rx	8 45 f5 48 f7 7f 00 00 fd
75851...	I	3	a5	TORQ_CRSH_1	Rx	8 fe f9 48 f7 7f 00 00 fd
75836...	F...	23		Rx	16 7c 10 05 05 ea f3 53 20 74 10 20 f...	
75851...	F...	26		Rx	0	



problem characterization



task: finding errors

process: test drives

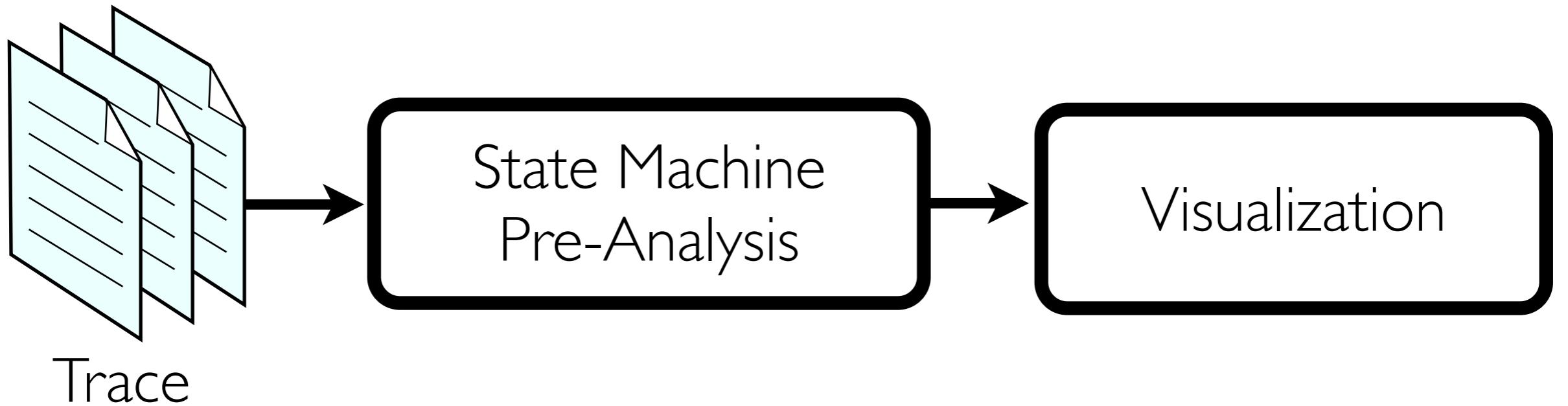
data: recorded traces (15k messages/sec)

current practices: mainly textual lists

problems:

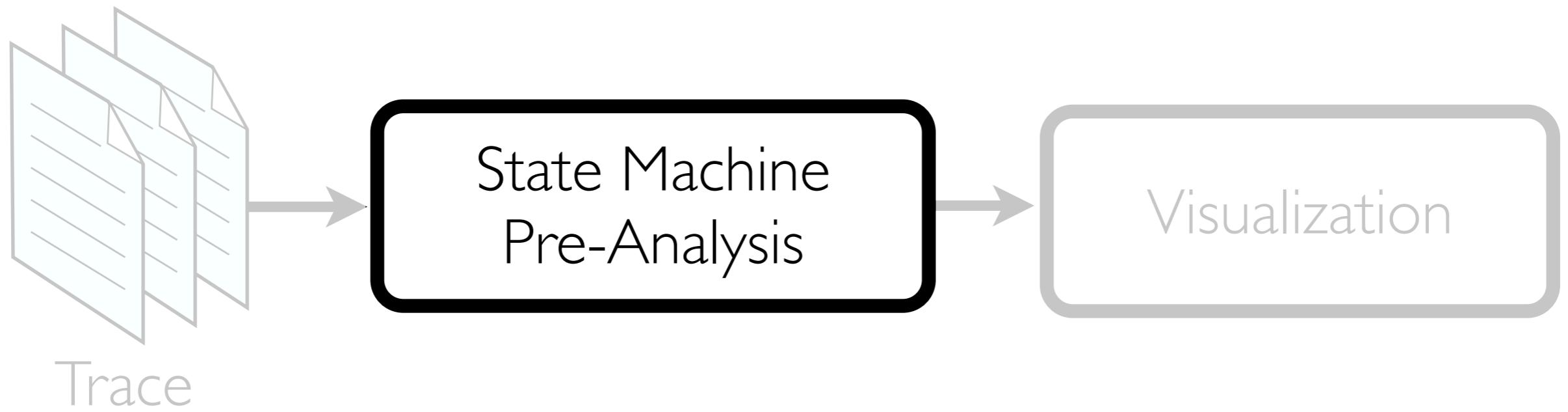
- handling masses of test traces
(large and many)
- understanding correlation between trace
and car behaviour
- ...

cardiogram: overview

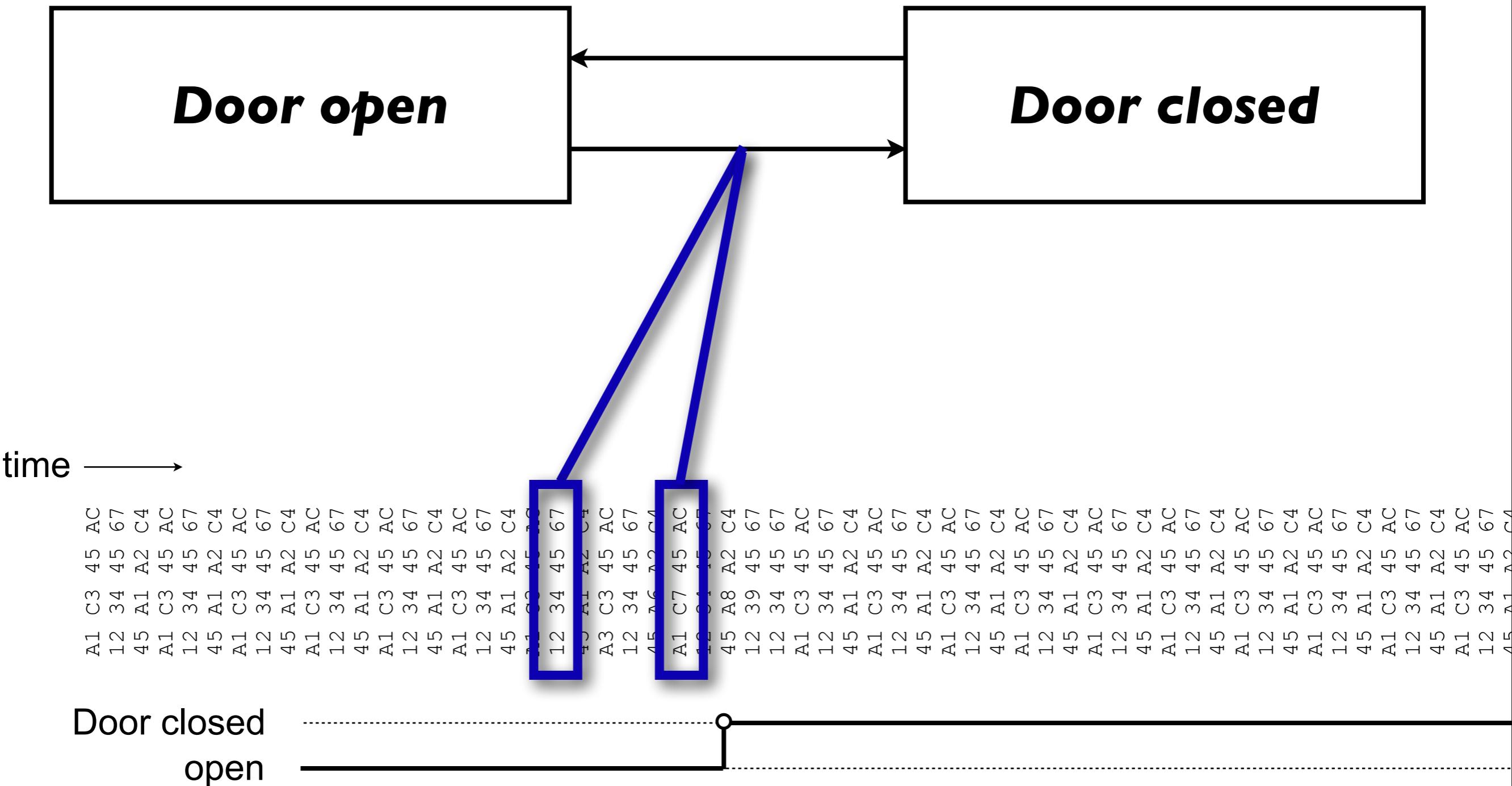


cardiogram:

