Dimensionality Reduction From Several Angles

Tamara Munzner

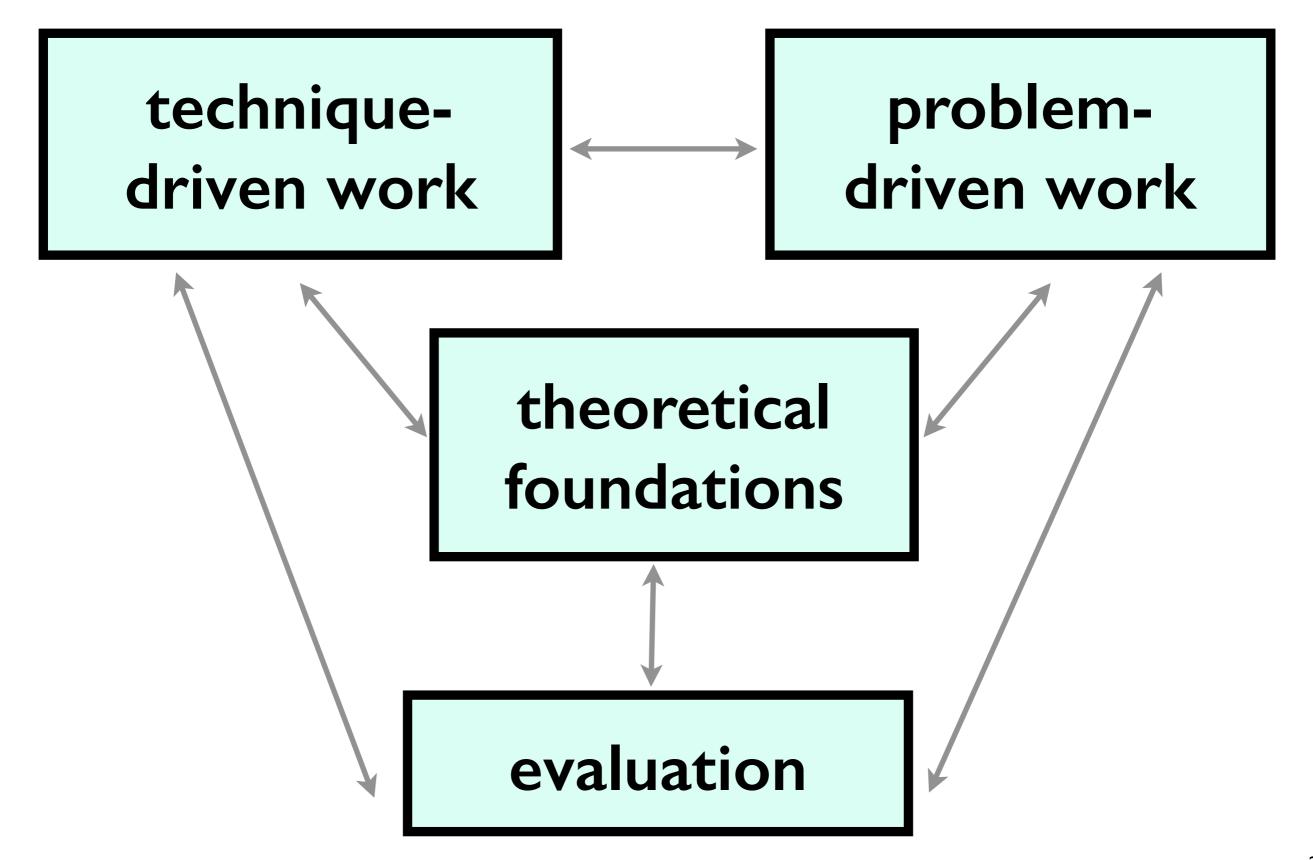
Department of Computer Science University of British Columbia

UBC-Okanagan, Kelowna BC 23 August 2016

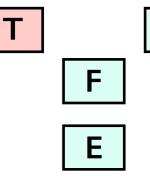
http://www.cs.ubc.ca/~tmm/talks.html#kelowna16

<u>@tamaramunzner</u>

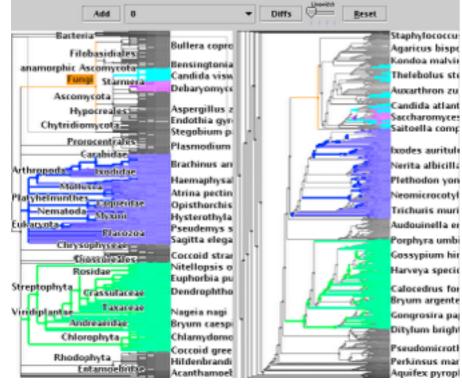
Quick Research Overview



Technique-driven: Graph Drawing



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TreeJuxtaposer

James Slack

Kristian Hildebrand

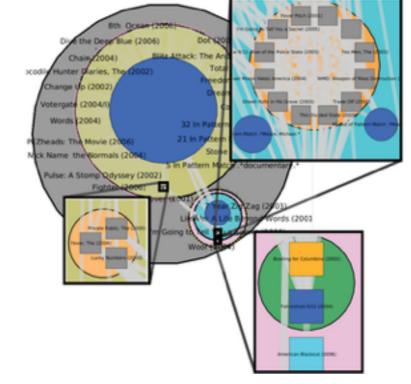


Daniel Archambault



David Auber (Bordeaux)

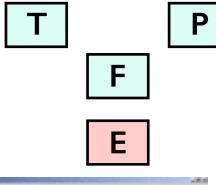




TopoLayout SPF Grouse GrouseFlocks TugGraph

3

Evaluation: Graph Drawing



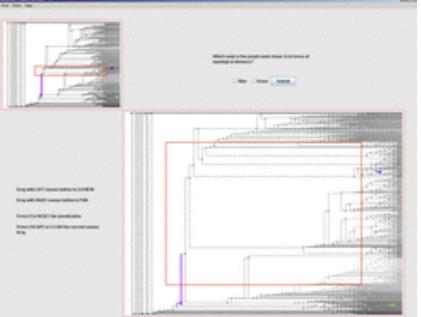


Adam Bodnar



(UBC)

Joanna McGrenere



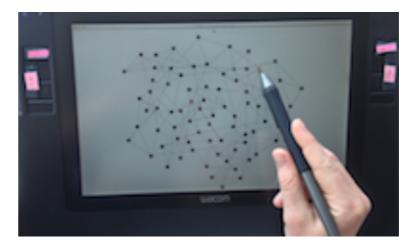
Stretch and squish navigation

Jessica Dawson



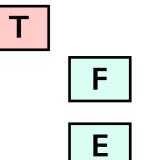
Joanna McGrenere (UBC)





Search set model of path tracing

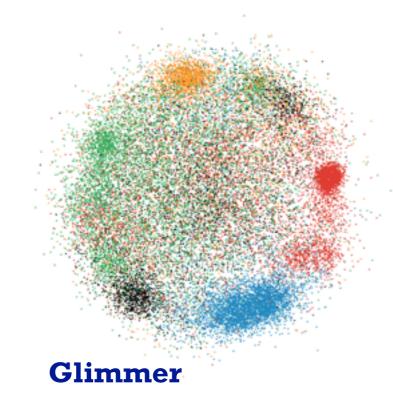
Technique-driven: Dimensionality Reduction

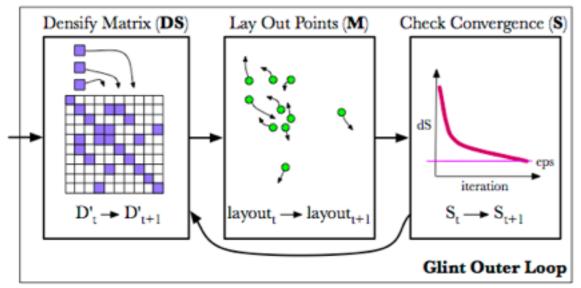


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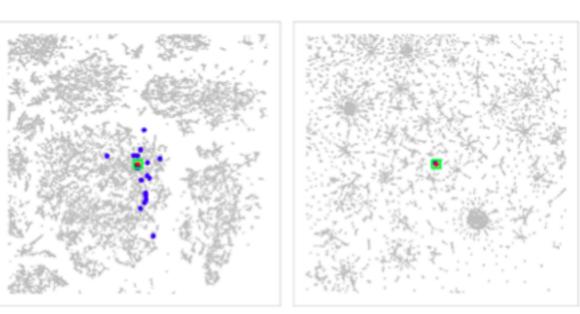
Stephen Ingram











QSNE

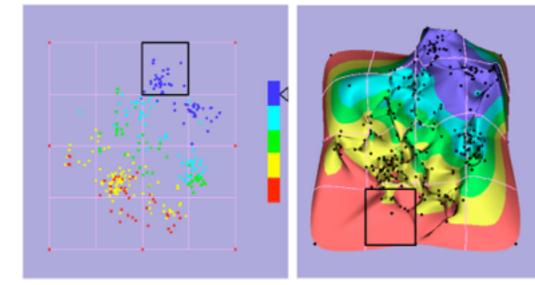
DimStiller

Glint

Evaluation: Dimensionality Reduction

Melanie Tory





Points vs landscapes for dimensionally reduced data

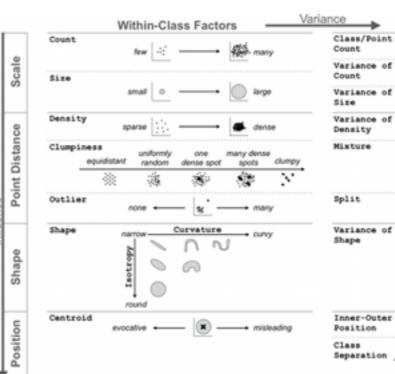
Т

Michael Sedlmair

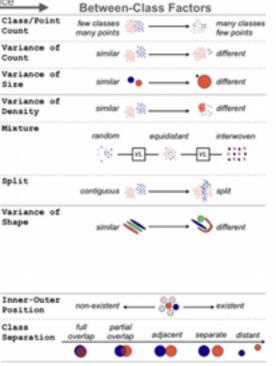


Melanie Tory (UVic)





Guidance on DR & scatterplot choices



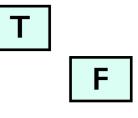
Taxonomy of cluster separation factors

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Problem-driven: Genomics



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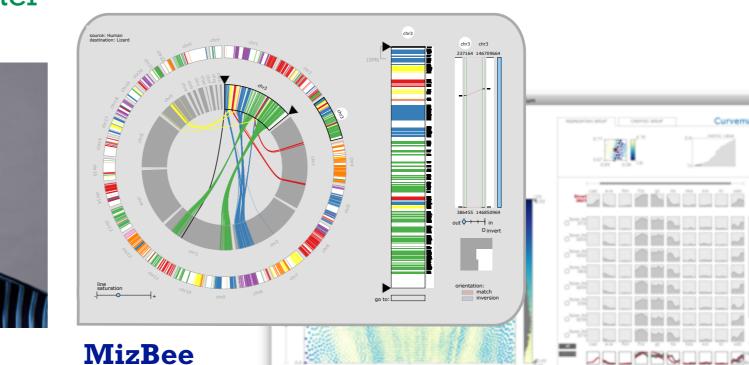


Robert Kincaid





Cerebral







MulteeSum, Pathline

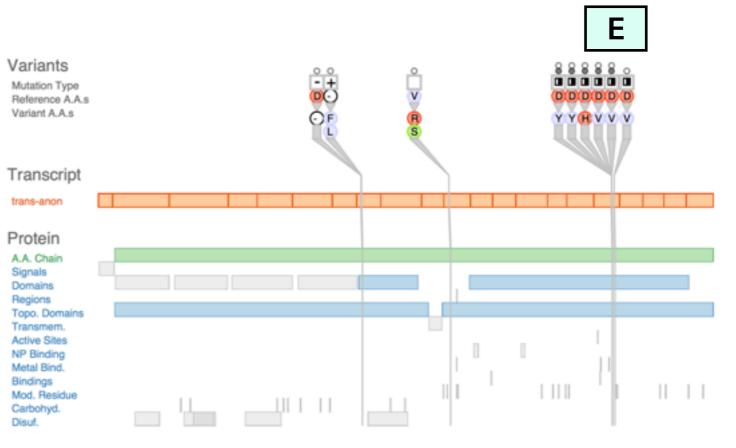
Problem-driven: Genomics, Fisheries Sim

Joel Ferstay



Cydney Nielsen (BC Cancer)





Variant View



Maryam Booshehrian



Torsten Moeller (SFU)

Т

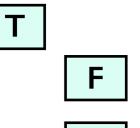
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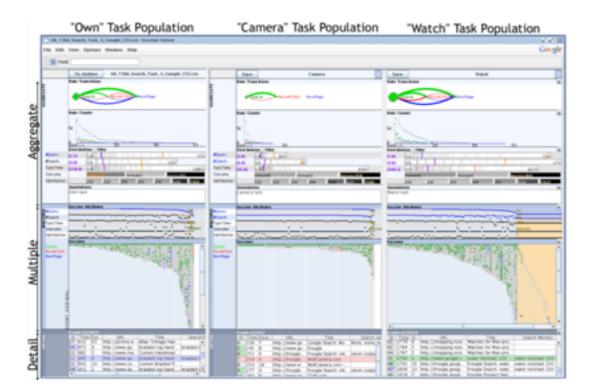


Vismon

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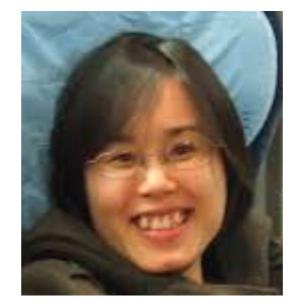
Problem-driven: Many Domains





SessionViewer: web log analysis

Heidi Lam



Diane Tang (Google)



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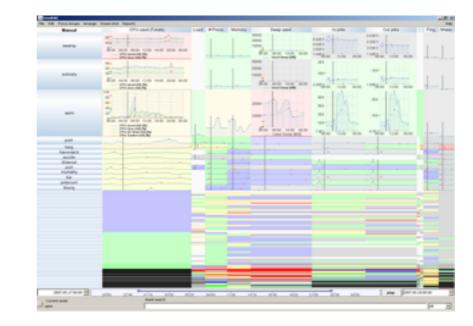


