

Dimensionality Reduction From Several Angles

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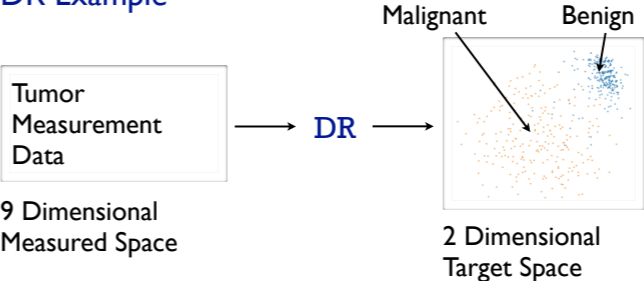
<http://www.cs.ubc.ca/~tmm/talks.html#linz14>

Dimensionality Reduction

- what is it?
 - map data from high-dimensional measured space into low-dimensional 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

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DR Example



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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

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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

Questions: A Progression

- 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 can we figure out what people need?
- how should people look at DR output?
 - how can we tell if we're drawing the right picture?
 - do metrics match up with human perception?
- why and how do people use DR?

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Even More Questions

- 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?

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Dimensionality Reduction In the Wild

Tasks and Challenges
joint work with:
Michael Sedlmair, Matthew Brehmer, Stephen Ingram
work in progress

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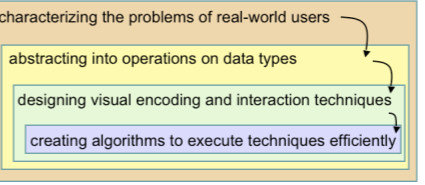
Two-Year Cross-Domain Qualitative Study

- 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
- final results coming soon
 - taxonomy of abstract tasks for DR
 - identified significant unmet user needs
- why and how do people use DR?
 - overarching question weaving through projects in this talk
 - preliminary results from study informed many of them

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!

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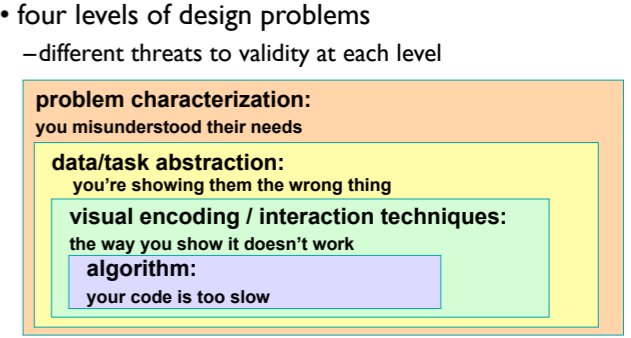


A Nested Model of Visualization Design and Validation

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

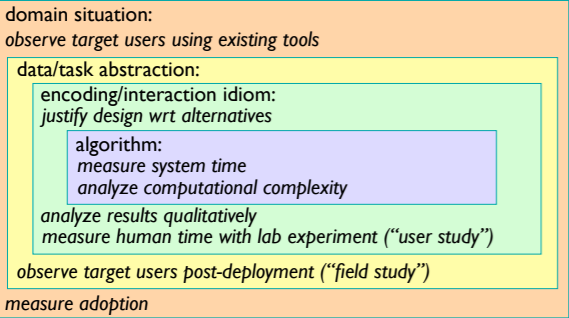
A Nested Model of Visualization Design and Validation.
Munzner. IEEE TVCG 15(6):921-928, 2009 (Proc. InfoVis 2009).

Four Levels of Design and Validation



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Nested Levels of Design and Validation



- mismatch: cannot show idiom good with system timings
- mismatch: cannot show abstraction good with lab study

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

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

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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.



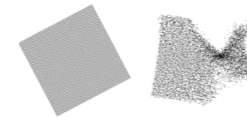
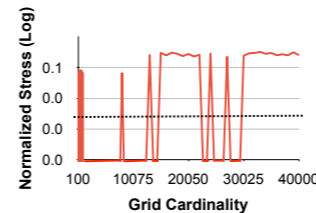
MDS: Multidimensional Scaling

- 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: $O(N^2)$
 - Stochastic Force [Chalmers 1996]
 - limitations: quality problems from local minima
- Glimmer goal: $O(N)$ speed and high quality

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Glimmer Strategy

- Stochastic force alg suitable for fast GPU port
 - but systematic testing shows it often terminates too soon

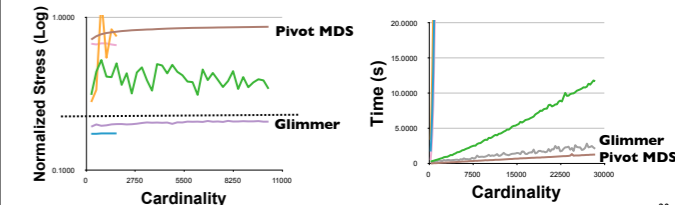
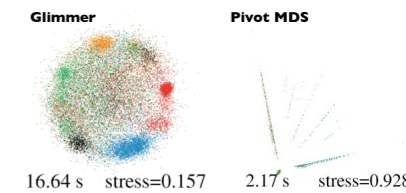