state machine pre-analysis

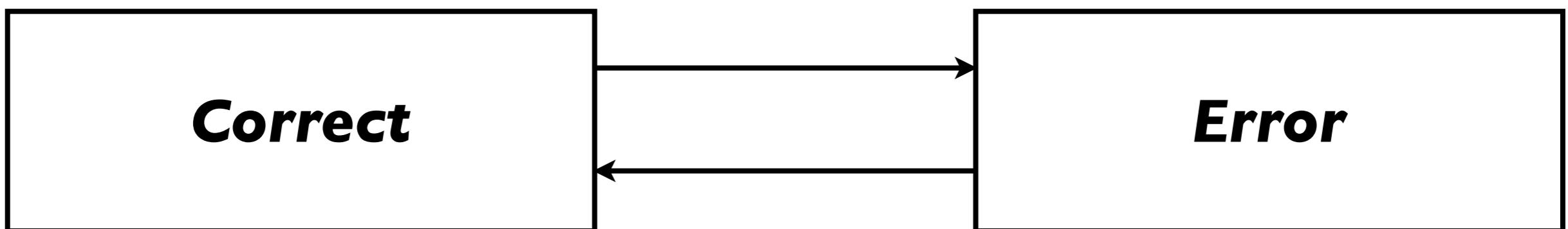


state machine: behaviour abstraction



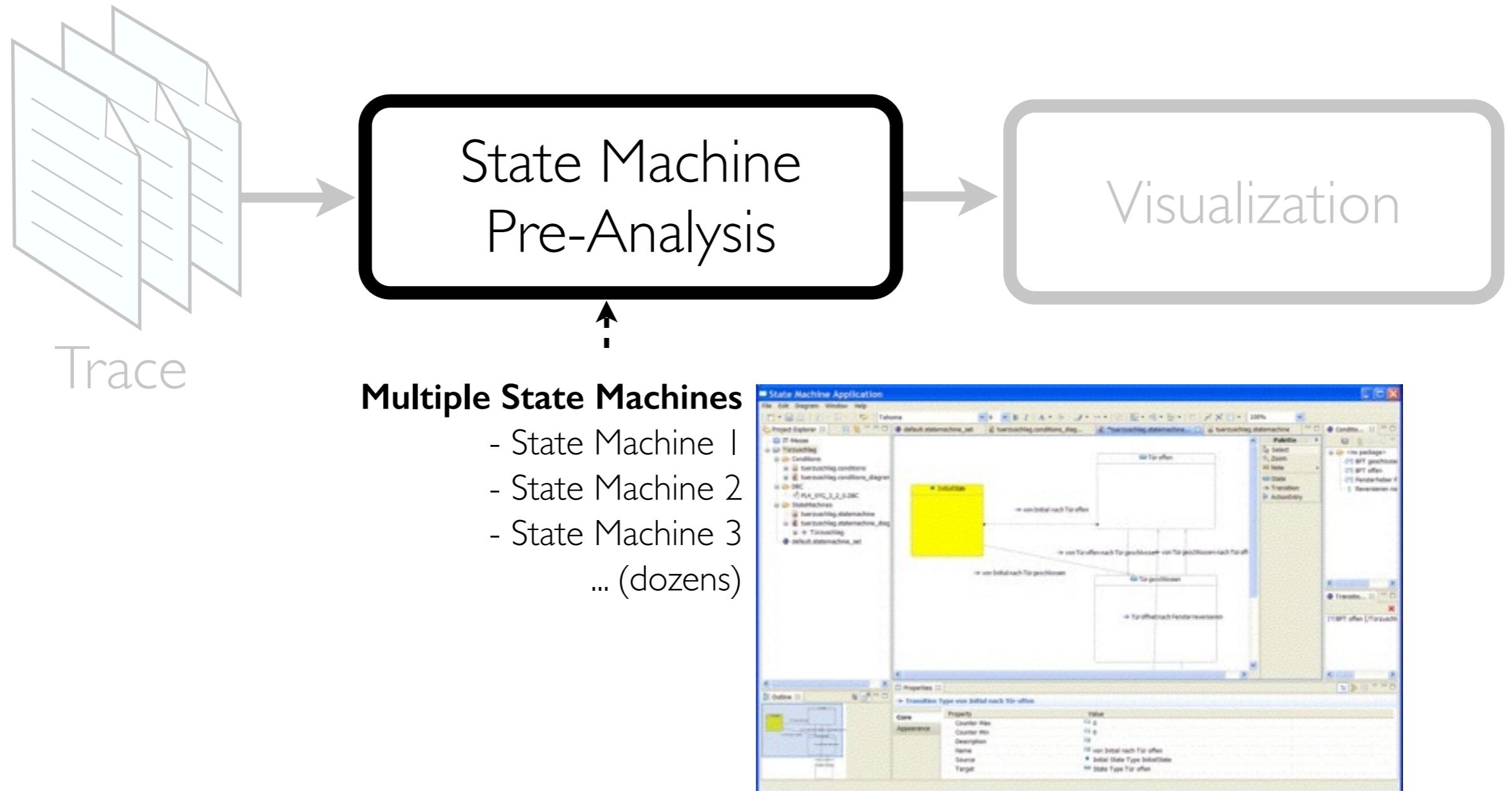
state machine:

automatic error detection



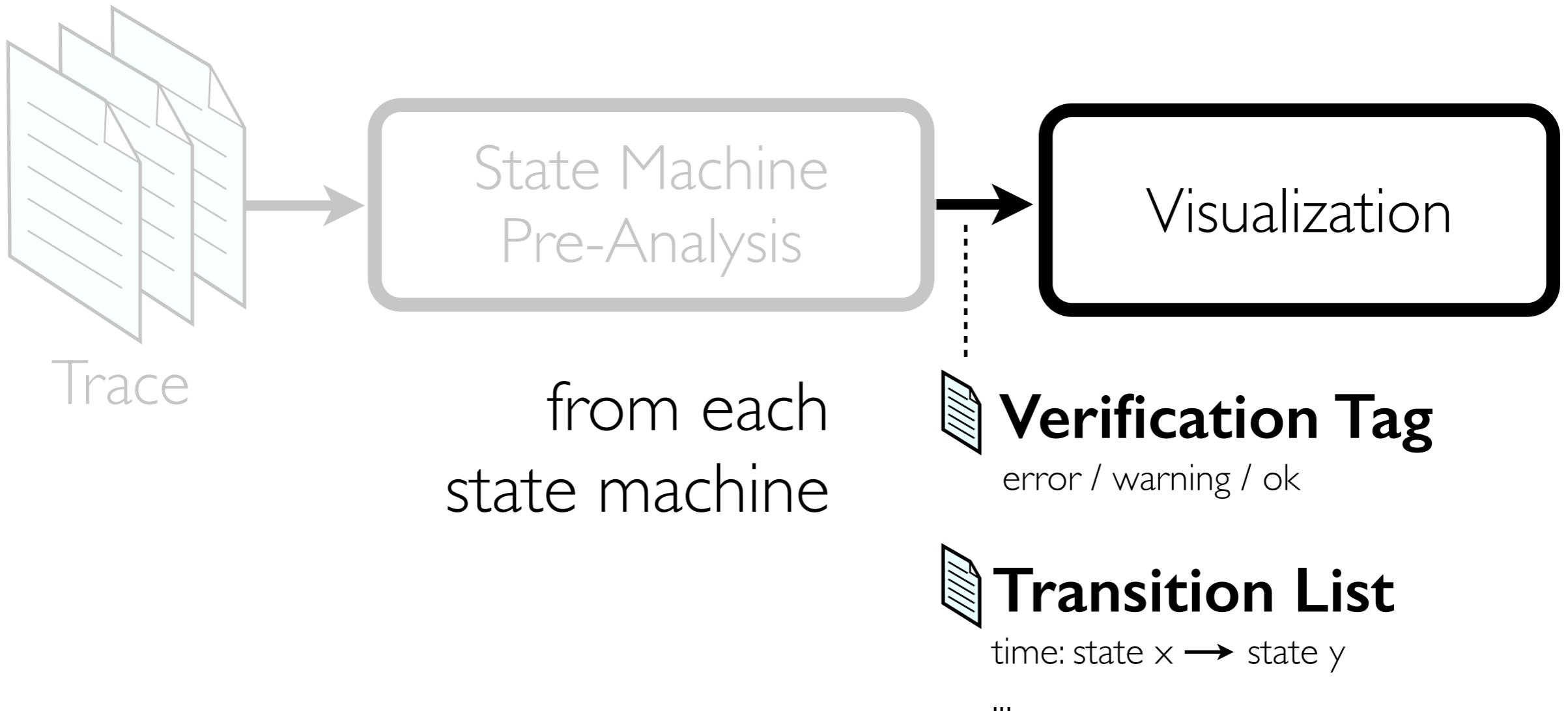
cardiogram:

create/select state machines



cardiogram:

- data interpretation
- data reduction



Available State Machines

diagnose_sg_id32	
diagnose_sg_id60	
diagnose_sg_id5F	
diagnose_sg_id27	
diagnose_sg_id29	
diagnose_sg_id56	
diagnose_sg_id1	
diagnose_sg_id67	
diagnose_sg_id36	
diagnose_sg_id16	
Diagnose_Funktional	
diagnose_sg_id40	
diagnose_sg_id0	
diagnose_sg_id78	
diagnose_sg_id72	
diagnose_sg_id62	
diagnose_sg_id63	
diagnose_sg_id73	
diagnose_sg_id64	
diagnose_sg_id44	
diagnose_sg_id50	
diagnose_sg_id60	
diagnose_sg_id55	
diagnose_sg_id4B	
diagnose_sg_id3F	
diagnose_sg_id47	
diagnose_sg_id5B	
diagnose_sg_idA0	
diagnose_sg_id18	
diagnose_sg_id41	
diagnose_sg_id71	
diagnose_sg_id37	
diagnose_sg_id3C	

Visualization View

diagnose_sg_id12 (9 state(s))

ERROR ! TimeOut sg_id11

WARN ! Functional_7F_Response_>

OK ! Pos Antwort (FC)

OK ! Anfrage FirstFrame

OK ! Pos Antwort (SF)

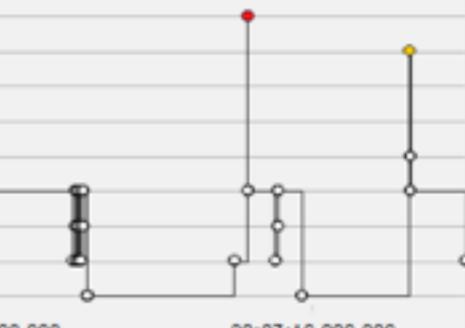
OK ! Ueberwachung_aktiv >

OK ! Pos Antwort (FF)

OK ! Anfrage SingleFrame

INIT ! Functional_Request_Test

00:06:20,000.000 00:06:30,000.000 00:06:40,000.000 00:06:50,000.000 00:07:00,000.000 00:07:10,000.000



diagnose_sg_id60 (9 state(s))

WARN ! Neg Antwort - Grund 21

WARN ! Neg Antwort - Grund 7B_Erst

OK ! Pos Antwort (FC)

OK ! Anfrage FirstFrame

OK ! Pos Antwort (SF)

OK ! Ueberwachung_aktiv

OK ! Pos Antwort (FF)

OK ! Anfrage SingleFrame

INIT ! Functional_Request_Test >

00:06:20,000.000 00:06:30,000.000 00:06:40,000.000 00:06:50,000.000 00:07:00,000.000 00:07:10,000.000