Peter McLachlan



Stephen North (AT&T Research)

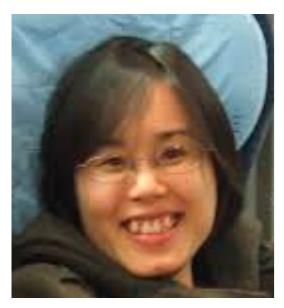




LiveRAC: systems time-series

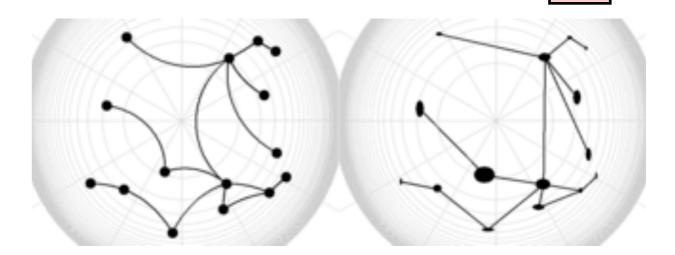
Evaluation: Focus+Context

Heidi Lam



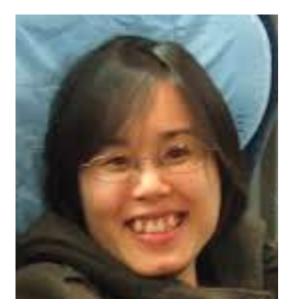


Ron Rensink



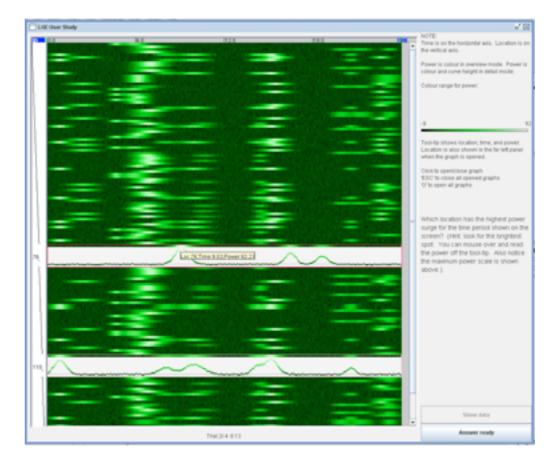
Distortion impact on search/memory

Heidi Lam



Robert Kincaid (Agilent)





Separate vs integrated views

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Journalism

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Matt Brehmer



Stephen Ingram



Jonathan Stray (Assoc Press)





Т

Overview

Johanna Fulda (Sud. Zeitung)



Matt Brehmer





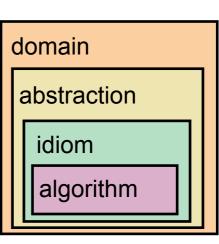
TimeLineCurator

Theoretical Foundations

- Visual Encoding Pitfalls
 - Unjustified Visual Encoding
 - Hammer In Search Of Nail
 - 2D Good, 3D Better
 - Color Cacophony
 - Rainbows Just Like In The Sky

Papers Process & Pitfalls

- Strategy Pitfalls
- What I Did Over My Summer
- Least Publishable Unit
- Dense As Plutonium
- Bad Slice and Dice



Nested Model

Marchandrage Computer Algorithm Algorithm Automation Possible DESIGN STUDY METHODOLOGY SUITABLE

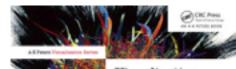
Design Study Methodology

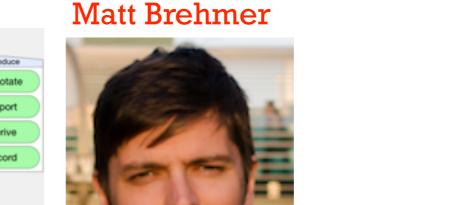
Michael Sedlmair



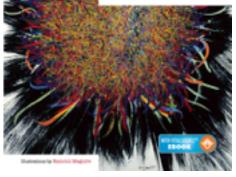
Miriah Meyer



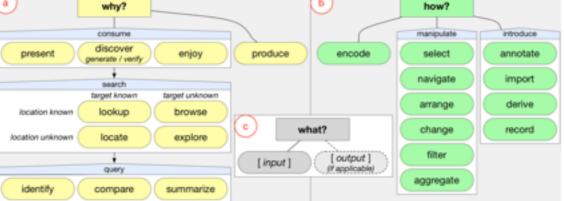




Visualization Analysis & Design



Visualization Analysis & Design



Abstract Tasks

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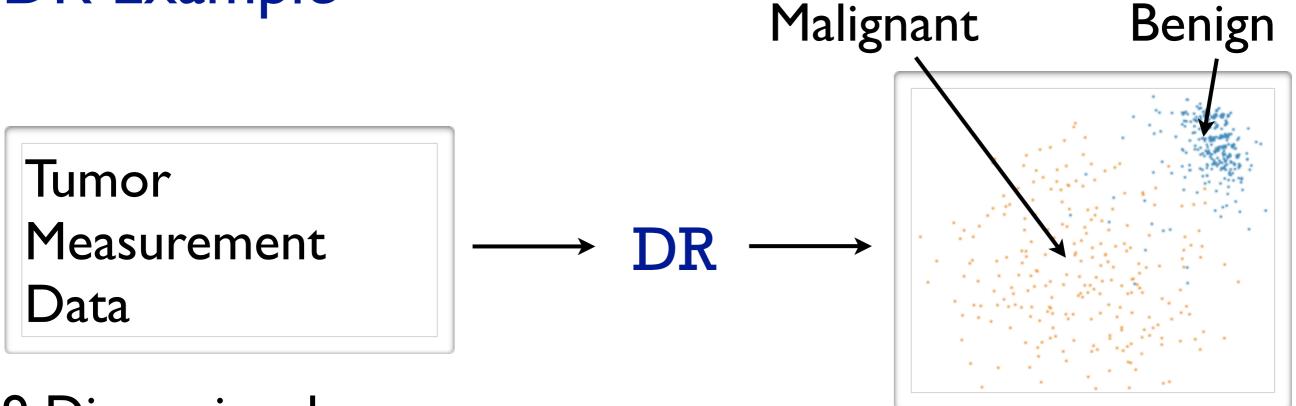
Ε

Т

Dimensionality Reduction

- what is it?
 - -map data from high-dimensional measured space into lowdimensional target space
- when to use it?
 - -when you can't directly measure what you care about
 - true dimensionality of dataset conjectured to be smaller than dimensionality of measurements
 - latent factors, hidden variables
- how can you tell when you need it?
 -could estimate true dimensionality

DR Example



9 Dimensional Measured Space

2 Dimensional Target Space

Dimensionality Reduction

- why do people do DR?
 - -improve performance of downstream algorithm
 - avoid curse of dimensionality
 - -data analysis
 - if look at the output: visual data analysis

Visualizing Dimensionally-Reduced Data:

Interviews with Analysts and a Characterization of Task Sequences

joint work with: Michael SedImair, Matthew Brehmer, Stephen Ingram

http://www.cs.ubc.ca/labs/imager/tr/2014/DRVisTasks/

Visualizing Dimensionally-Reduced Data: Interviews with Analysts and a Characterization of Task Sequences Brehmer, SedImair, Ingram, and Munzner.

Proc. Beyond Time & Errors: Novel Evaluation Methods For Information Visualization (BELIV) 2014, p. 1-8. ¹⁶

Motivation

open questions

- -how are real people actually using DR tools/techniques?
 - does it match up with what we think/hope/assert/assume?
- -why are they using it?
 - what are their goals and tasks, at abstract level?
- -is it working?
 - how do their goals match up with implicit assumptions behind different benchmarks?
 - do current state of the art tools meet their needs?
- why and how do people use DR?

-overarching question weaving through projects in this talk -preliminary results from study informed many of them

Two-Year Cross-Domain Qualitative Study

• in the wild

- HCI term for work in the field with real users
 - vs controlled lab setting
- interviewed two dozen high-dim data analysts
 - across over a dozen domains and past several years
- five abstract tasks
 - naming synthesized dimensions
 - mapping synthesized dimension to original dimensions
 - verifying clusters
 - naming clusters
 - matching clusters and classes

Questions and Answers

- can we design DR algorithms/techniques that are better than previous ones?
- can we build a DR system that real people use?
- when do people need to look at DR output?
- how should people look at DR output?
- why and how do people use DR?
- so... how do we answer these questions?
 many validation methods to choose from!

characterizing the problems of real-world users

abstracting into operations on data types

designing visual encoding and interaction techniques

creating algorithms to execute techniques efficiently

A Nested Model of Visualization Design and Validation

http://www.cs.ubc.ca/labs/imager/tr/2009/NestedModel/

A Nested Model of Visualization Design and Validation. Munzner. IEEE TVCG 15(6):921-928, 2009 (Proc. InfoVis 2009).

Analysis Framework: Four Levels, Three Questions

- domain situation
 - -who are the target users?
- abstraction
 - -translate from specifics of domain to vocabulary of vis
- what is shown? data abstraction
 - often don't just draw what you're given: transform to [A Nested Model of Visualization Design and Validation. Munzner. IEEE TVCG 15(6): 921-928, 2009 (Proc. InfoVis 2009).]
- why is the user looking at it? task abstraction
- idiom
- how is it shown?
 - visual encoding idiom: how to draw
 - interaction idiom: how to manipulate
- algorithm
 - -efficient computation

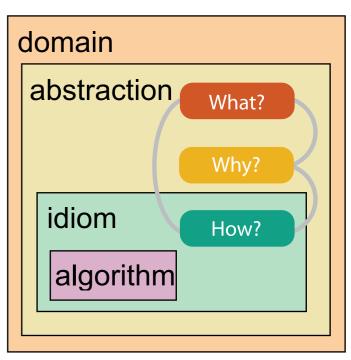
 abstraction

 idiom

 algorithm

 Sector Model of Visualization Design

domain



[A Multi-Level Typology of Abstract Visualization Tasks Brehmer and Munzner. IEEE TVCG 19(12):2376-2385, 2013 (Proc. InfoVis 2013).]

Why Is Validation Difficult?

four levels of design problems

 different threats to validity at each level

Domain situation You misunderstood their needs

Data/task abstractionYou're showing them the wrong thing

Wisual encoding/interaction idiom The way you show it doesn't work



Validation Solution: Methods From Many Fields

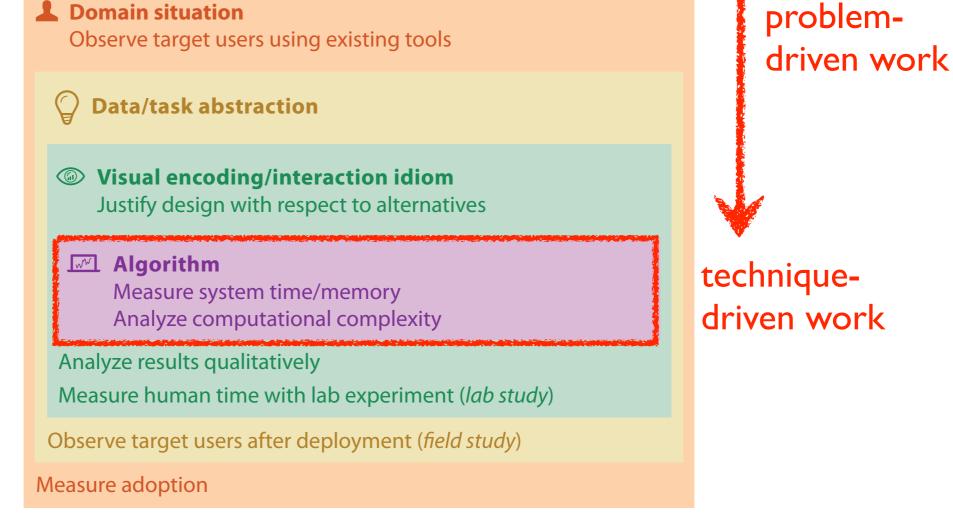
anthropology/ ethnography

L Domain situation

design

computer science cognitive psychology

anthropology/ ethnography



- mismatch: algorithm benchmarks for idiom validation
- mismatch: lab study for abstraction validation

[A Nested Model of Visualization Design and Validation. Munzner. IEEE TVCG 15(6):921-928, 2009 (Proc. InfoVis 2009).]

Where Do We Go From Here?

- no single paper includes all methods of validation –pick methods based on angle of attack
- in this talk
 - -cover many different methods and kinds of questions they can help with answering

Angles of Attack

- design algorithms
- design systems
- design tools to solve real-world user problems
- evaluate/validate all of these
- create taxonomies to characterize existing things
- benefits of multiple angles

 parallax view of what's important
 outcomes cross-pollinate

Outline

- can we design better DR algorithms?
- can we build a DR system for real people?
- how should we show people DR results?
- when do people need to use DR?

Outline

- can we design better DR algorithms? -algorithm for GPU MDS: Glimmer
 - -algorithm for MDS with costly distances: Glint
 - -algorithm for DR for sparse document data: QSNE
- can we build a DR system for real people?
- how should we show people DR results?
- when do people need to use DR?

Glimmer *Multilevel MDS on the GPU*

joint work with: Stephen Ingram, Marc Olano

http://www.cs.ubc.ca/labs/imager/tr/2008/glimmer/

Glimmer: Multilevel MDS on the GPU. Ingram, Munzner, Olano. IEEE TVCG 15(2):249-261, 2009.