- Use as subsystem within new multilevel GPU alg with much better convergence properties

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

- quality higher
- speed equivalent

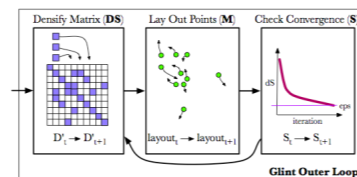


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Methods and Outcomes

- methods
 - quantitative algorithm benchmarks: speed, quality
 - systematic comparison across 1K-10K 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

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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.

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MDS Algorithm Speeds

- newer algorithms linear, but...

Age	Algorithm	Author/Year	Complexity
↓	Classic MDS	Torgersen '52	$O(N^3)$
	SMACOF	de Leeuw '77	$O(N^3)$
	Pivot MDS	Brandes '07	$O(kN)$
	Glimmer	Ingram '09	$O(cN)$
	LAMP	Joia '11	$O(kN)$

MDS Speed on Coordinate Data

shuttle benchmark
N = 43K
D = 9

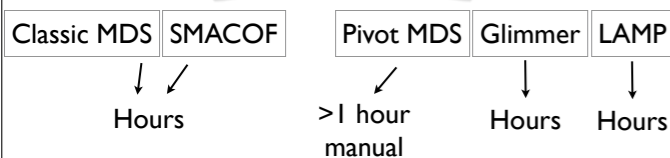


- time to calculate distance between two points
 - 0.00001 second

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MDS Speed on Distance Matrix Data

flickr benchmark
N = 1925
d = EMD



- time to calculate distance between two points
 - 0.01 second

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MDS Input: Coordinates vs Distances



- some systems intrinsically require coordinates
 - fundamental to LAMP speedup approach
- some handle both
 - including Glimmer

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Costly Distances

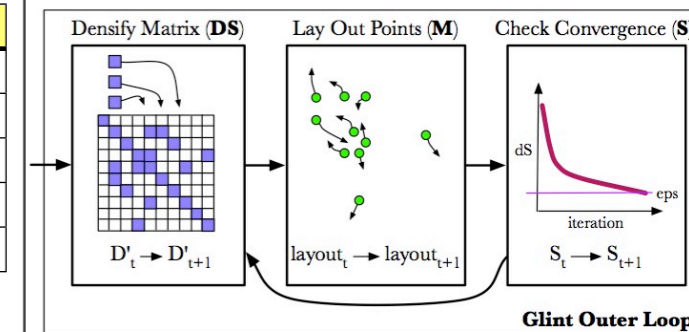
- DR in the Wild revealed many real-world examples

	Distance function	Cost (seconds)
Cheap	Euclidean on 9-D data	0.00001
	Database Query	0.001
Costly	Earth Mover Distance	0.01
	Euclidean on 4M-D data	1.0
	Human-in-the-loop	10.0

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Glint Framework

- calculate as few distances as possible, maintain quality
- three-stage architecture



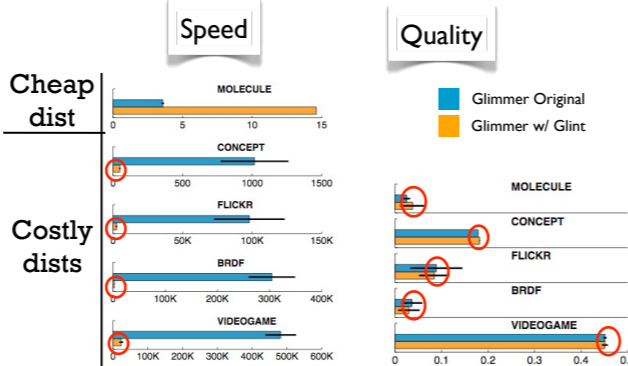
Glint Instantiations

- framework accommodates broad spectrum of algorithm types
 - three instantiations provided

MDS Algorithm Type	Chosen Algorithm
Gradient-based Optimization	SMACOF
Spectral/Analytic	Pivot MDS
Force-Directed	Glimmer

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Force-Directed Instantiation Results



major speed improvements while quality maintained

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Methods and Outcomes

- methods
 - algorithm benchmarks
- outcomes
 - dataset characterization different from previous work motivated by needs of real-world users
 - characterized distance metrics where architecture yields speed improvements
- then what?
 - keep talking to real users as way to discover more unmet needs

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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?