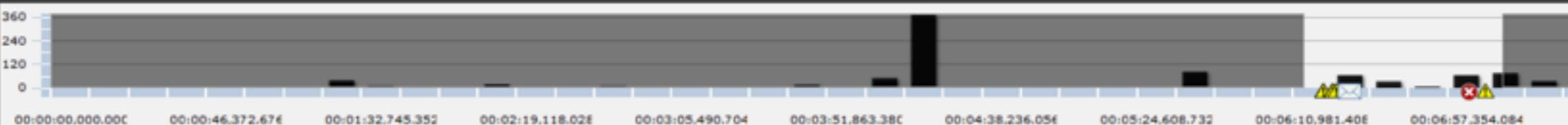


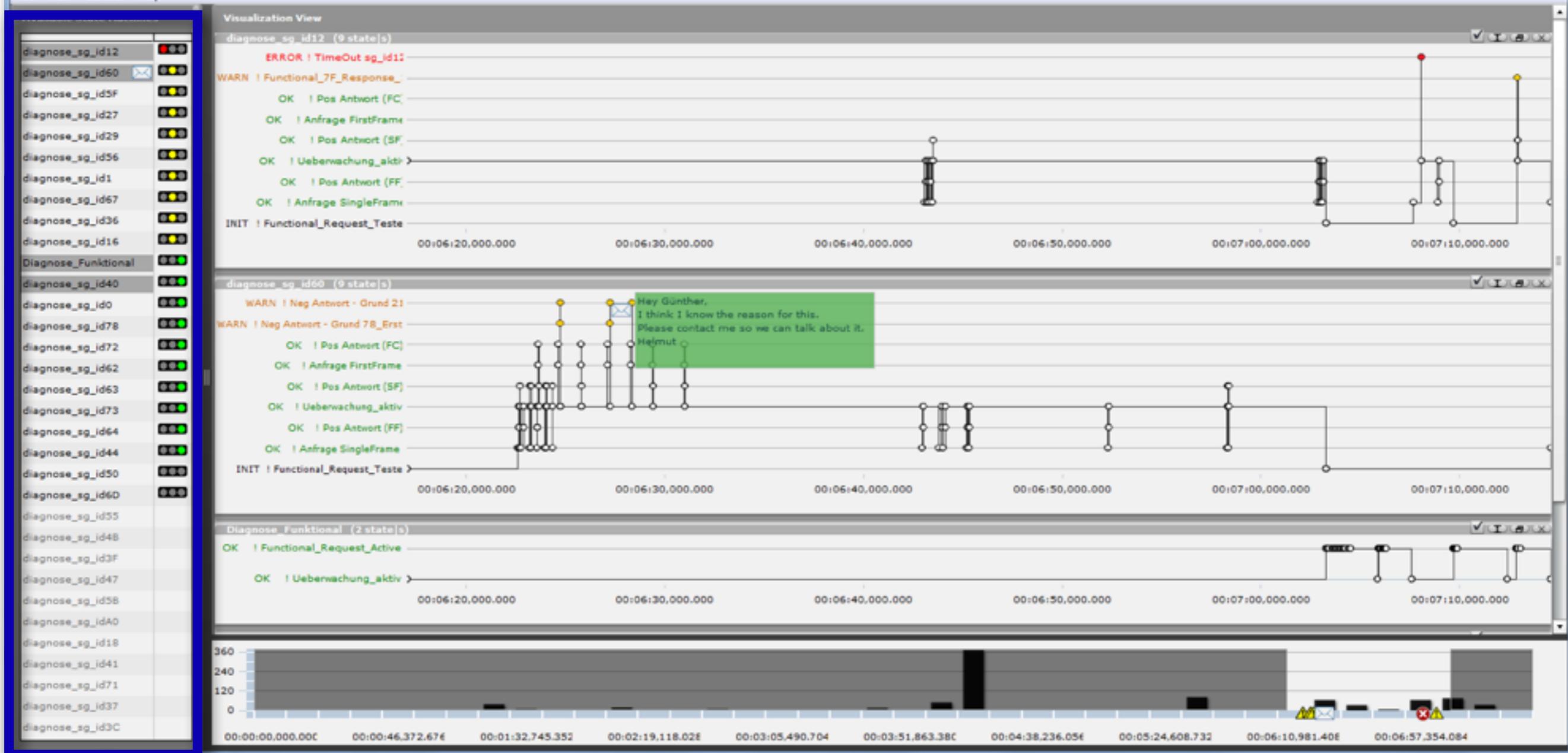
Diagnose_Funktional (2 state(s))

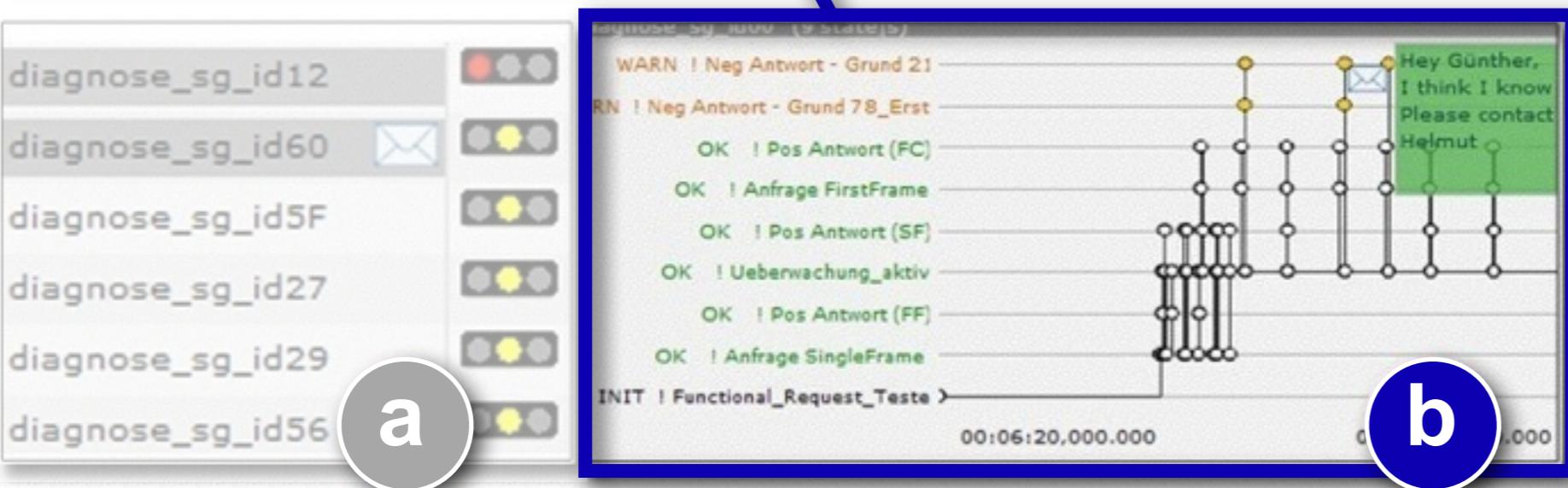
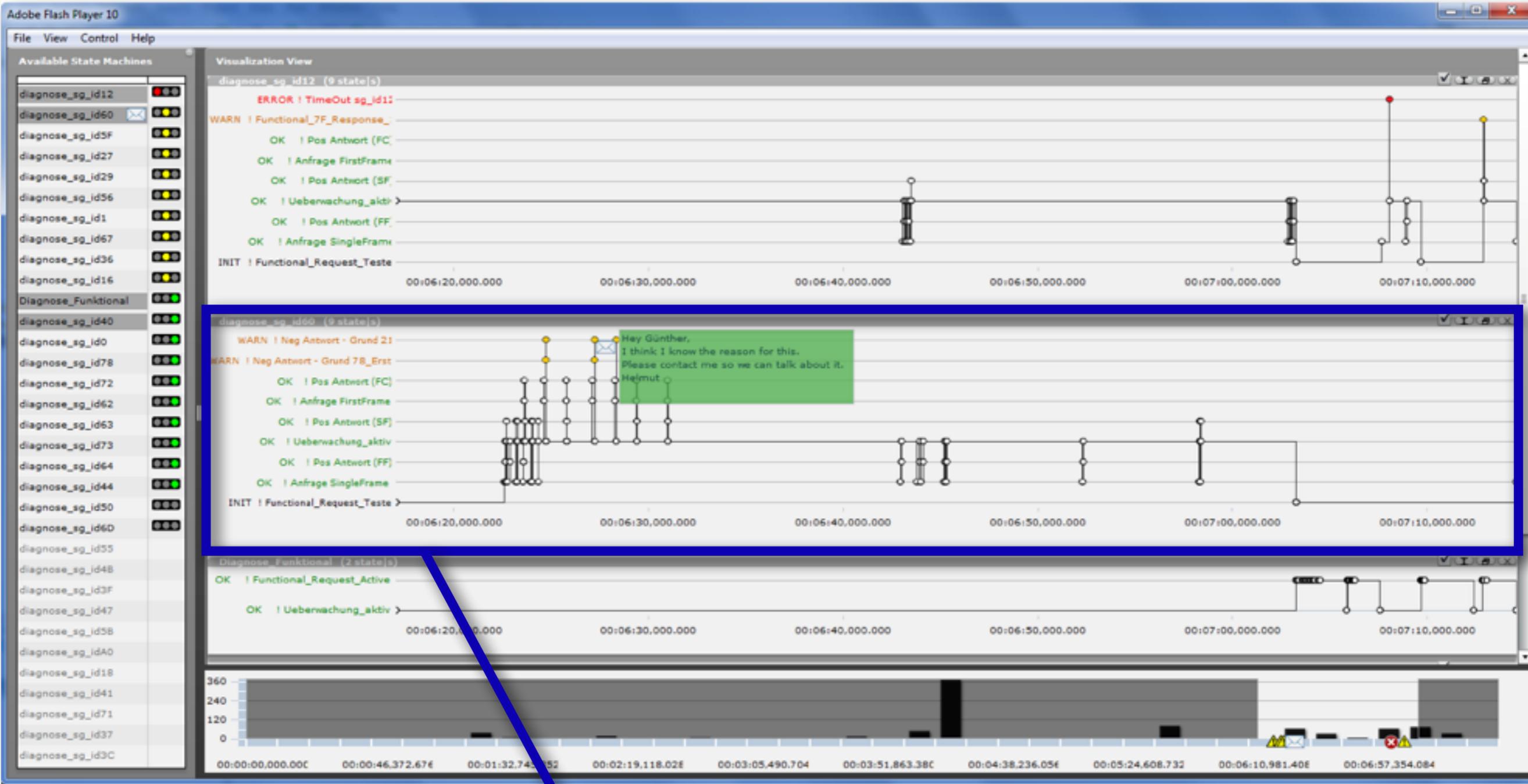
OK ! Functional_Request_Active