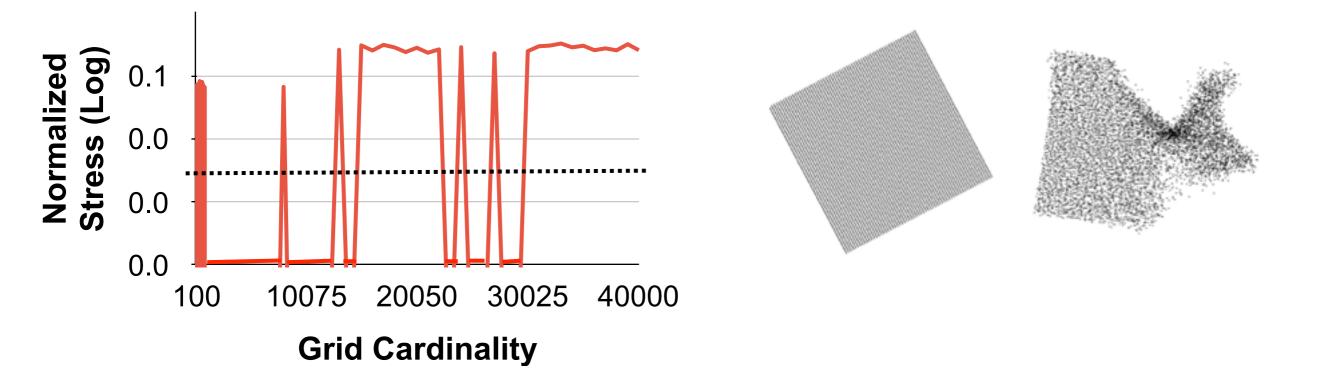
MDS: Multidimensional Scaling

- entire family of methods, linear and nonlinear
- classical scaling: minimize strain
 - -Nystrom/spectral methods: O(N)
 - Landmark MDS [de Silva 2004], PivotMDS [Brandes & Pich 2006]
 - -limitations: quality for very high dimensional sparse data
- distance scaling: minimize stress
 - -nonlinear optimization: $O(N^2)$
 - SMACOF [de Leeuw 1977]
 - -force-directed placement: O(N²)
 - Stochastic Force [Chalmers 1996]
 - limitations: quality problems from local minima
- Glimmer goal: O(N) speed and high quality

Glimmer Strategy

Stochastic force alg suitable for fast GPU port

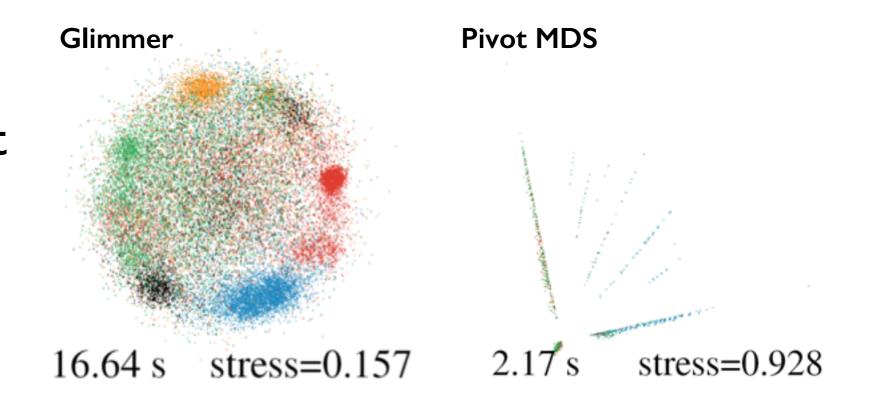
 but systematic testing shows it often terminates too soon

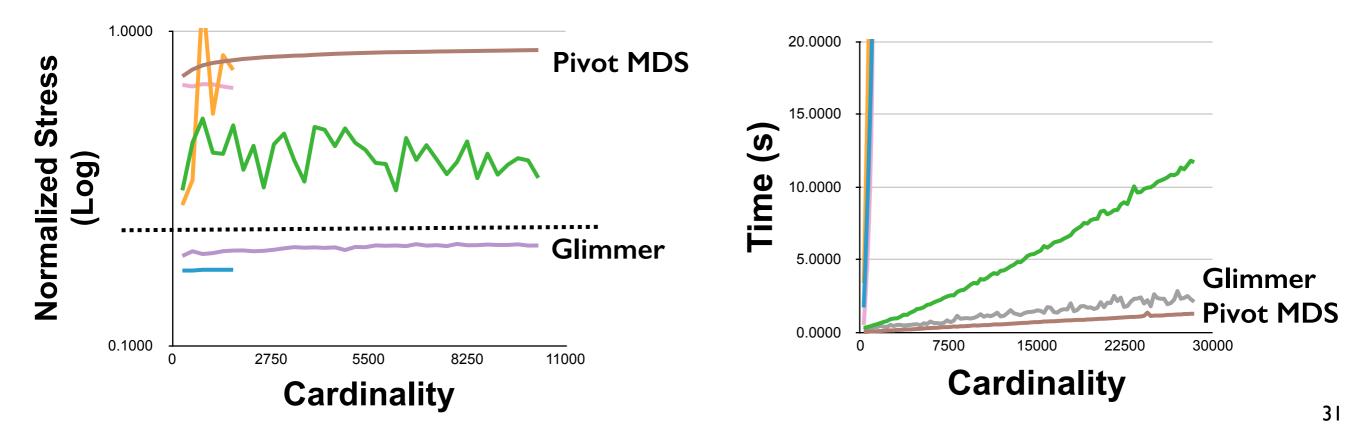


 Use as subsystem within new multilevel GPU alg with much better convergence properties

Sparse Dataset (docs): N=D=28K

–quality higher–speed equivalent

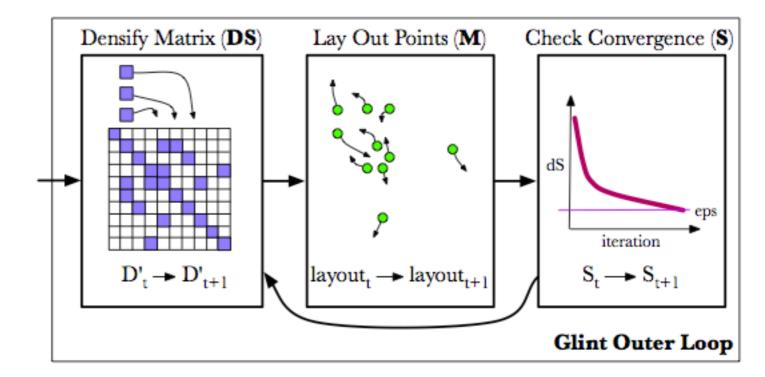




Methods and Outcomes

methods

- -quantitative algorithm benchmarks: speed, quality
 - systematic comparison across IK-I0K instances vs a few spot checks
- -qualitative judgements of layout quality
- outcomes
 - -characterized kinds of datasets where technique yields quality improvements
- then what?
 - -saw what real users could do with it after release
 - identified limitations

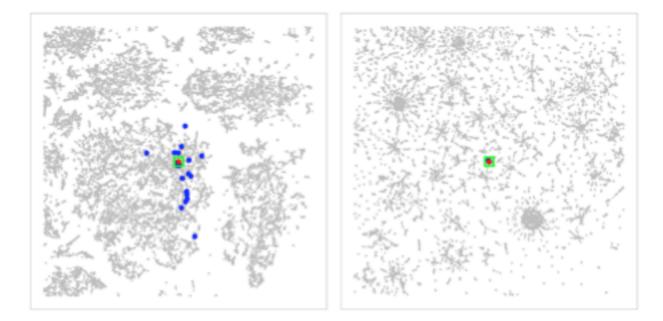


Glint An MDS Framework for Costly Distance Functions

joint work with: Stephen Ingram

http://www.cs.ubc.ca/labs/imager/tr/2012/Glint/

Glint: An MDS Framework for Costly Distance Functions. Ingram, Munzner. Proc. SIGRAD 2012.



Dimensionality Reduction for Documents with Nearest Neighbour Queries

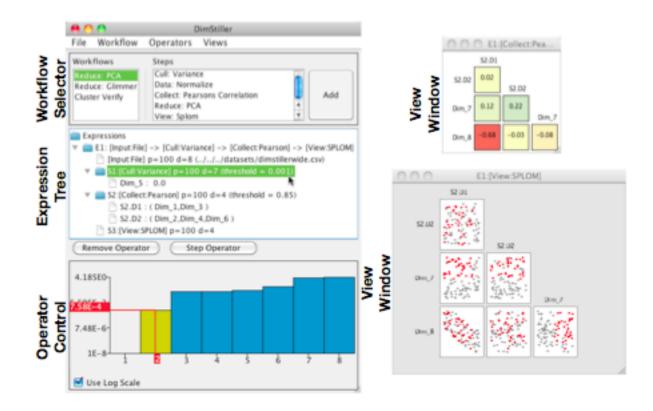
joint work with: Stephen Ingram

http://www.cs.ubc.ca/labs/imager/tr/2014/QSNE

Dimensionality Reduction for Documents with Nearest Neighbor Queries. Ingram, Munzner. Neurocomputing (Special Issue for Workshop on Visual Analytics using Multidimensional Projections (VAMP) held at ÉuroVis 2013), Volume 150 Part B, p 557-569, 2015. 34

Outline

- can we design better DR algorithms?
 - next: how do we get people to use DR properly?
 move emphasis from solo algorithms to entire system
- can we build a DR system for real people?
 –system that provides guidance: DimStiller
- when do people need to use DR?
- how should we show people DR results?
- why and how do people use DR?



DimStiller

Workflows for Dimensional Analysis and Reduction

joint work with:

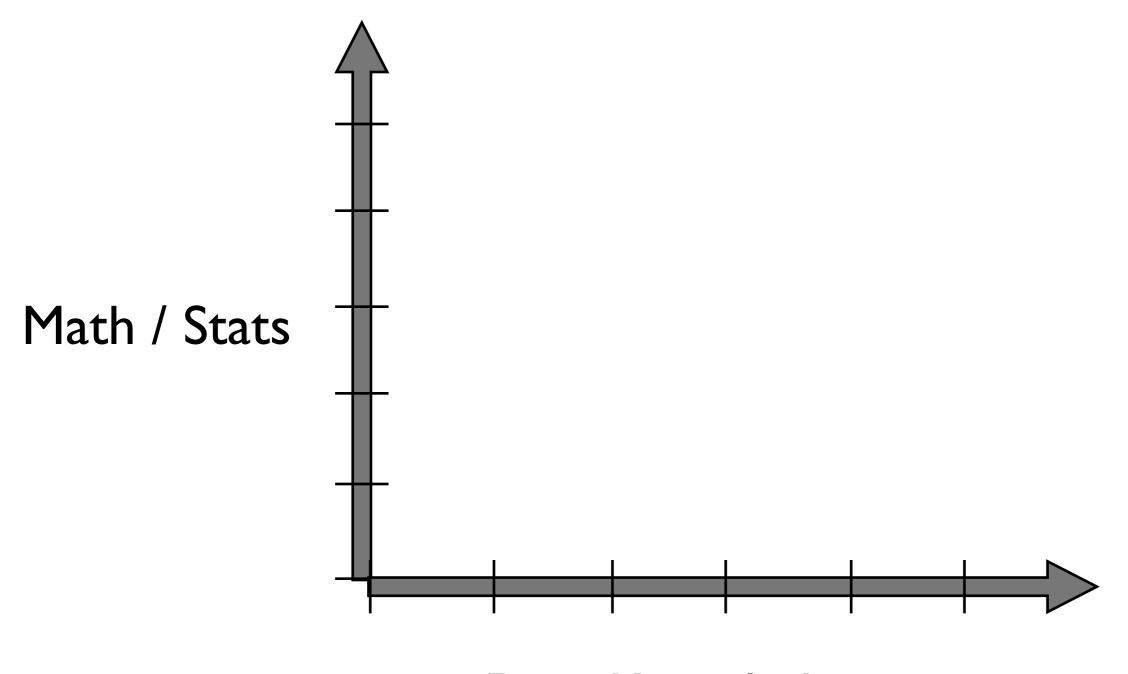
Stephen Ingram, Veronika Irvine, Melanie Tory, Steven Bergner, Torsten Möller

http://www.cs.ubc.ca/labs/imager/tr/2010/DimStiller/

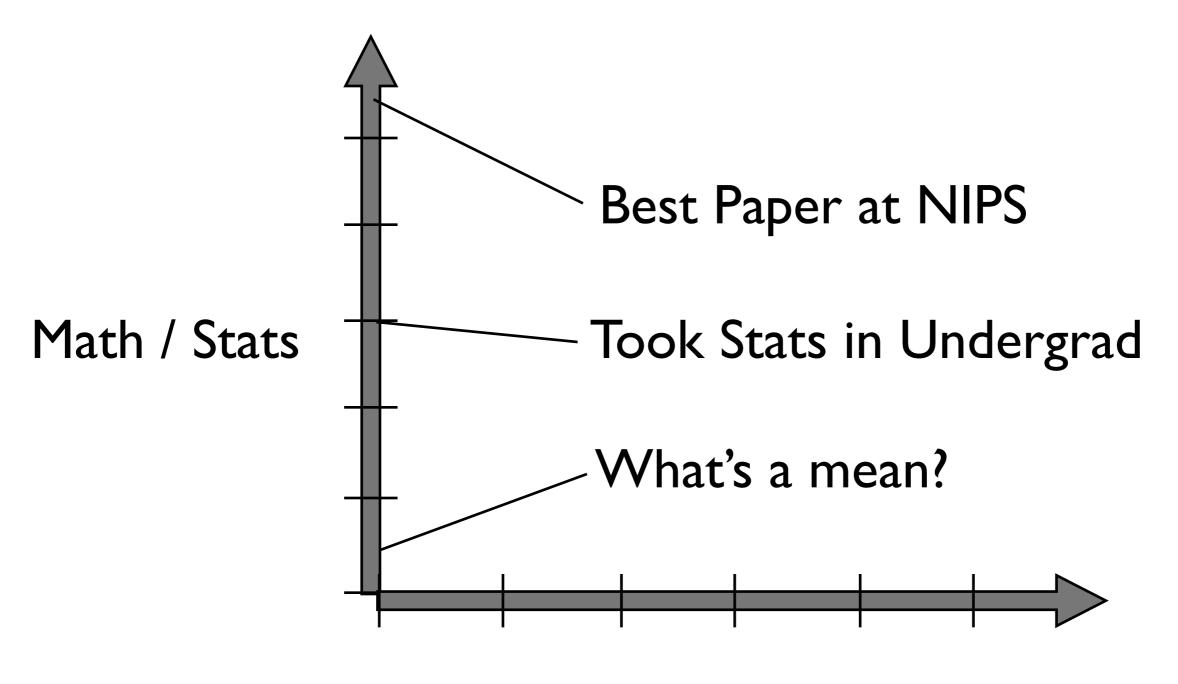
DimStiller: Workflows for dimensional analysis and reduction. Ingram, Munzner, Irvine, Tory, Bergner, Moeller. Proc. VAST 2010, p 3-10.