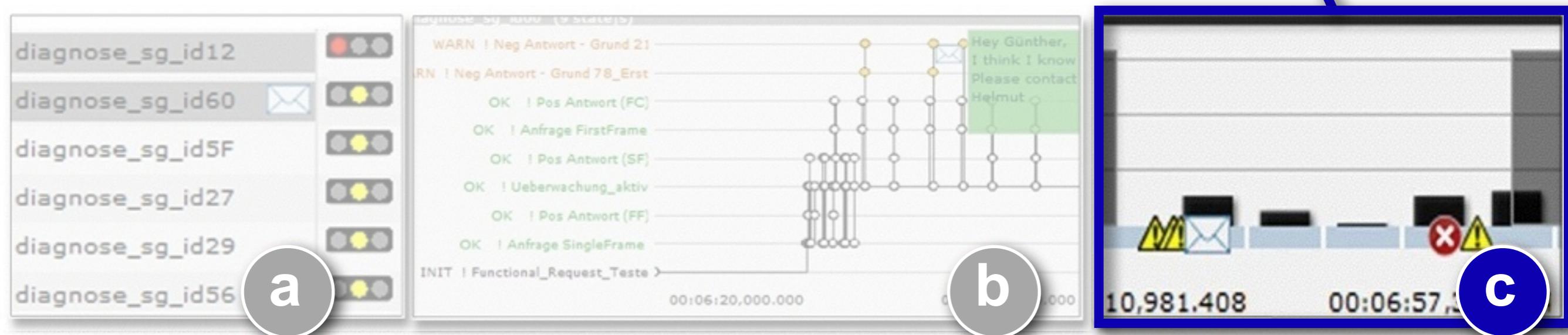
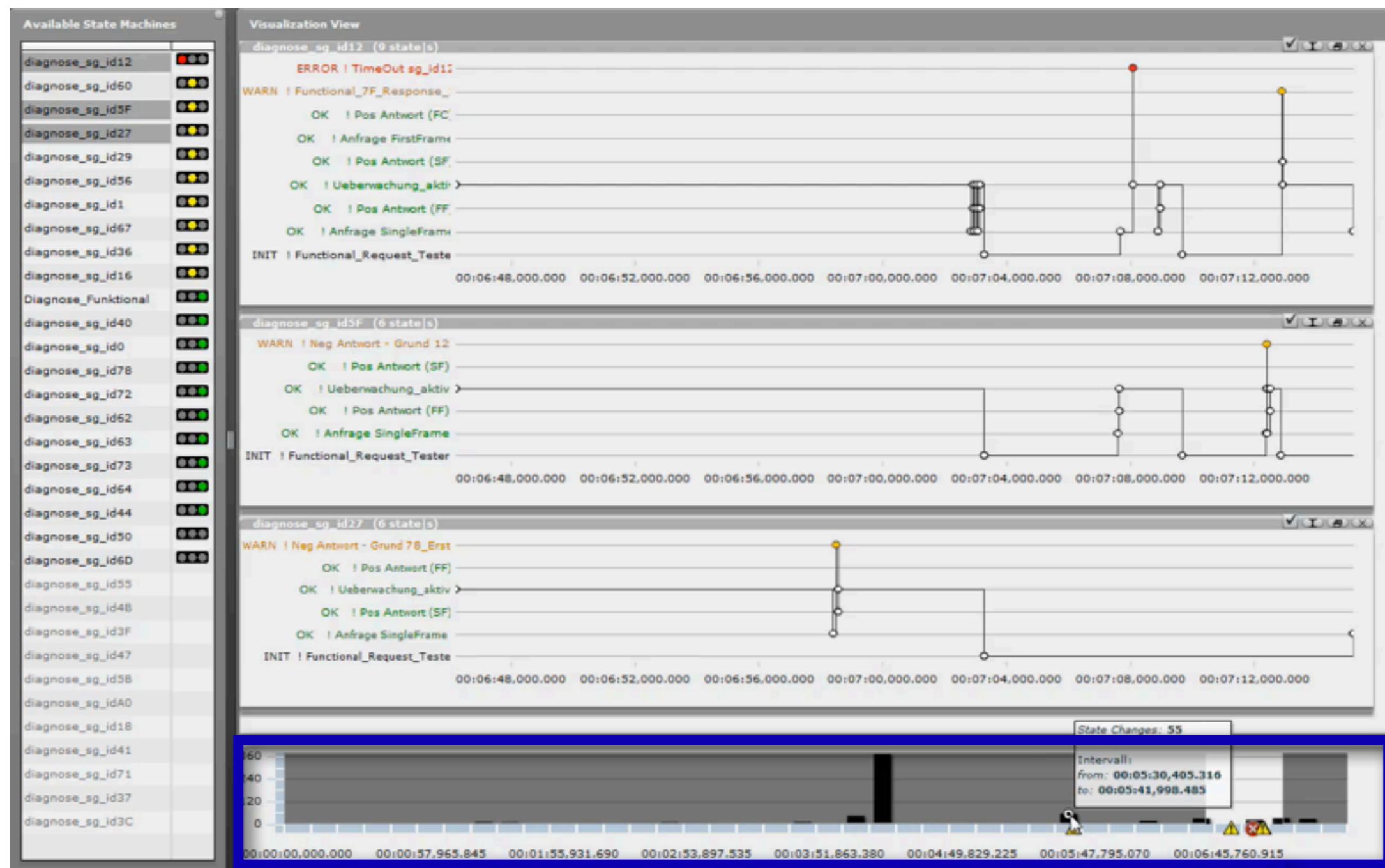
OK ! Ueberwachung_aktiv >

00:06:20,000.000 00:06:30,000.000 00:06:40,000.000 00:06:50,000.000 00:07:00,000.000 00:07:10,000.000









longitudinal field study:

1 year, 15 engineers

results

- externalization and sharing of expert knowledge

longitudinal field study:

1 year, 15 engineers

results

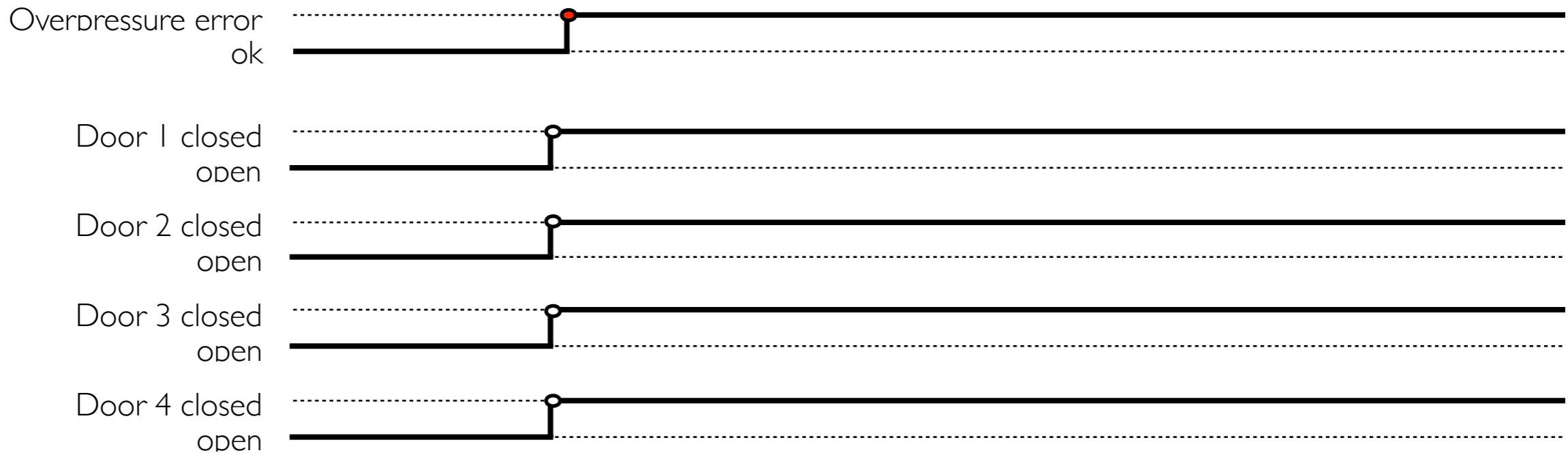
- externalization and sharing of expert knowledge
- complete coverage of traces vs. sparse sampling

longitudinal field study:

1 year, 15 engineers

results

- externalization and sharing of expert knowledge
- complete coverage of traces vs. sparse sampling
- understand behavioral correlations



longitudinal field study:

1 year, 15 engineers

results

- externalization and sharing of expert knowledge
- complete coverage of traces vs. sparse sampling
- understand behavioral correlations

deployed and adopted

real users/real data:

Studies on high-dimensional data analysis techniques

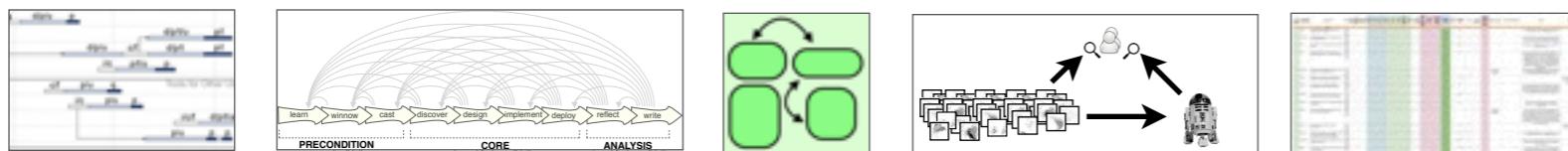


Applied visualization projects (9 BMW, 3 others)



right methods:

Novel and refined research methods/methodologies



design studies:
long and winding road with many pitfalls!



Information Visualization Evaluation in Large Companies: Challenges, Experiences and Recommendations

[Information Visualization 10(3), 2011]

M. Sedlmair, P. Isenberg, D. Baur, A. Butz

<http://homepage.univie.ac.at/michael.sedlmair/papers/sedlmair2011ivs.pdf>



Design Study Methodology: Reflections from the Trenches and the Stacks

[InfoVis 2012]

M. Sedlmair, M. Meyer, T. Munzner

<http://www.cs.ubc.ca/nest/imager/tr/2012/dsm/>



how to?

“A **design study** is a project in which visualization researchers analyze a specific real-world problem faced by domain experts, design a visualization system that supports solving this problem, validate the design, and reflect about lessons learned in order to refine visualization design guidelines.”

[Sedlmair et al.: Design Study Methodology: Reflections from the Trenches and the Stacks, InfoVis 2012]

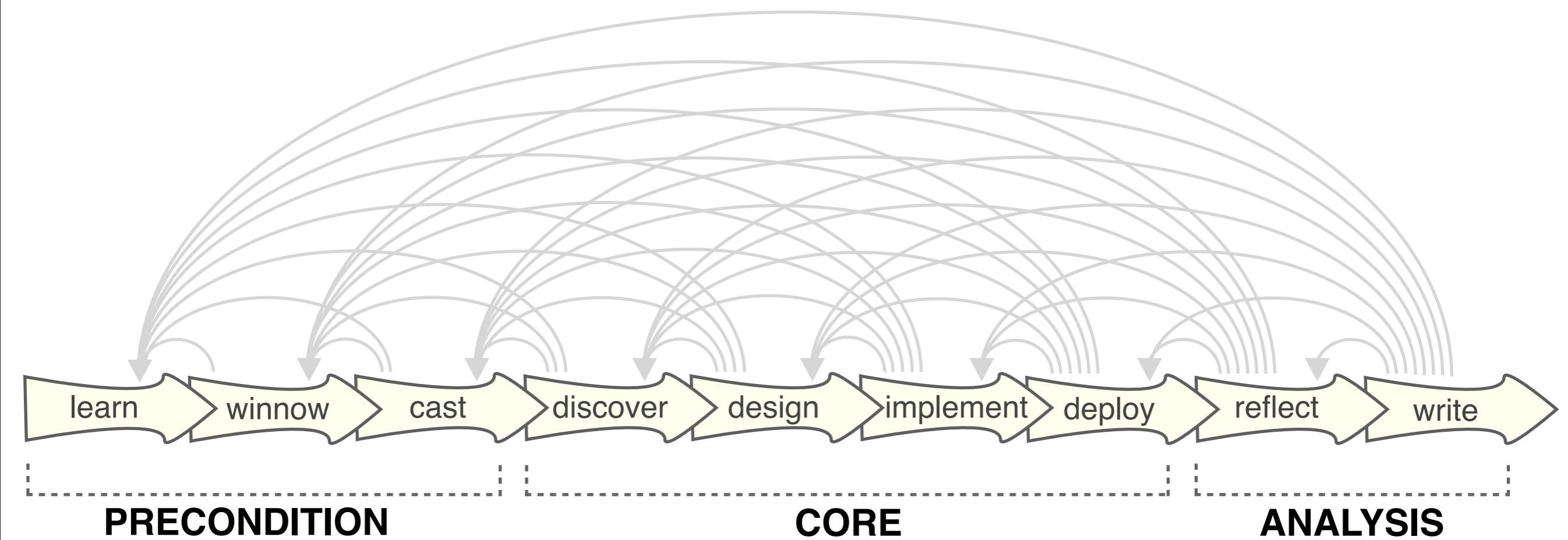
Design Study Methodology: Reflections from the Trenches and the Stacks

[InfoVis 2012]