Who Might Use DR?

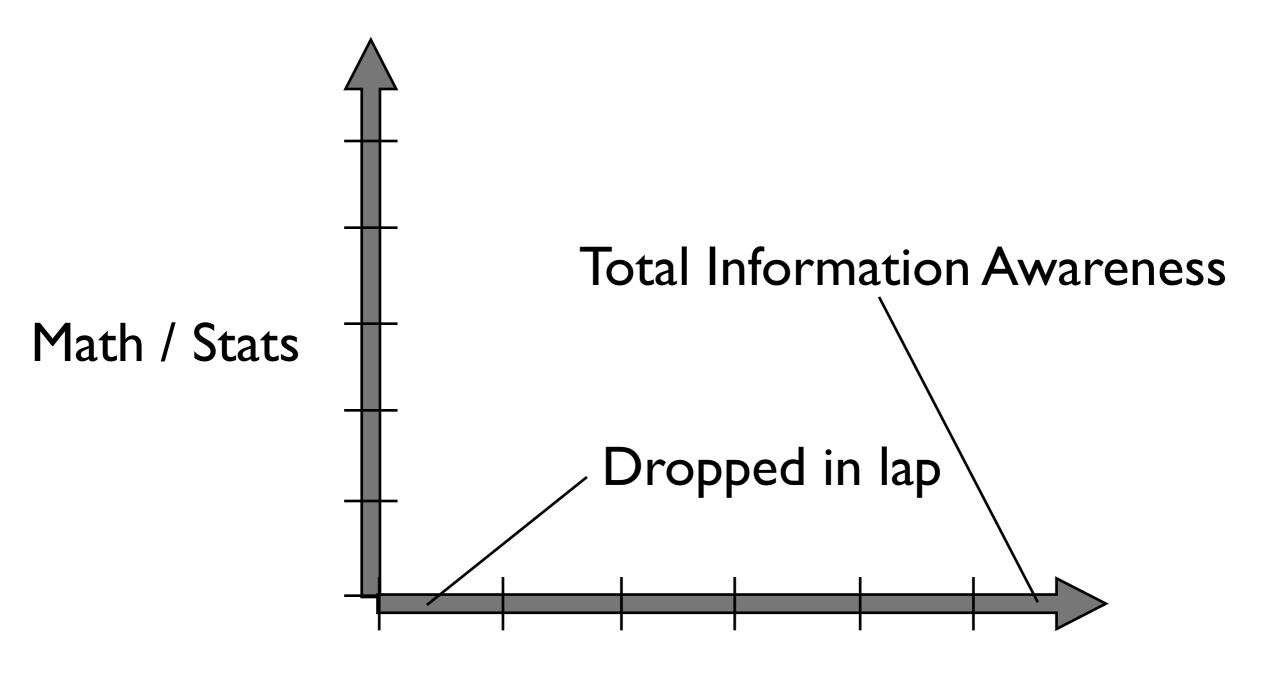
• DR in the Wild revealed broad set of users



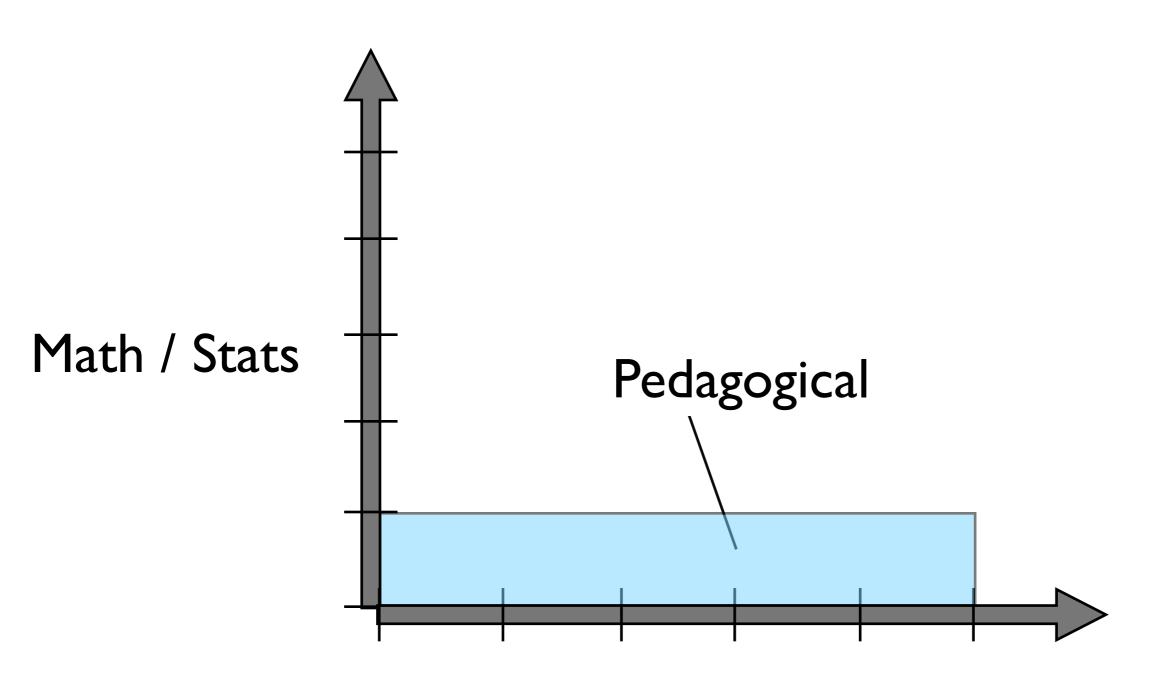
Who Might Use DR?



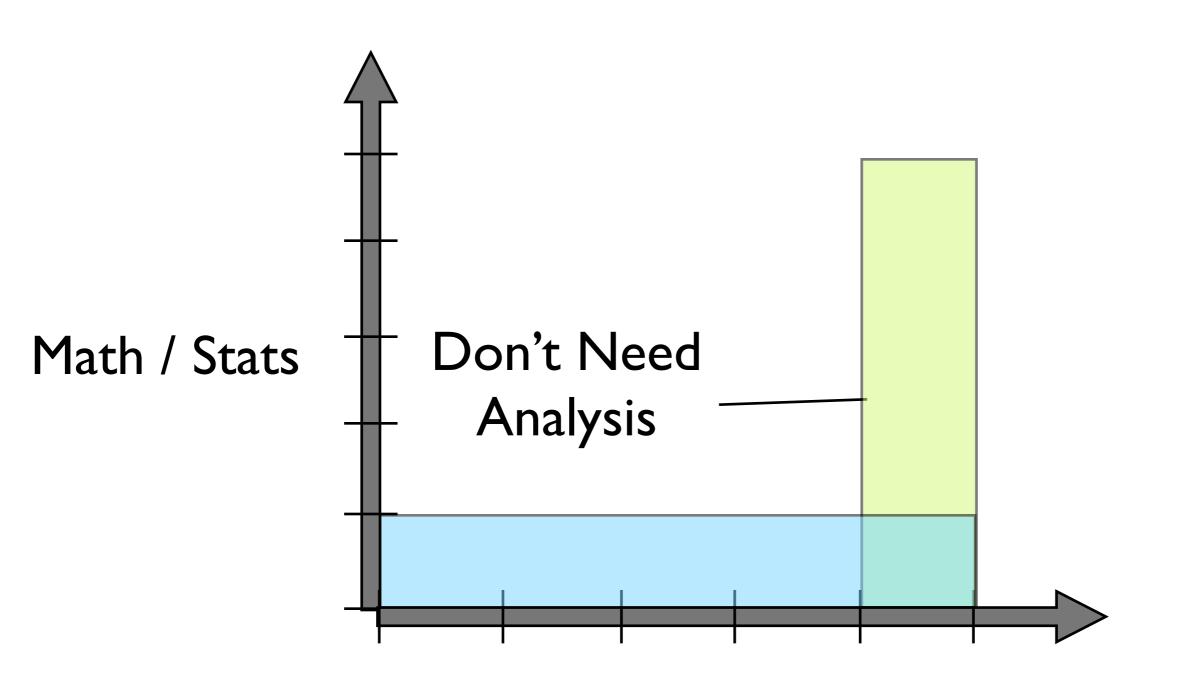




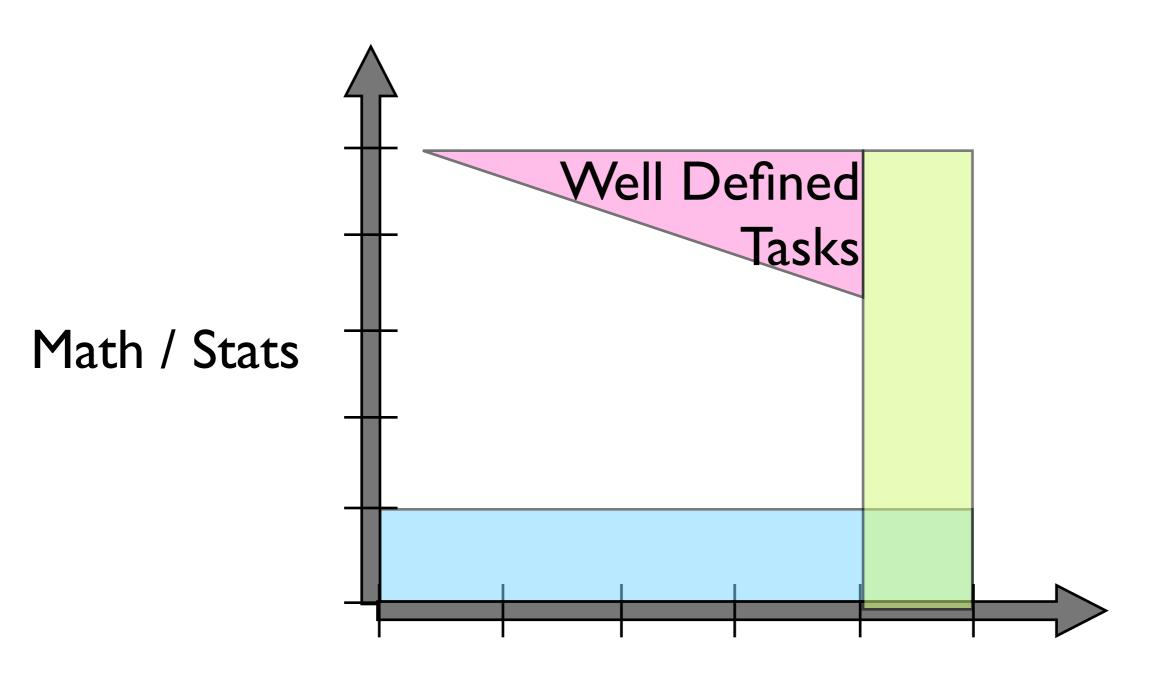




Who Might Use DR?

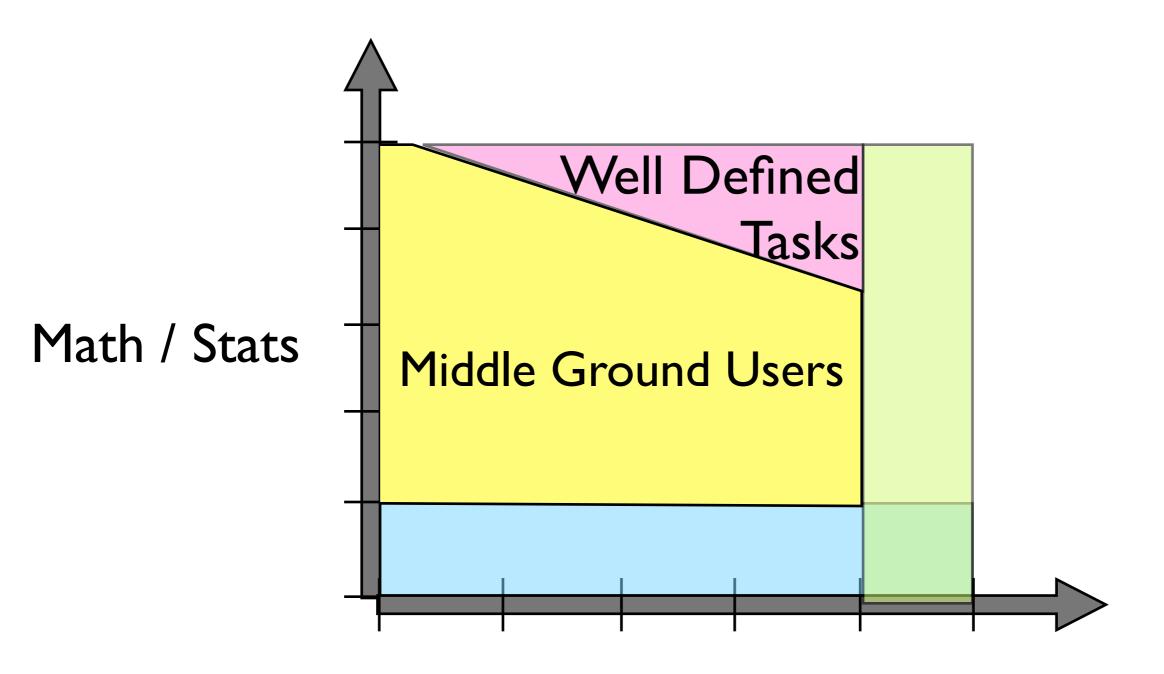


Who Might Use DR?

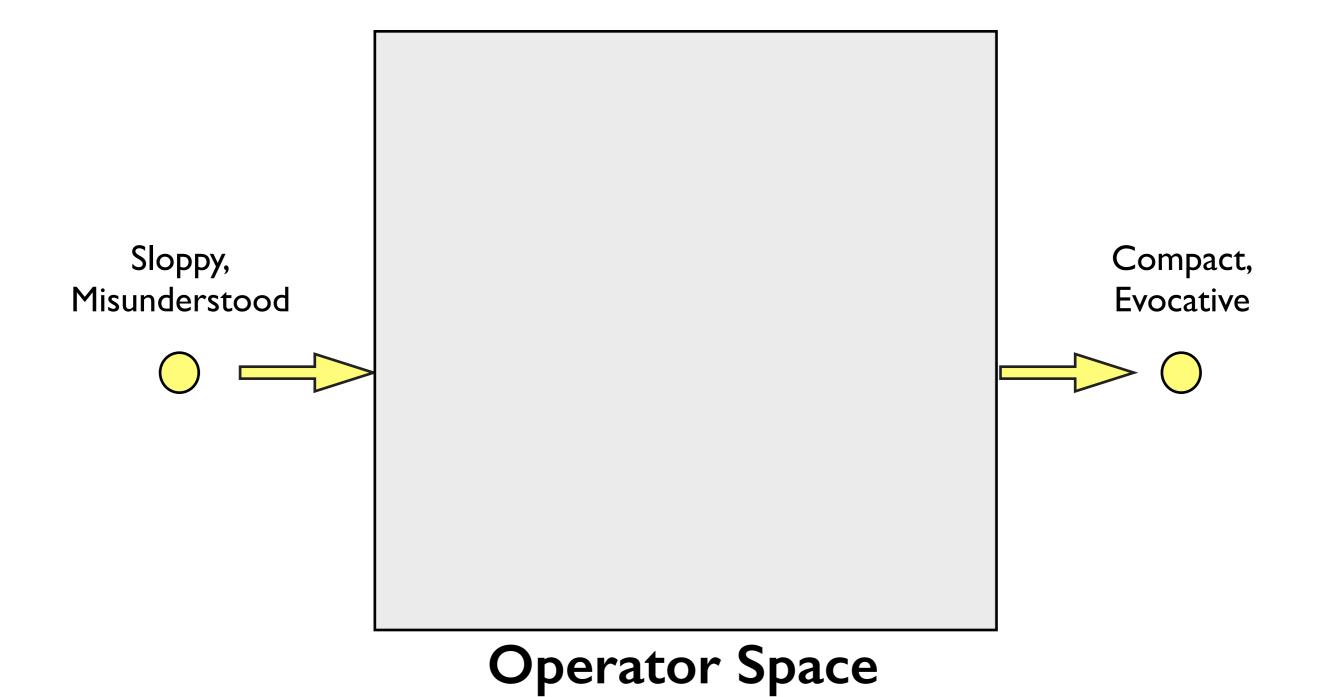


Who Might Use DR?

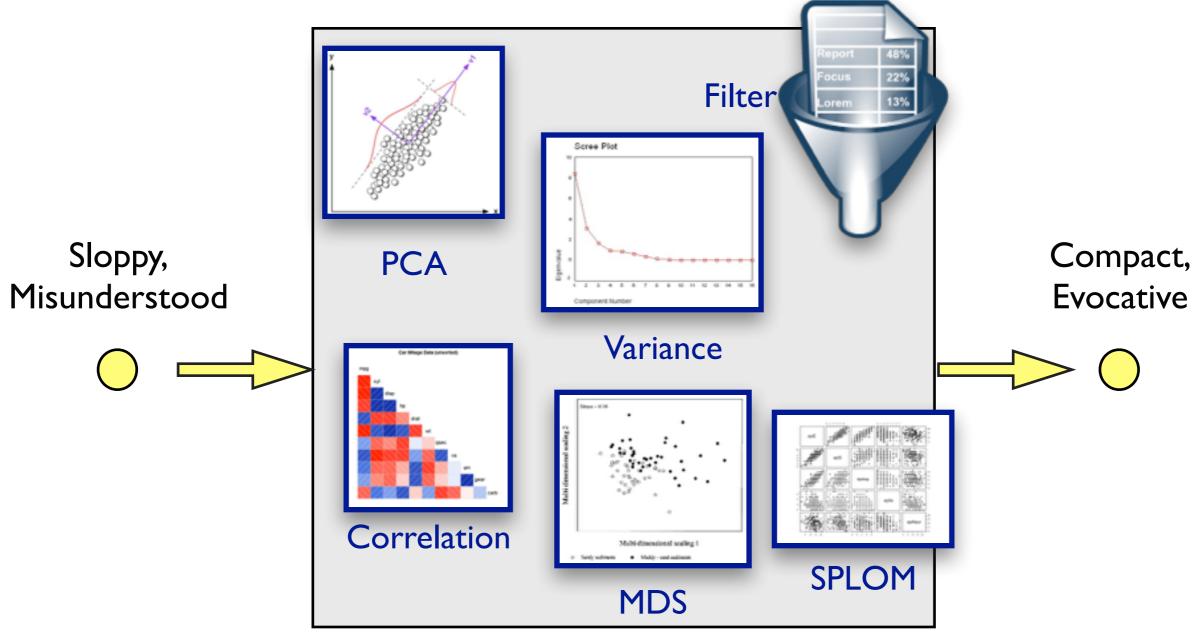
middle ground users benefit from guidance



Global Guidance



Global Guidance

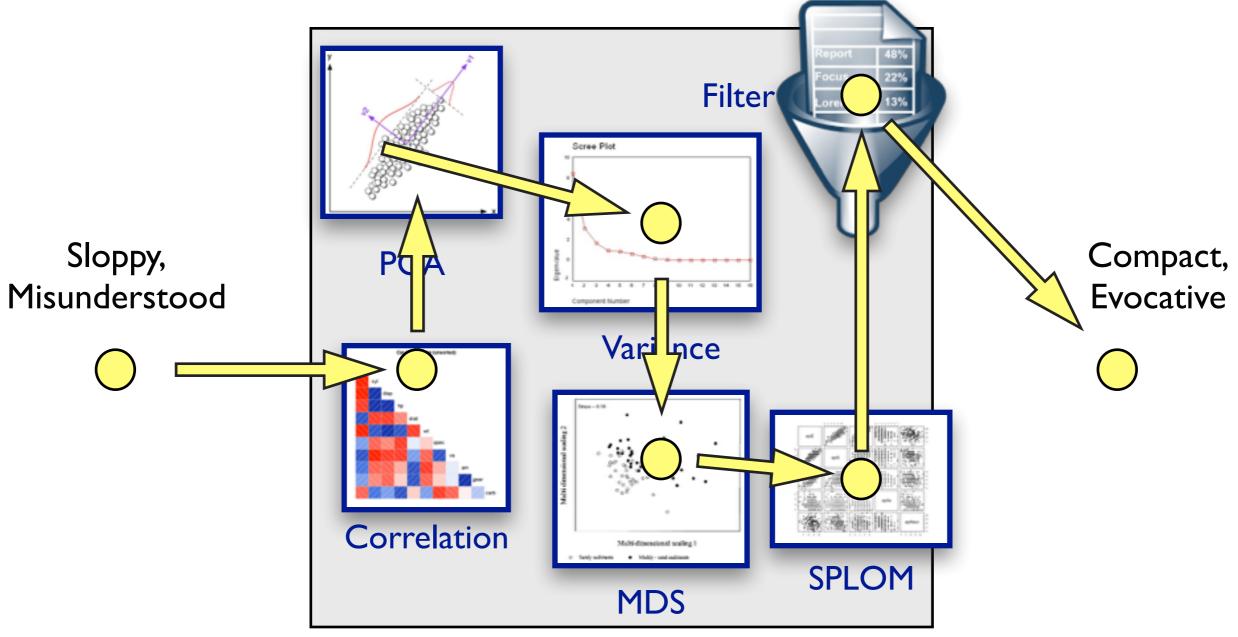


Operator Space

http://www.cs.cornell.edu/courses/cs322/2008sp/schedule.html http://www.statmethods.net/advgraphs/images/corrgram3.png http://en.wikibooks.org/wiki/File:Scree_plot_for_the_initial_dataset_Figure_36.jpg http://www.scielo.cl/scielo.php?pid=S0716-078X2001000200019&script=sci_arttext http://www.iconfinder.com/icondetails/44818/400/data_filter_icon?r=1 http://www.personality-project.org/R/

Global Guidance

• which operations and in which order?

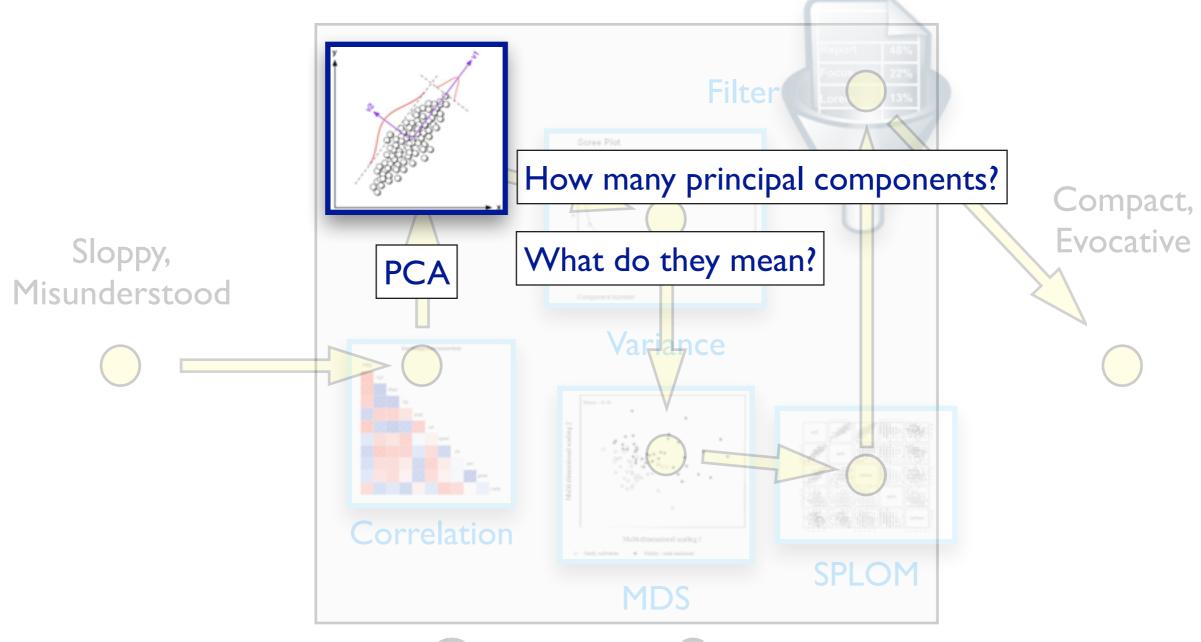


Operator Space

http://www.cs.cornell.edu/courses/cs322/2008sp/schedule.html http://www.statmethods.net/advgraphs/images/corrgram3.png http://en.wikibooks.org/wiki/File:Scree_plot_for_the_initial_dataset_Figure_36.jpg http://www.scielo.cl/scielo.php?pid=S0716-078X2001000200019&script=sci_arttext http://www.iconfinder.com/icondetails/44818/400/data_filter_icon?r=1 http://www.personality-project.org/R/

Local Guidance

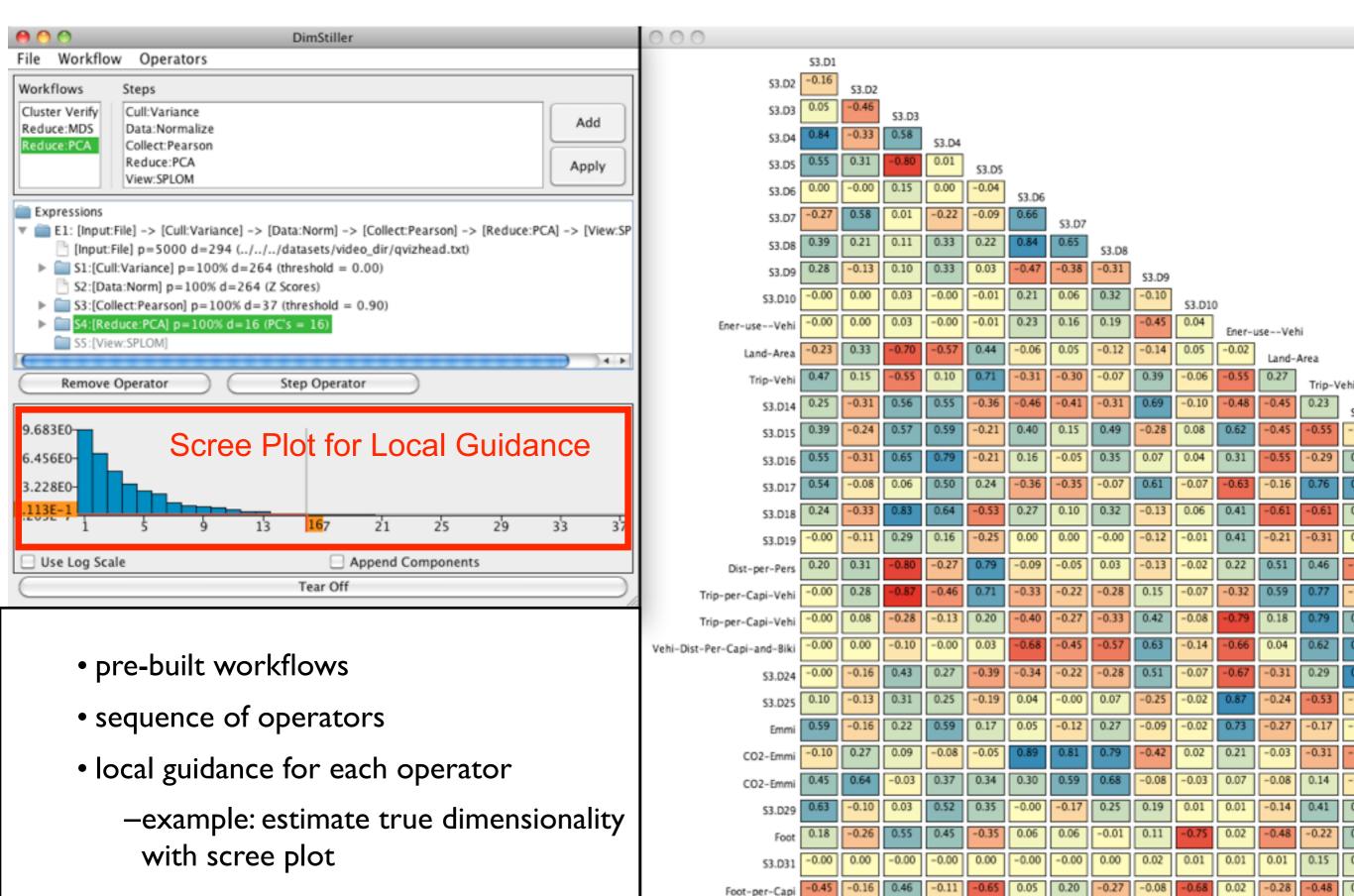
• what to do with a given operator?