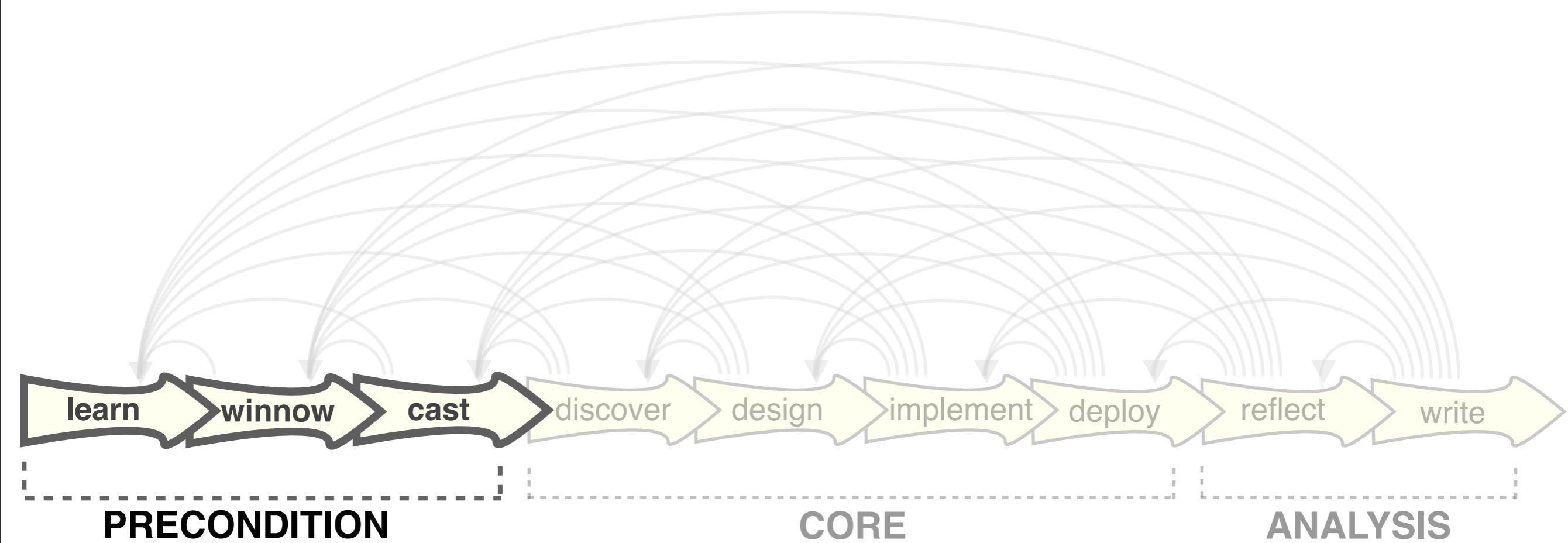
M. Sedlmair, M. Meyer, T. Munzner

<http://www.cs.ubc.ca/nest/imager/tr/2012/dsm/>

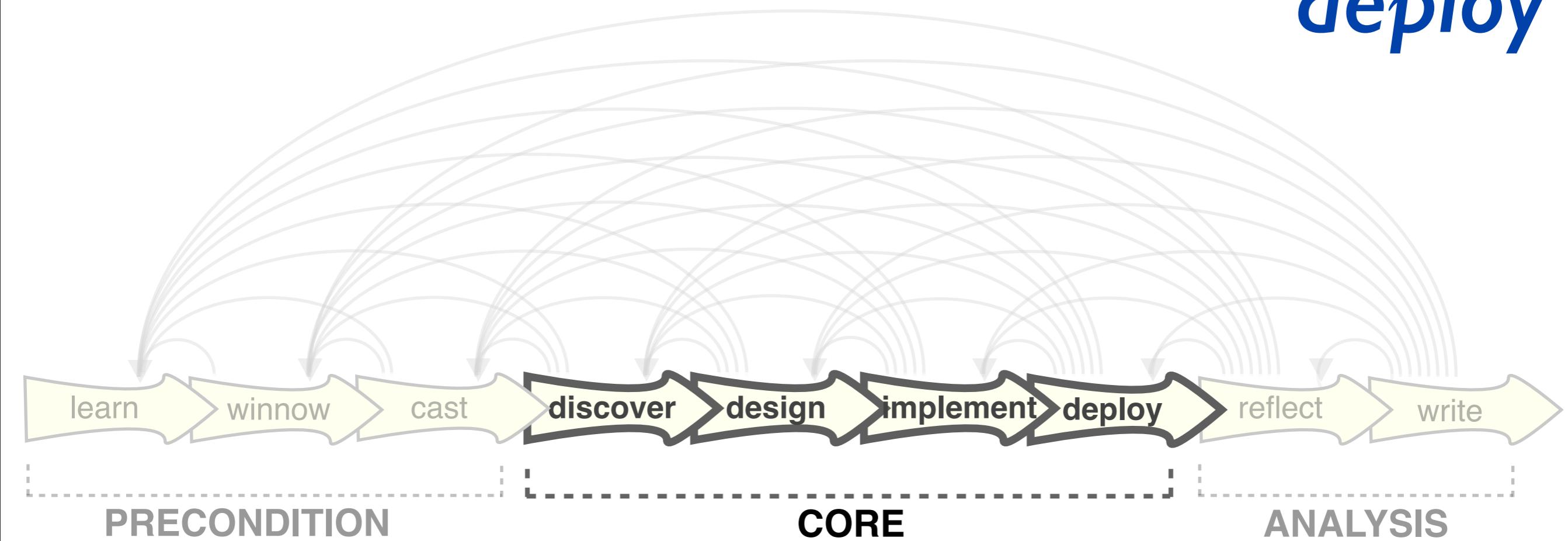




learn
winnow
cast

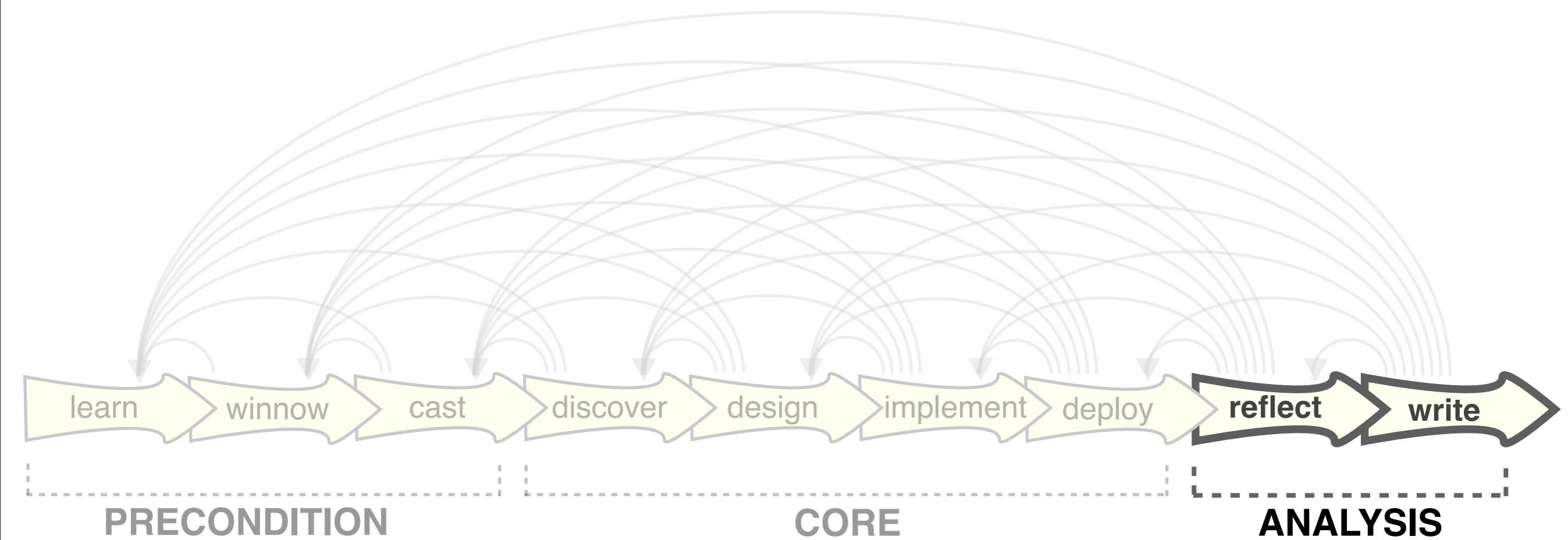


discover
design
implement
deploy



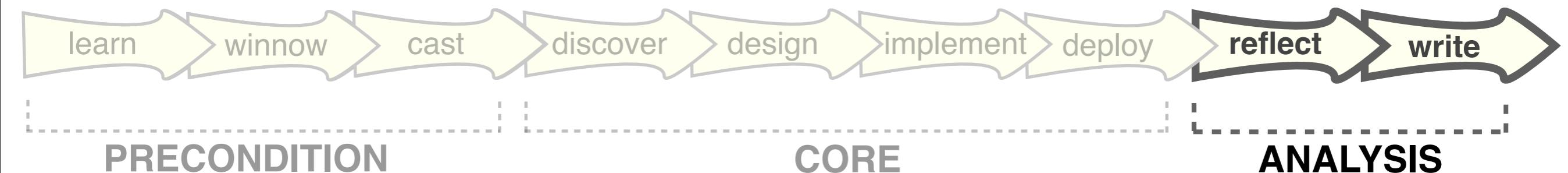
reflect

write



32 pitfalls along the way

Example: Premature publishing



I can write a design study
paper in a week!



“writing is research”

[Wolcott: Writing up qualitative research, 2009]

metaphor

horse race vs. music debut

Must be first!



Am I ready?



http://www.alaineknipes.com/interests/violin_concert.jpg

<http://www.prlog.org/10480334-wolverhampton-horse-racing-live-streaming-wolverhampton-handicap-8-jan-2010.html>

technique-driven

problem-driven

vision

design studies

“the visualization and data analysis cookbook”