Operator Space

http://www.cs.cornell.edu/courses/cs322/2008sp/schedule.html http://www.statmethods.net/advgraphs/images/corrgram3.png http://en.wikibooks.org/wiki/File:Scree_plot_for_the_initial_dataset_Figure_36.jpg http://www.scielo.cl/scielo.php?pid=S0716-078X2001000200019&script=sci_arttext

DimStiller



Cost-of-Livi -0.03 -0.17 0.56 0.28 -0.48

0.14 0.07 0.17 -0.08 0.48 0.40

-0.34 -0.48

Methods and Outcomes

- methods
 - -usage scenarios: workflows
 - identified several (preliminary DRITW results)
 - built system to accommodate new ones as they're uncovered
- outcomes
 - -prototype system: "DR for the rest of us"
- then what?

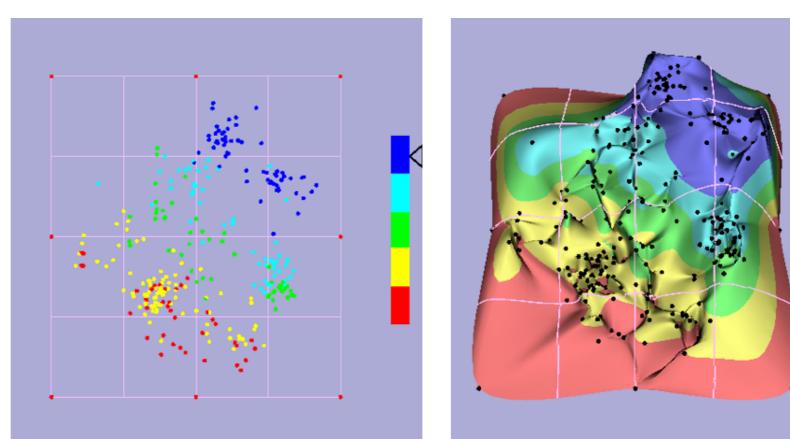
-who else needs guidance? not just end users!

Outline

- can we design better DR algorithms/techniques?
- can we build a DR system for real people?

-next: more guidance about visual encoding

- how should we show people DR results?
 - -visual encoding guidance for system developers: Points vs Landscapes
 - -visual encoding guidance for metric developers wrt human perception: Visual Cluster Separation Factors
- when do people need to use DR?



Spatialization Design Comparing Points and Landscapes

joint work with: Melanie Tory, David W. Sprague, Fuqu Wu, Wing Yan So

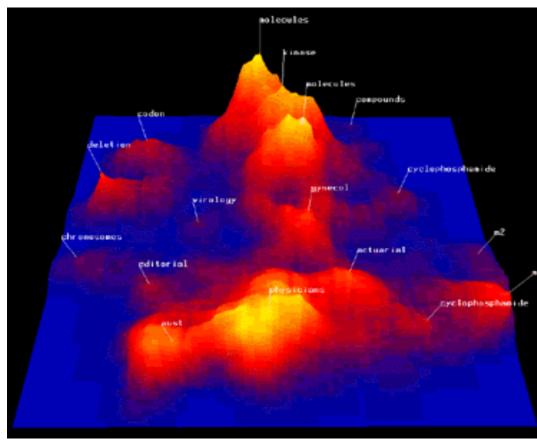
http://webhome.cs.uvic.ca/~mtory/publications/infovis2007.pdf

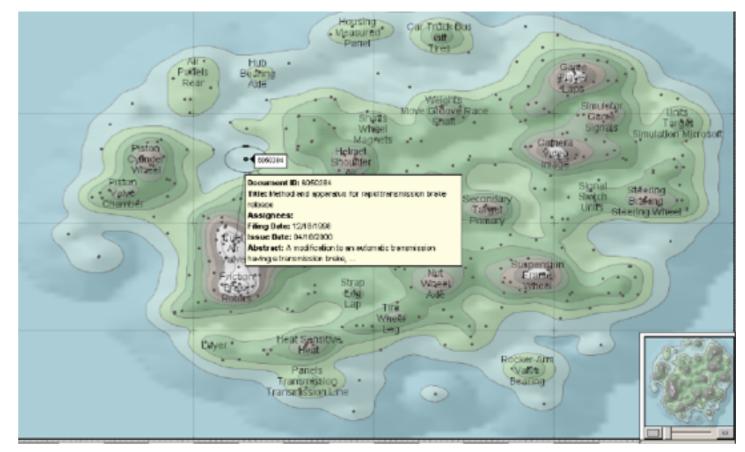
Spatialization Design: Comparing Points and Landscapes. Tory, Sprague, Wu, So, and Munzner. IEEETVCG 13(6):1262–1269, 2007 (Proc. InfoVis 07).

Information Landscapes

- 2D or 3D landscape from set of DR points –height based on density
- oddly popular choice in DR
 - -despite known occlusion/distortion problems with 3D

-assertions: pattern recognition, spatial reasoning, familiar





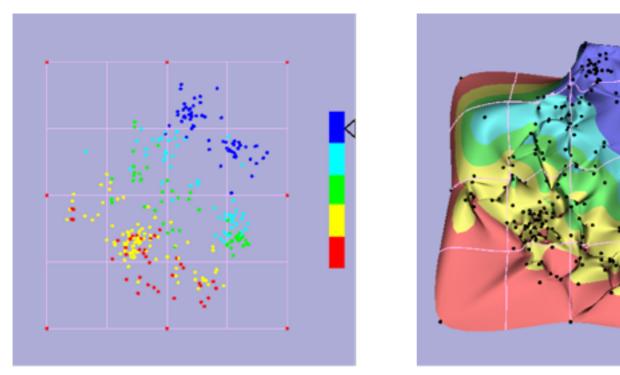
Themescape: [http://www.k-n-o-r-z.de/publ/example/retriev1.htm]

[Guide to MicroPatent Aureka 9 ThemeScape]

Understanding User Task

abstract: search involving spatial areas and estimation

Estimate which grid cell has the most points of the target color

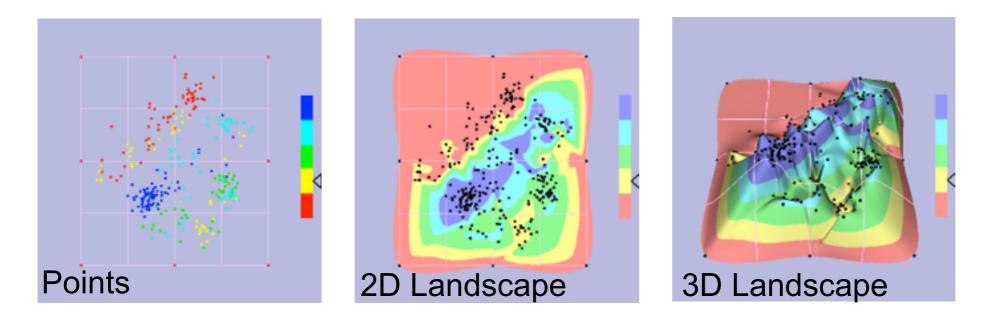


domain-specific examples

"Where in the display are people with high incomes?" "Does this area also have high education levels?" "Does this area correspond to a particular work sector?"

- non-trivial complexity yet fast response time
- frequent subtask in pilot test of real data analysis

Lab Study: Test Human Response Time and Error



hypotheses

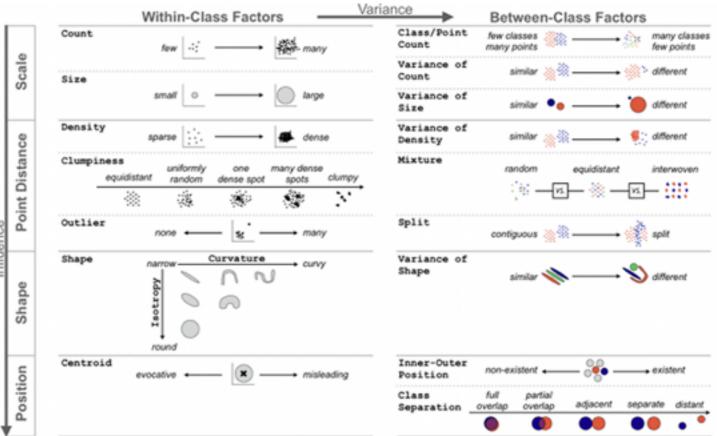
-points are better than landscapes

- result: yes!
- much better: 2-4 × faster, 5-14 × more accurate
- -2D landscapes (color only) better than 3D landscapes (color + height redundantly encoded)
 - result: yes
 - significantly faster, no significant difference in accuracy

Methods and Outcomes

- methods
 - -lab study: controlled experiment
- outcomes
 - -prescriptive advice at visual encoding level
 - avoid 3D landscapes
- then what?

-yet more guidance from user studies? not so fast...



A Taxonomy of Visual Cluster Separation Factors

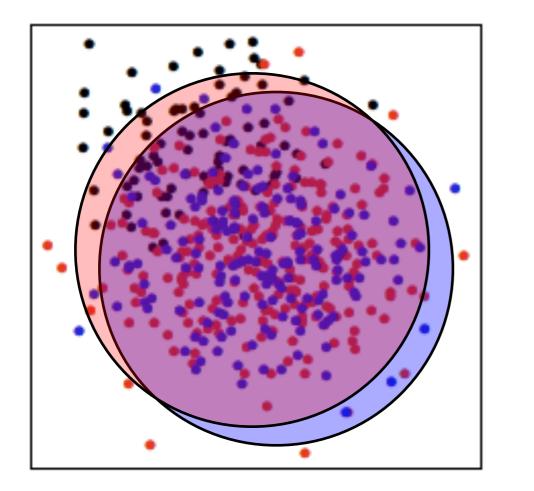
joint work with: Michael SedImair, Andrada Tatu, Melanie Tory

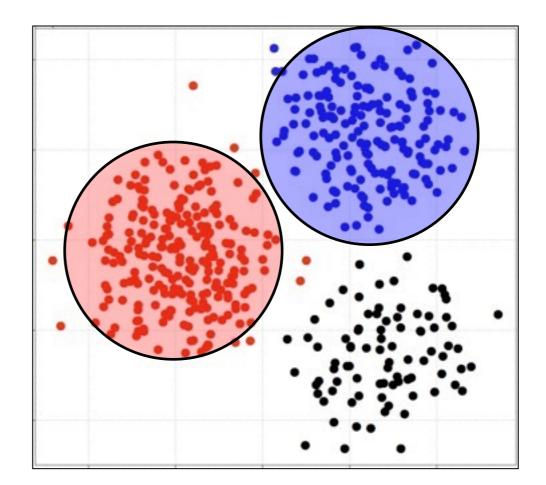
http://www.cs.ubc.ca/labs/imager/tr/2012/VisClusterSep/

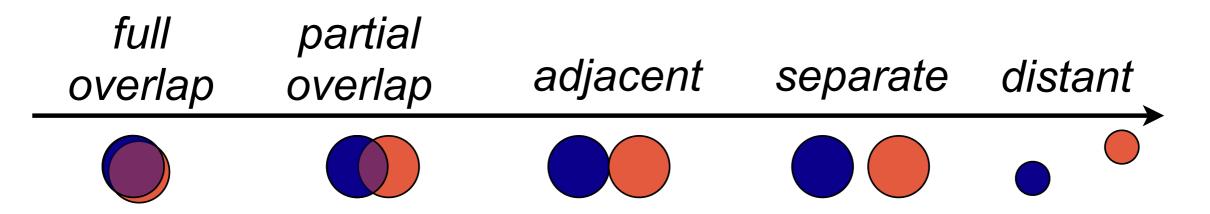
A Taxonomy of Visual Cluster Separation Factors. SedImair, Tatu, Munzner, Tory. Computer Graphics Forum 31(3):1335-1344, 2012 (Proc. EuroVis 2012).