abstract data & task



data analysis technique



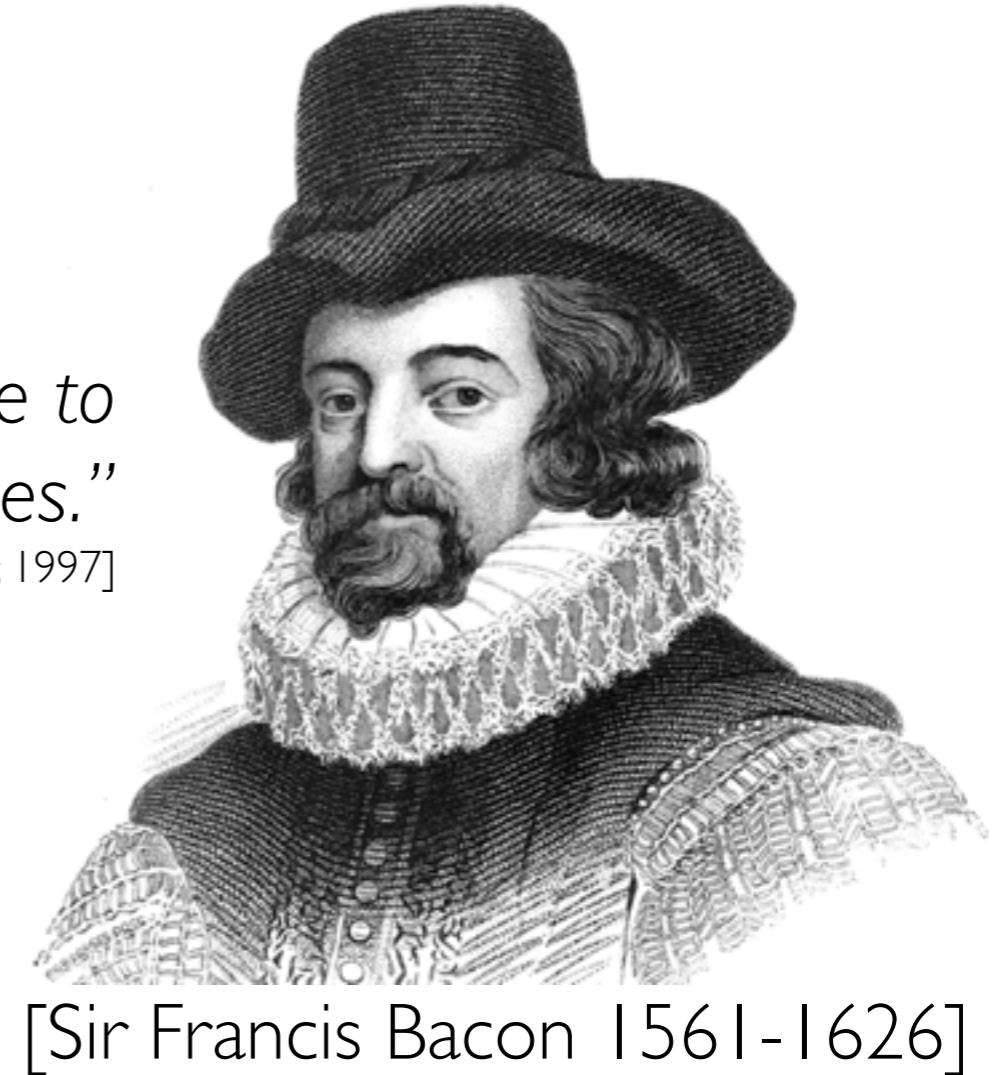
“the visualization and data analysis cookbook”

“Real practical experiments [...] are indispensable to an understanding of natural processes.”

[Brewer, 1997]

vast amounts of real users/
real data work necessary

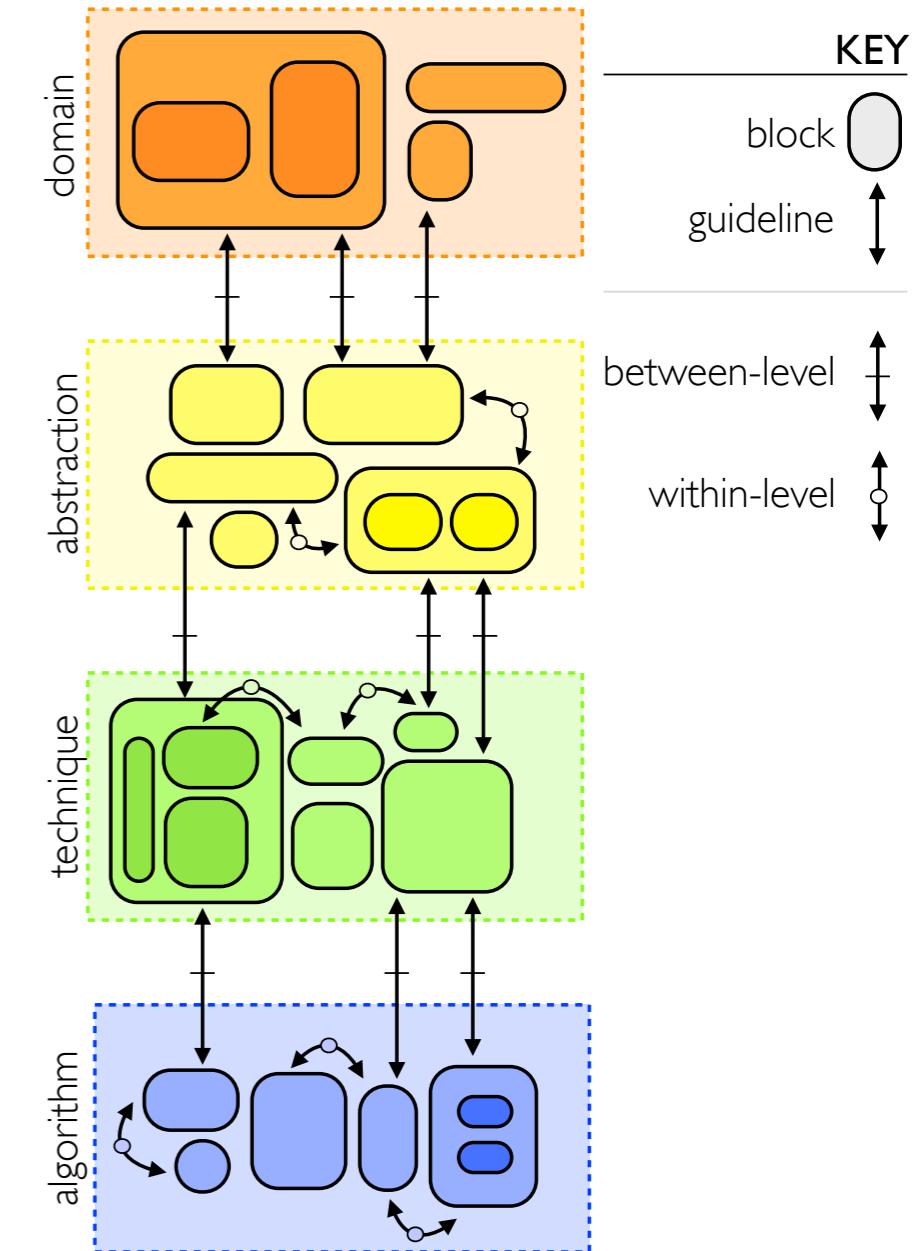
natural science
vs. design research



[Sir Francis Bacon 1561-1626]

“the visualization and data analysis cookbook”

blocks and guidelines



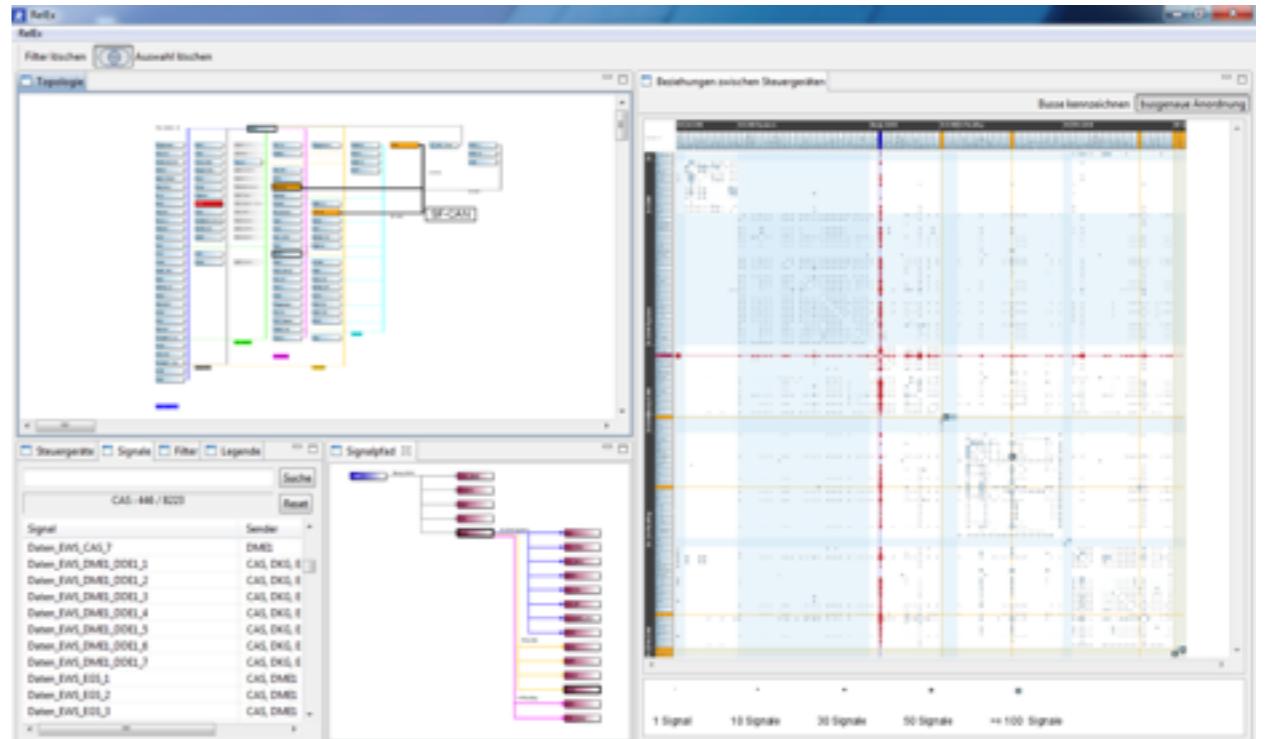
The Nested Blocks and Guidelines Model

M. Meyer, M. Sedlmair, T. Munzner [IVI 2013, to appear]



“the visualization and data analysis cookbook”

abstraction crucial!



RelEx: Visualization for Actively Changing Overlay Network Specifications

M. Sedlmair, A. Frank, T. Munzner, A. Butz [InfoVis 2012]

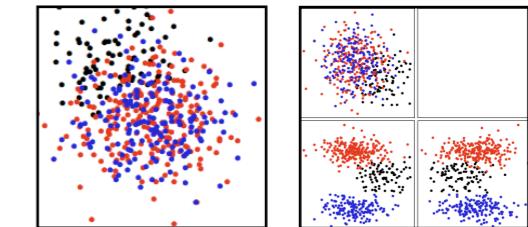
<http://www.cs.ubc.ca/labs/imager/tr/2012/RelEx/relex.pdf>



summary

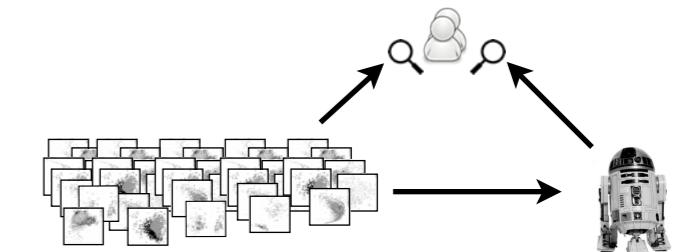
real data:

- taxonomy of separation factors / evaluation of measures
- evaluation of 2D vs. 3D vs. SPLOM



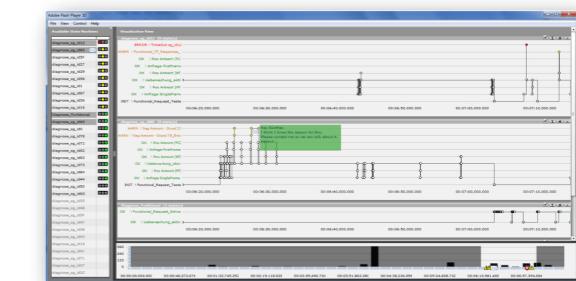
right methods:

- data study



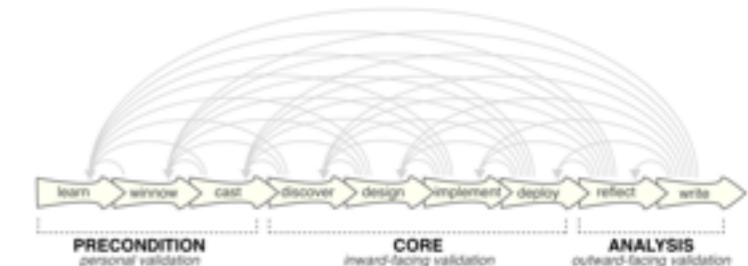
real users:

- Cardiogram



right methods:

- design study



vision:

- the visualization cook book

Visual Data Analysis: real users, real data, right methods

thank you!