Cluster Separation

• simple idea





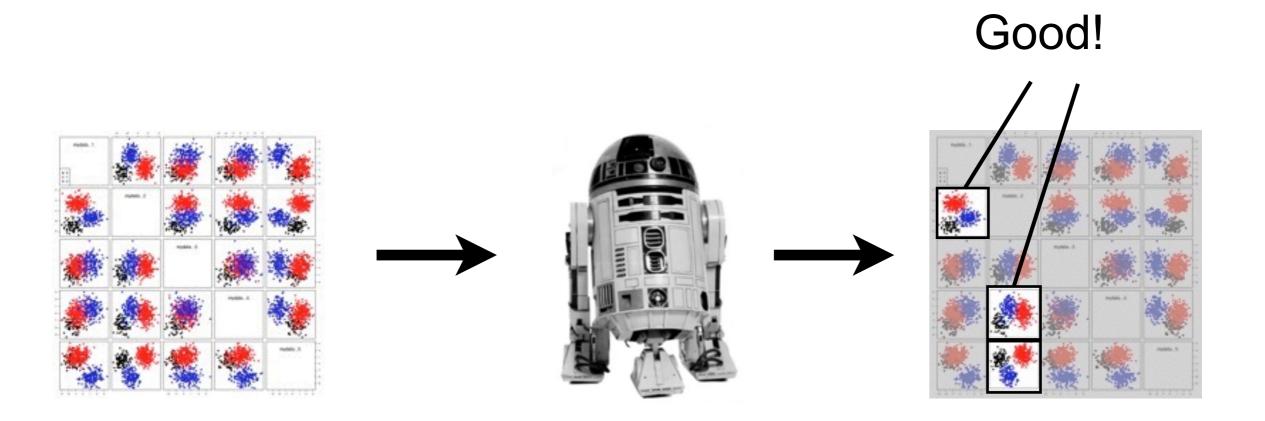


Visual Cluster Separation Measures

 Many cluster separation measures proposed for semi-automatic guidance in high-dim data analysis

Sips et al.: Selecting good views of high-dimensional data using class consistency [EuroVis 2009]

Tatu et al.: Combining automated analysis and visualization techniques for effective exploration of high-dimensional data [VAST 2009]



Visual Cluster Separation Measures

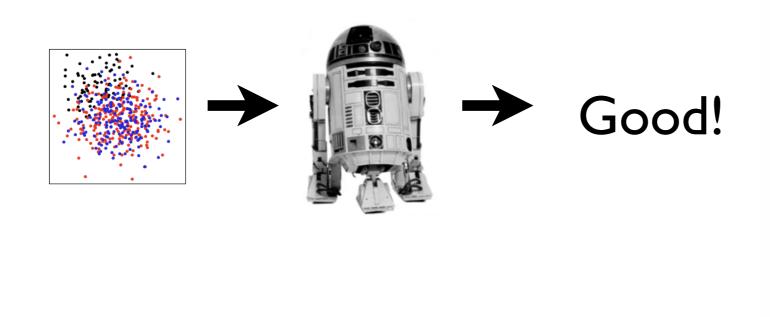
 goal: number captures whether human looking at layout sees something interesting

-after computation is done, not to refine clustering

measures checked with user studies

Tatu et al.: Visual quality metrics and human perception: an initial study on 2D projections of large multidimensional data [AVI 2010]

but our attempt to use for guidance showed problems





User vs. Data Study

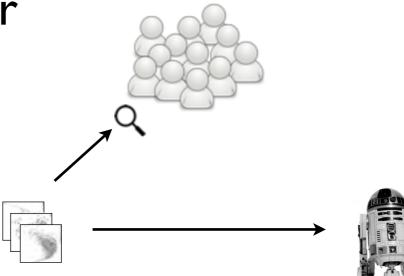
user study

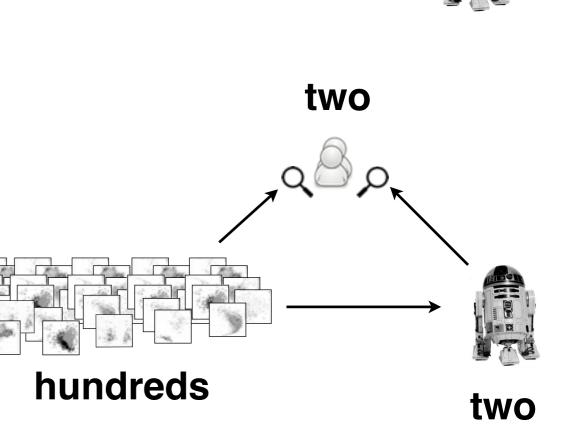
-previous work on validating cluster measures

many users, few datasetsmissing: dataset variety

• data study

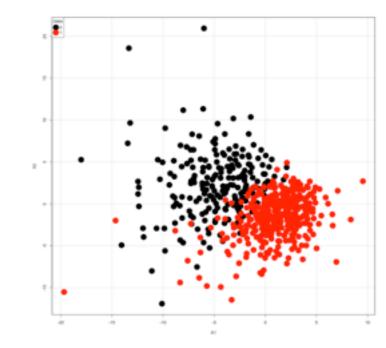
-few users, many datasets

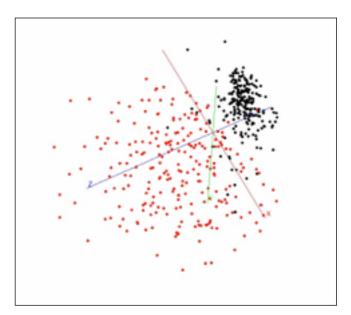


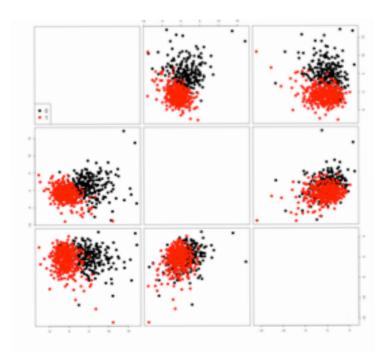


816 Dataset Instances

- 75 datasets
 - -31 real, 44 synthetic -pre-classified
- 4 DR methods
 - -PCA
 - -Robust PCA
 - -Glimmer MDS
 - -t-SNE
- 3 visual encoding methods
 - –2D scatterplots, 3D scatterplots,
 2D SPLOMs
 - -color-coded by class

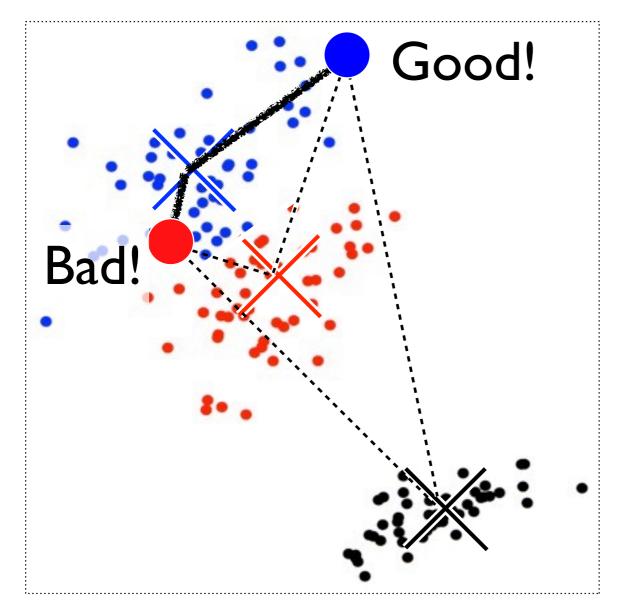






Centroid Measure





Centroid: 93

Analysis Approach

 qualitative method out of social science: coding –open coding: gradually build/refine code set –axial coding: relationships between categories

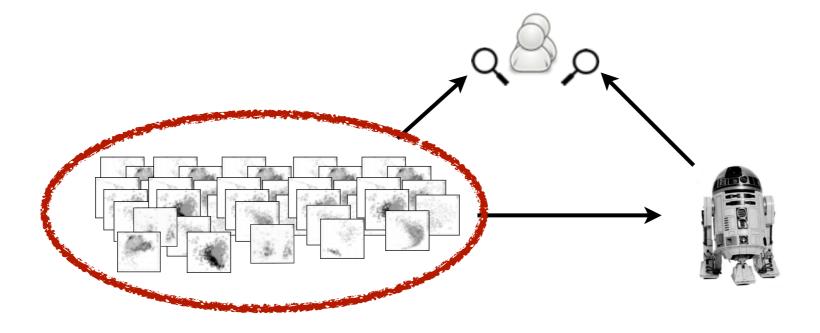
Charmaz, K. Constructing Grounded Theory: A Practical Guide through Qualitative Analysis. 2006.

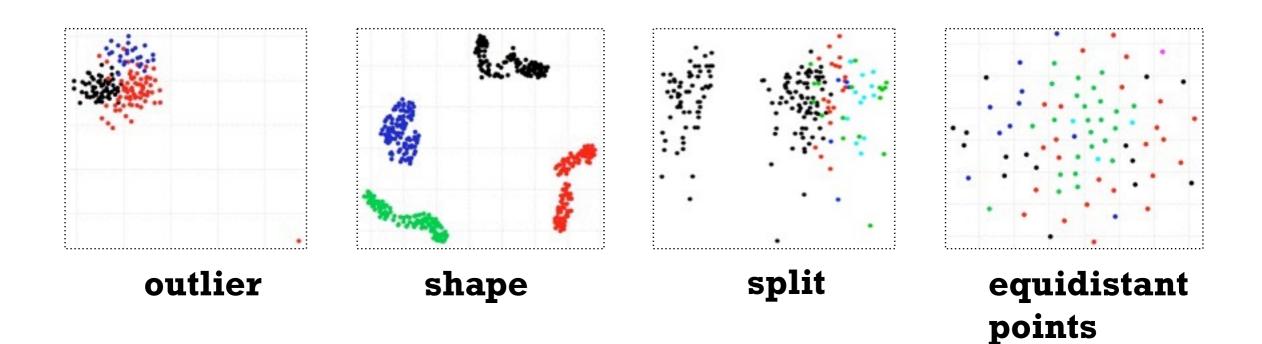
Furniss, D., Blandford, A., Curzon, P. and Mary, Q. (2011). Confessions from a grounded theory PhD: experiences and lessons learnt. Proc. ACM CHI 2011, p 113-122.

evaluating the measures

- -metric aligns with human judgement?
- -if not: what are the reasons?

Qualitative Analysis I: Cluster Separation Factors





Analysis Approach

 qualitative method out of social science: coding –open coding: gradually build/refine code set
 –axial coding: relationships between categories

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.

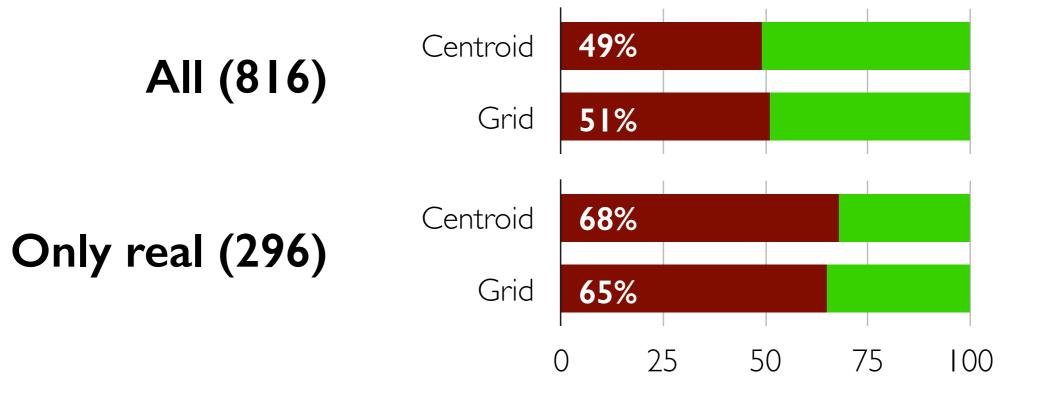
- evaluating the measures
 - -metric aligns with human judgement?
 - -if not: what are the reasons?
- building taxonomy of factors from reasons
- mapping measure failures onto taxonomy

A Taxonomy of Cluster Separation Factors

		Within-Class Factors Varia	ance	Between-Class Factors
ence		Count few \cdots many	Class/Point Count	few classes many classes few points
	Scale	Size	Variance of Count	similar 🥁 🎆 ────→ 🌼 🤄 different
		small O large	Variance of Size	similar • e
	ce	Density $sparse \begin{bmatrix} \vdots \\ \vdots \\ \vdots \\ \vdots \end{bmatrix} \longrightarrow dense$	Variance of Density	similar 🎎 🦾 🛶 🍕 🔆 different
	istance	Clumpiness uniformly one many dense equidistant random dense spot spots clumpy	Mixture	random equidistant interwoven
				VSVSVS
	Point	Outlier $mone \longleftarrow $ $many$	Split	contiguous
Influence	Shape	Shape $narrow \xrightarrow{Curvature} curvy$ $\downarrow \qquad \qquad$	Variance of Shape	similar 💊
	uo	Centroid evocative	Inner-Outer Position	non-existent
	Position		Class Separation	full partial overlap overlap adjacent separate distant

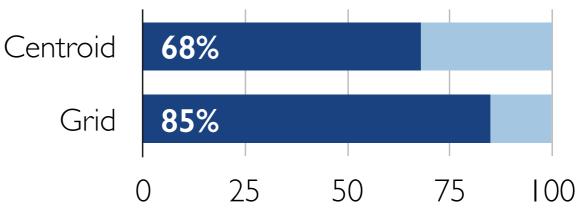
High-Level Results





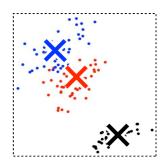
False Positives False Negatives

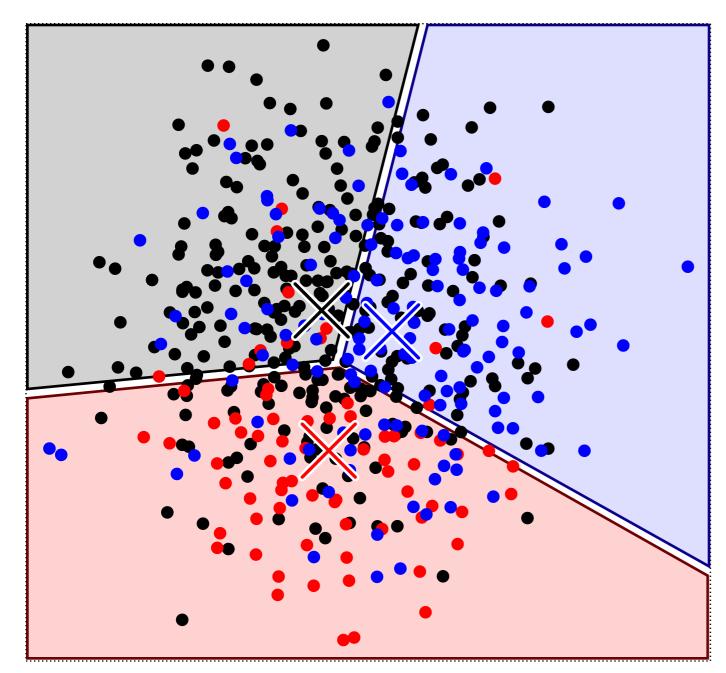




Centroid Failure Example

big classes overspread small ones





Red: **77 (Good)** Problem: **FP**

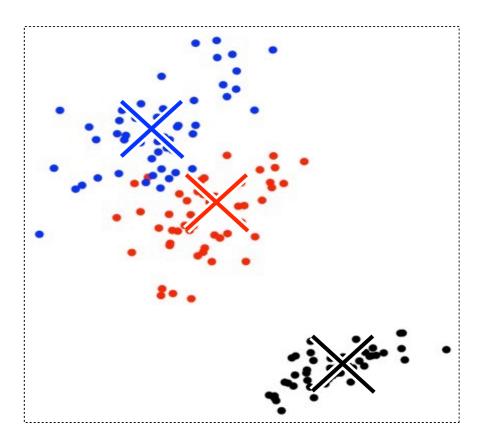
Data: Gaussian, synthetic DR: MDS

Relevant Taxonomy Factors

Scale	Count	Class/Point			
ale	few many	Count	few classes many points		few points
0	Size	Variance of Count	similar		different
0)	small o large	Variance of Size	similar		different
ce	Density sparse dense	Variance of Density	similar	→	different
Distance	Clumpiness uniformly one many dense equidistant random dense spot spots clumpy	Mixture	random	equidistant	interwoven
nt D			- 11 -		VS
Point	Outlier none	Split	contiguous		split
Shape P.	Shape Curvature curvy	Variance of Shape	similar	₩	S different
uoi	Centroid evocative	Inner-Outer Position	non-existent		→ existent
Position		Class Separation _	full pan overlap over	lap adjacent	separate distant