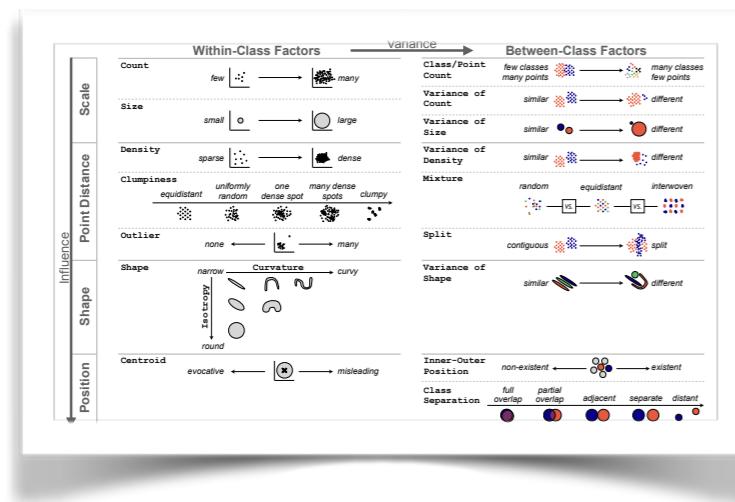
Michael Sedlmair

<https://homepage.univie.ac.at/michael.sedlmair>
michael.sedlmair@univie.ac.at

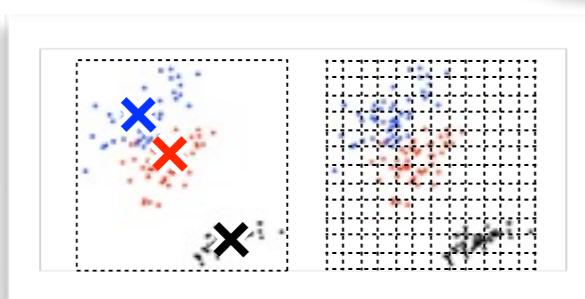
appendix

A Taxonomy of Visual Cluster Separation Factors [EuroVis 2012]

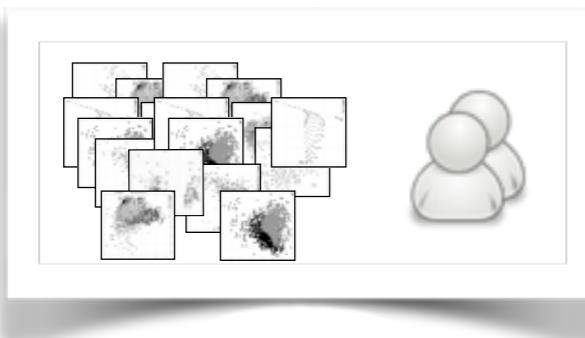
Contributions



Taxonomy of visual cluster separation factors



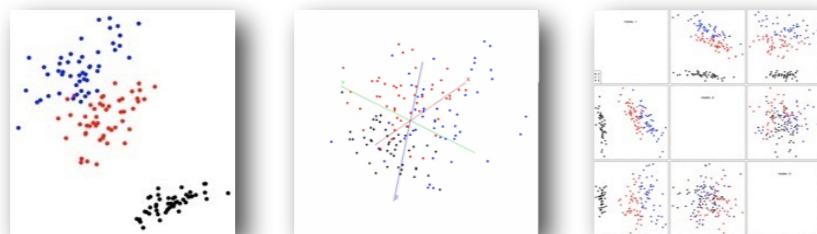
In-depth evaluation of 2 state-of-the-art separation measures



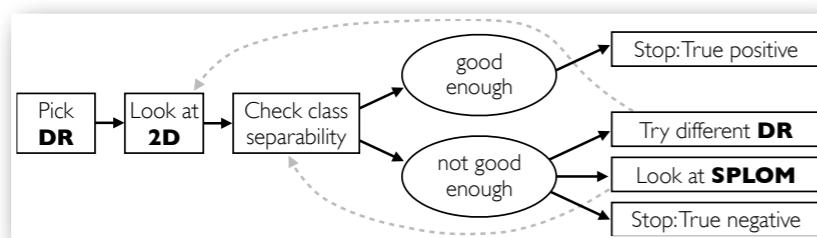
Qualitative data study

Empirical Guidance on Scatterplot and Dimension Reduction Technique Choices
[InfoVis 2013]

Contributions



In-depth evaluation of 3 visual encoding techniques for DR data

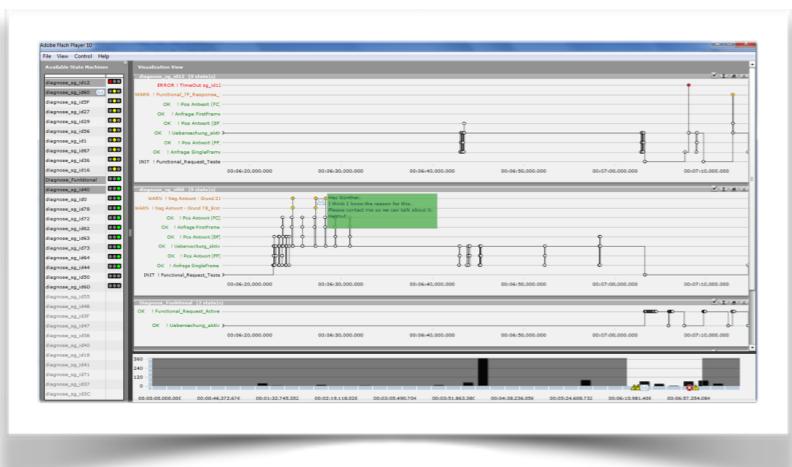


Workflow model (see paper)

Contributions



Problem and requirements analysis

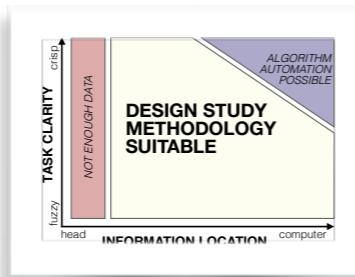


Cardiogram: computational and visual analysis approach

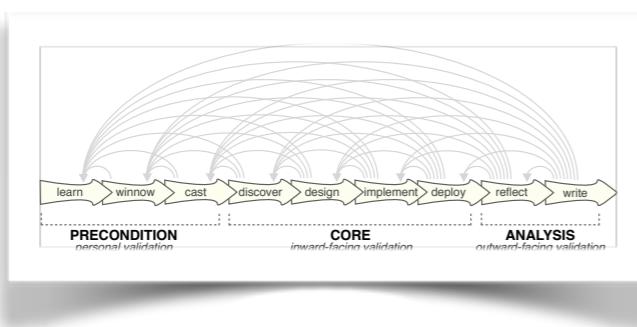


Longitudinal evaluation and adoption

Contributions



Definitions



9-stage framework

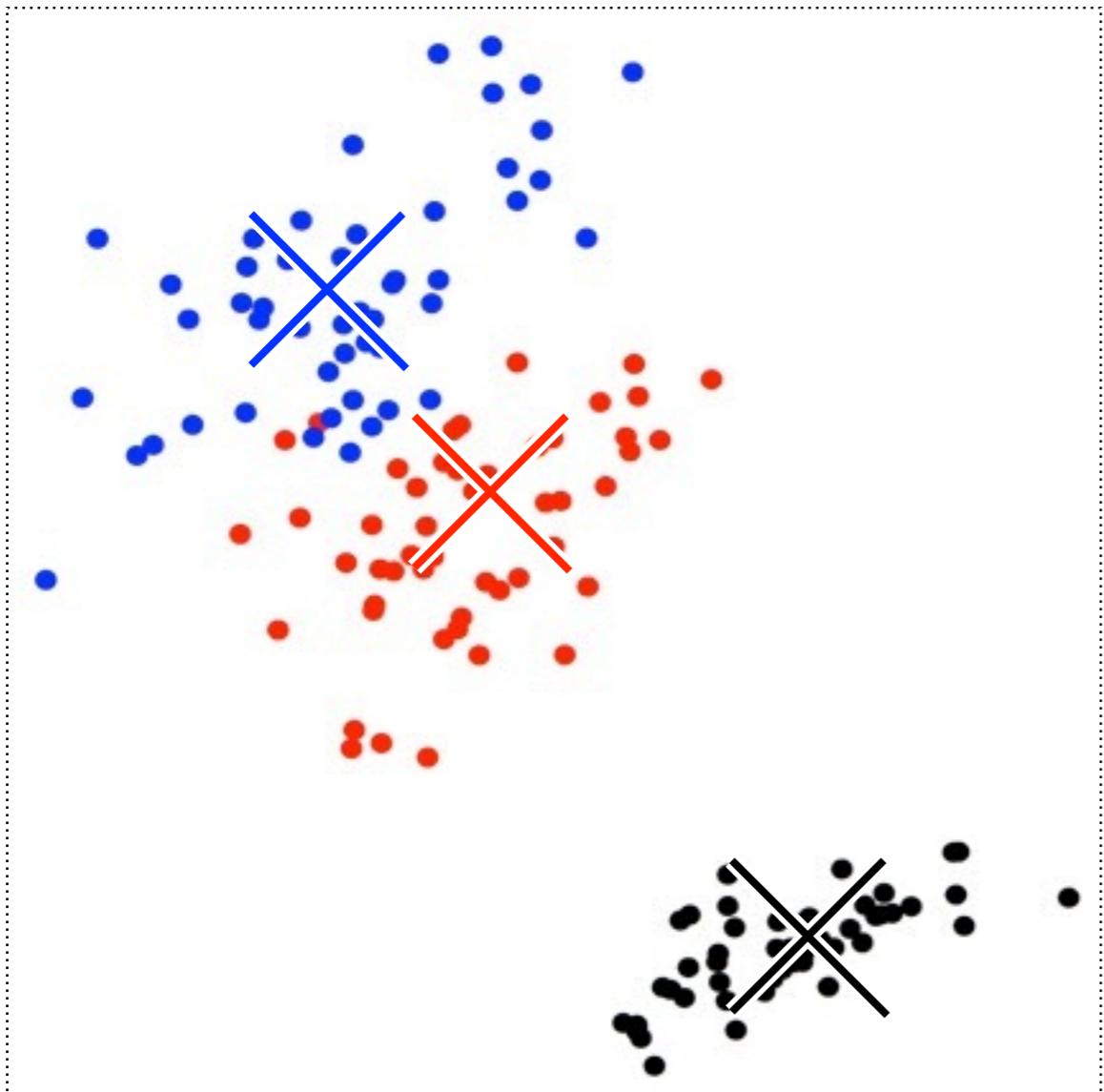
PF-1	premature advance: jumping forward over stages	general
PF-2	premature start: insufficient knowledge of vis literature	learn
PF-3	premature commitment: collaboration with wrong people	winnow
PF-4	no real data available yet)	winnow
PF-5	insufficient time available from potential collaborators	winnow
PF-6	no need for visualization: problem can be automated	winnow
PF-7	researcher expertise does not match domain problem	winnow
PF-8	no need for research: engineering vs. research project	winnow
PF-9	no need for change: existing tools are good enough	winnow

32 pitfalls



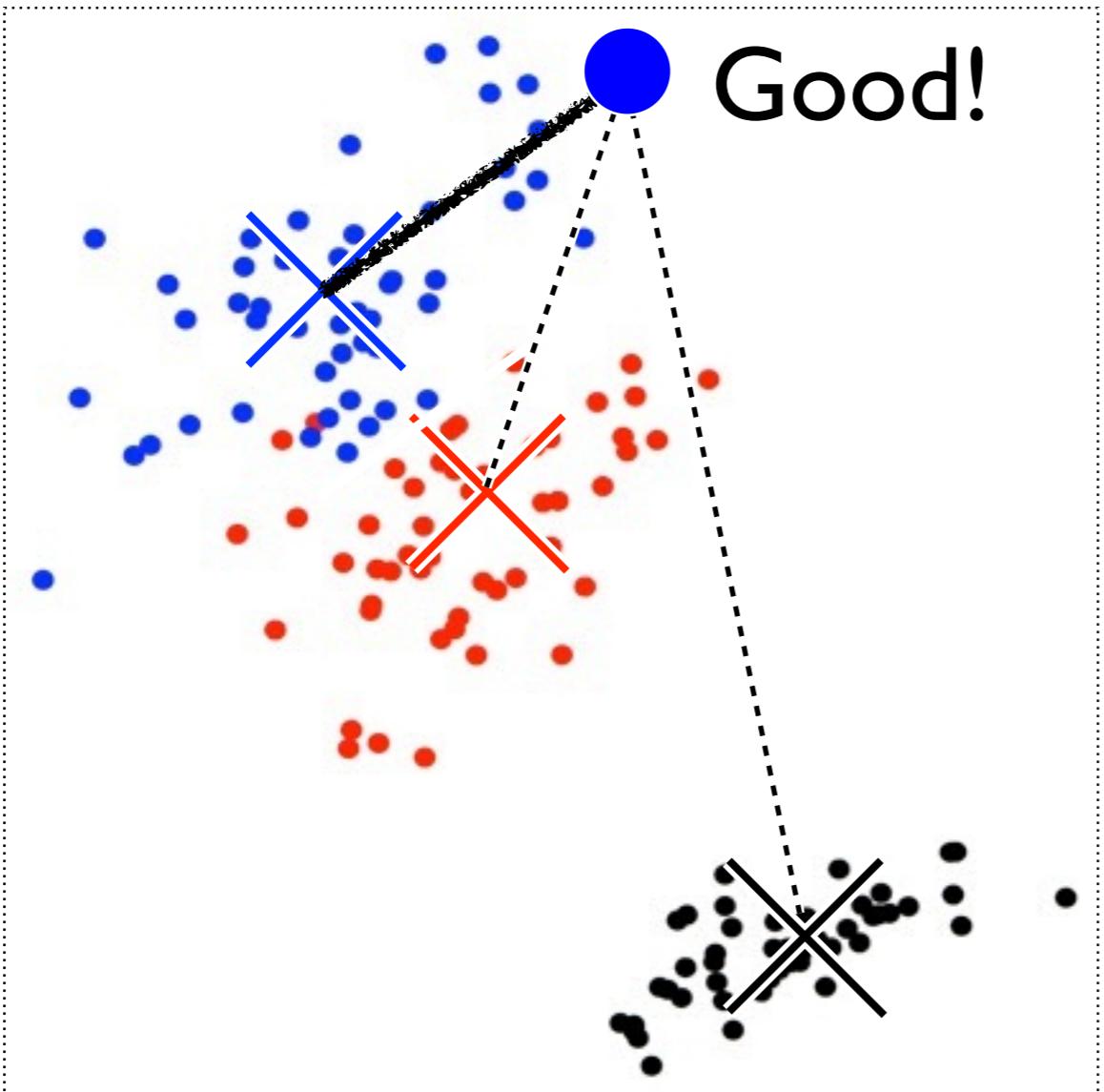
Comparison to related methodologies

Centroid Measure



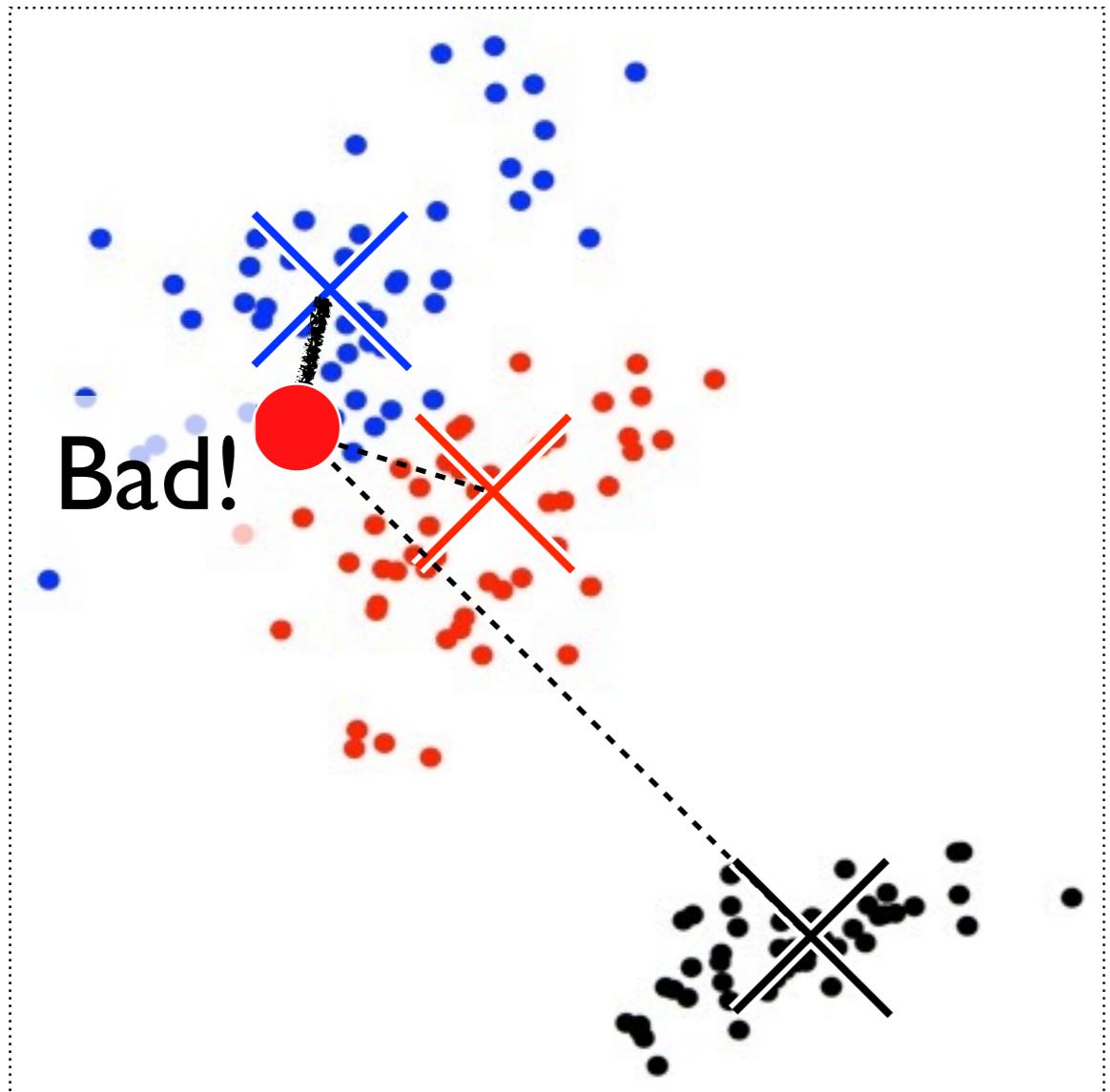
Centroid: 93

Centroid Measure



Centroid: 93

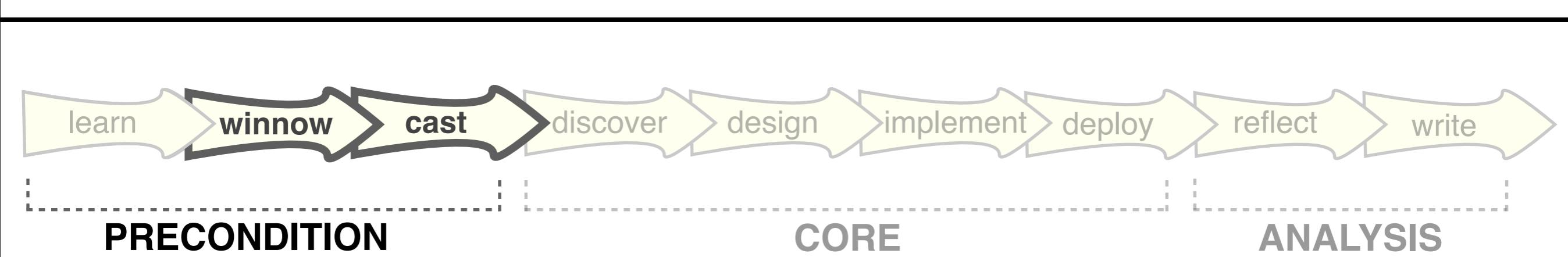
Centroid Measure



Centroid: 93

32 pitfalls

Example: Premature collaboration



I'm a domain expert!
Wanna collaborate?

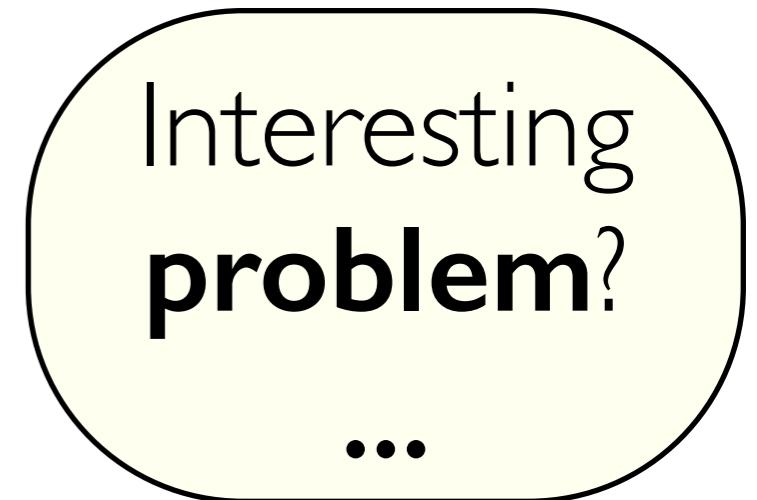
Of course!!!



considerations



COLLABORATOR



MR. VIS

roles



COLLABORATOR

Are you a
user???

... or maybe a
**fellow tool
builder?**



MR. VIS