Centroid: Mapping Assumptions Into Taxonomy

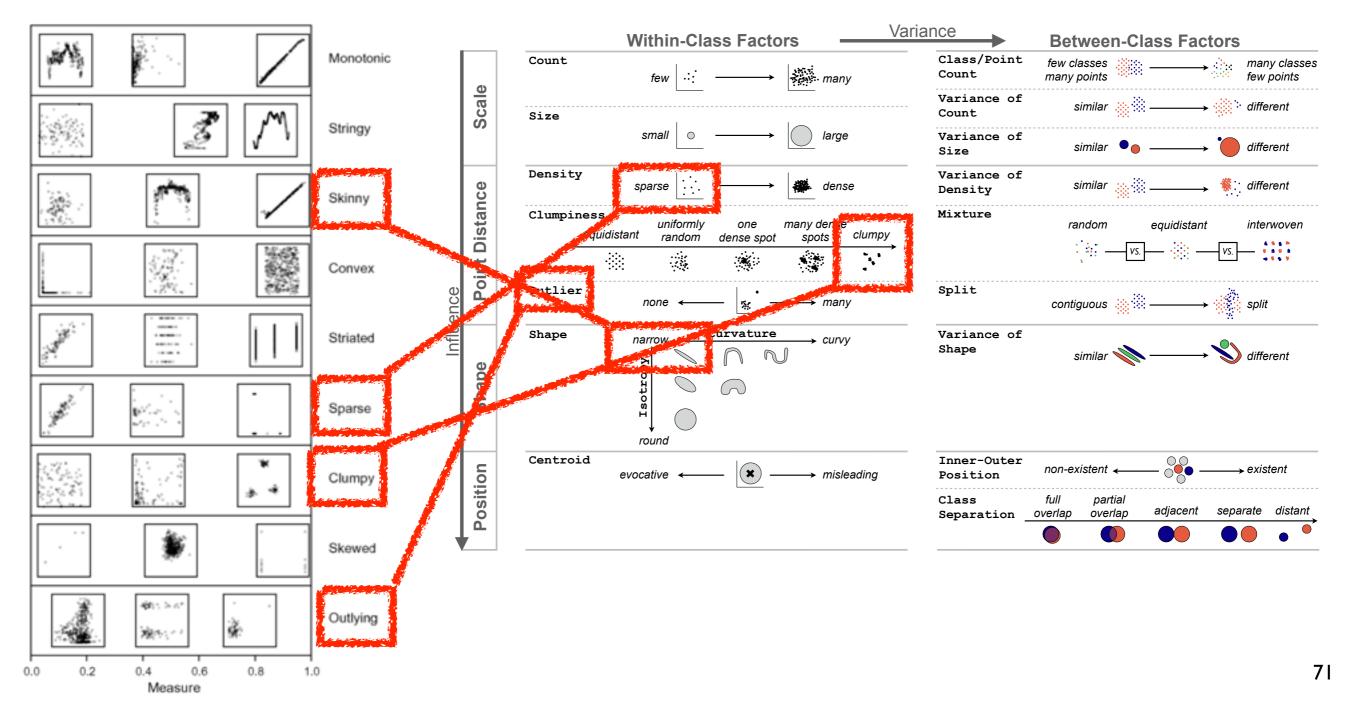
- centroid only reliable if –round-ish clusters
 - -not more than one dense spot
 - -no outliers
 - -similar sizes & number of points
- rarely true for real datasets



Related Work

• Scagnostics [Wilkinson et al. 2005]

-mathematical description and algorithmic instantiation vs human perception



Methods and Outcomes

- methods
 - -qualitative data study
 - we encourage more work along these lines
- outcomes
 - -taxonomy to understand current problems
 - measures
 - -taxonomy to advise future development
 - measures, techniques, systems
- then what?

-from how to help them do DR better to understanding when they need to do it at all

Outline

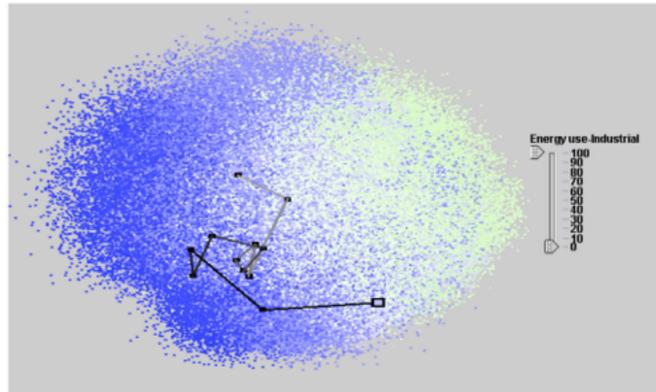
- how can we design better DR algorithms/ techniques?
- how can we build a DR system for real people?
- how should we show people DR results?

-next: continue figuring out what people need

- when do people need to use DR? -sometimes they don't: QuestVis
 - -how to figure out when they do or don't: Design Study Methodology

Reflections on

QuestVis A Visualization System for a



A Visualization System for an Environmental Sustainability Model

joint work with: Aaron Barsky, Matt Williams

http://www.cs.ubc.ca/labs/imager/tr/2011/QuestVis/

Reflections on QuestVis: A Visualization System for an Environmental Sustainability Model Munzner, Barsky, Williams. Scientific Visualization: Interactions, Features, Metaphors. Dagstuhl Follow-Ups 2, 2011, Chapter 17, p 240–259.

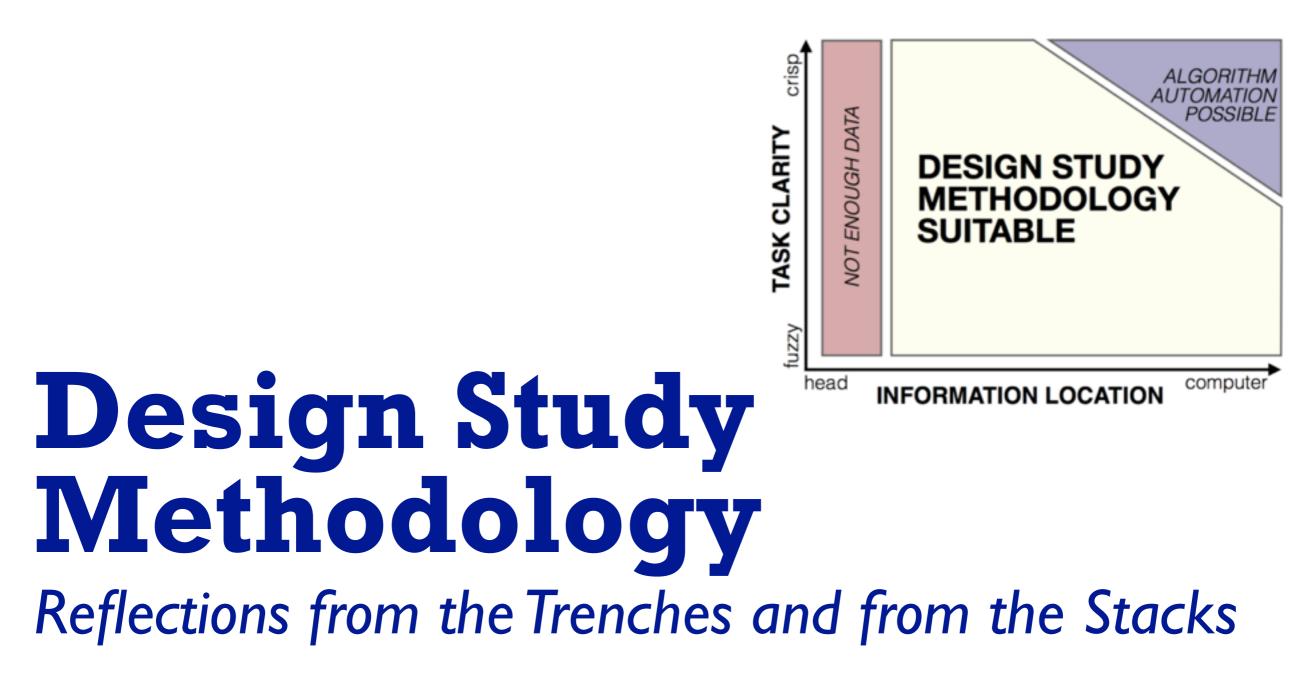
Application Domain: Sustainability

- user data: sustainability simulation model
 - -high-dimensional inputs/outputs
 - our decision: show relationship between input choices and output indicators with linked views including DR layout



Hammer Looking for A Nail

- wrong task abstraction: they didn't need DR! –goal mismatch
 - discussion of issues and behavior change from general public
 - not data analysis to understand exact relationships between input and output variables
 - -this failure case was one of motivations for nested model
- how can we tell what users actually need?
 - -talking to users: necessary but not sufficient
 - -we now have some answers!
 - we have proposed a methodology for problem-driven research
 - -design studies: build vis tools to solve user problems
 - -DR as one of many possible techniques that might be used



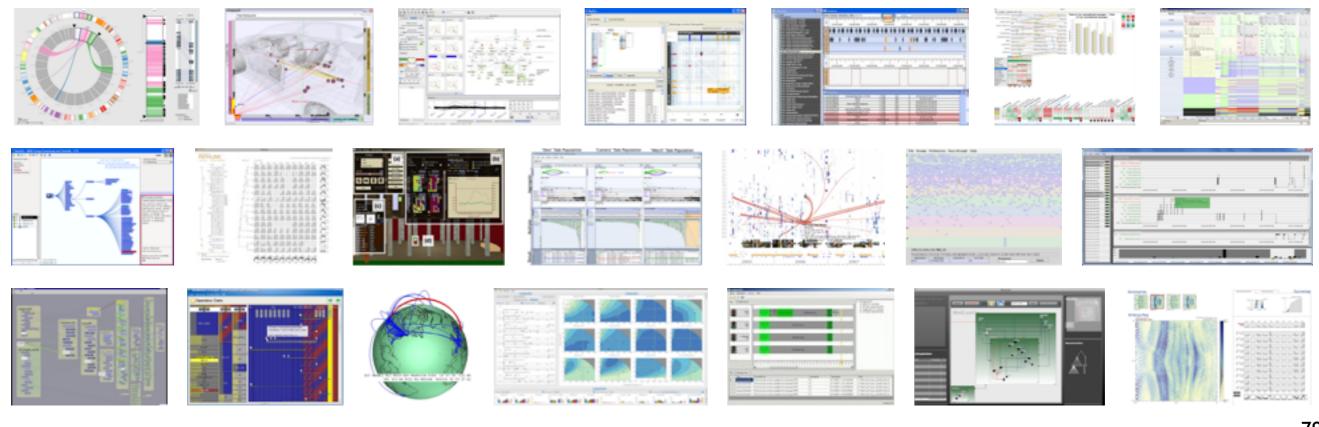
joint work with: Michael SedImair, Miriah Meyer

http://www.cs.ubc.ca/labs/imager/tr/2012/dsm/

Design Study Methodology: Reflections from the Trenches and from the Stacks. SedImair, Meyer, Munzner. IEEE TVCG 18(12): 2431-2440, 2012 (Proc. InfoVis 2012).

Design Studies

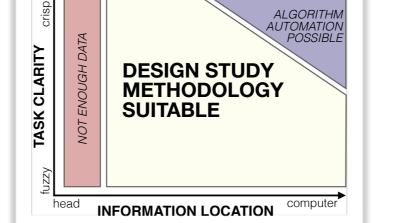
- long and winding road with many pitfalls –reflections after doing 21 of them
 - many successes, a few failures, many lessons learned

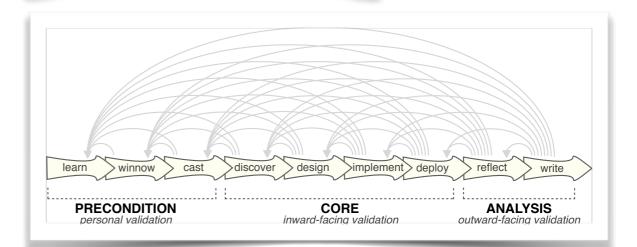


How To Do Design Studies

definitions

• 9-stage framework





 32 pitfalls and how to avoid them

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

Pitfall Example: Premature Publishing

technique-driven

problem-driven









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

Methods and Outcomes

methods

-introspection on lessons learned as authors and reviewers

-extensive literature search

outcomes

- -prescriptive methodology advice
 - here's a way to do design studies
 - avoid these pitfalls
- exhortation
 - -meta/how-to/reflection papers are worth doing

-thinking about methods and methodologies is fruitful for any flavor of research!

Conclusions

- cross-fertilization from attacking DR through different methodological angles
 - -scratching own itches often leads to problems that are important and high impact
 - outcomes of evaluation informs how to build
 - grappling with issues of building informs what studies to run
 - taxonomy creation informs what to build: unsolved problems
- finding mismatches
 - -between principles and practice
 - -between practice and needs
 - need parallax view of principles, practices, and needs!

Thanks and Questions

- this talk
 - http://www.cs.ubc.ca/~tmm/talks.html#kelowna16
- papers, videos, software, talks, courses
 - http://www.cs.ubc.ca/~tmm
 - http://www.cs.ubc.ca/group/infovis
- book:Visualization Analysis & Design
 - http://www.cs.ubc.ca/~tmm/vadbook
- acknowledgements
 - joint work: all collaborators
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 - -feedback on this talk
 - Matthew Brehmer, Joel Ferstay, Stephen Ingram, Torsten Möller, Michael SedImair, Jessica Dawson
 - funding: NSERC Strategic Grant