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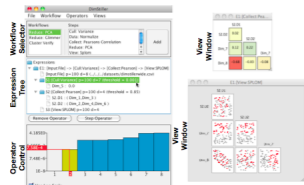
DimStiller

Workflows for Dimensional Analysis and Reduction

joint work with:
Stephen Ingram, Veronika Irvine, Melanie Tory, Steven Bergner, Torsten Möller

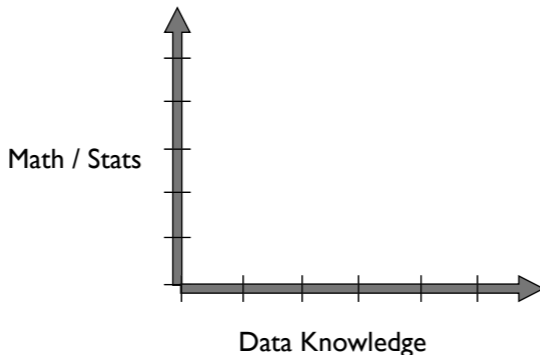
<http://www.cs.ubc.ca/labs/imager/tr/2010/DimStiller/>

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



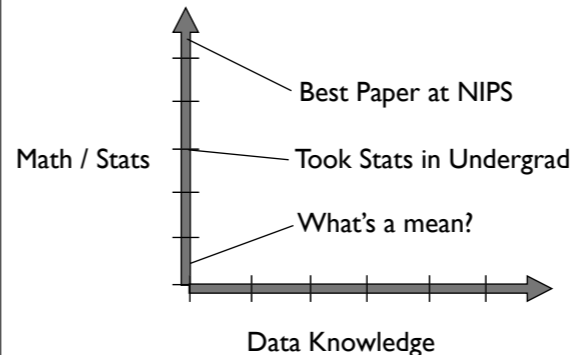
Who Might Use DR?

- DR in the Wild revealed broad set of users



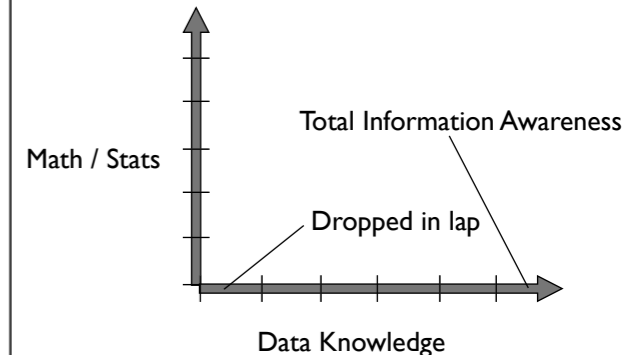
Who Might Use DR?

- Best Paper at NIPS
- Took Stats in Undergrad
- What's a mean?



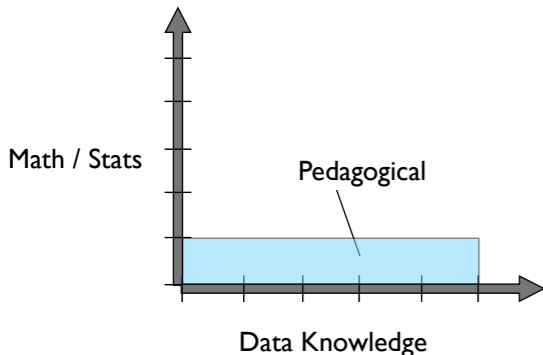
Who Might Use DR?

- Total Information Awareness
- Dropped in lap



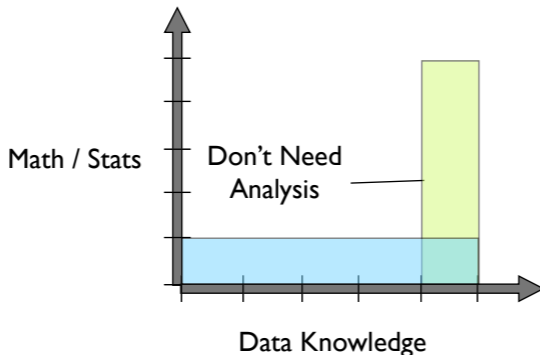
Who Might Use DR?

- Pedagogical



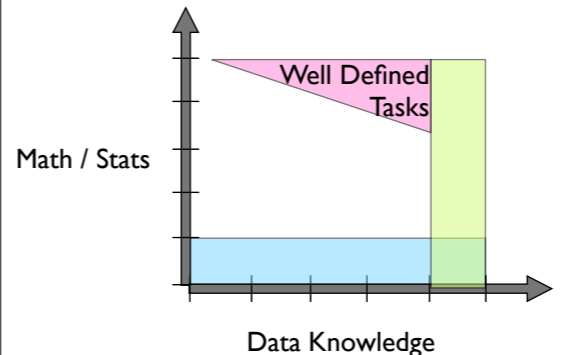
Who Might Use DR?

- Don't Need Analysis



Who Might Use DR?

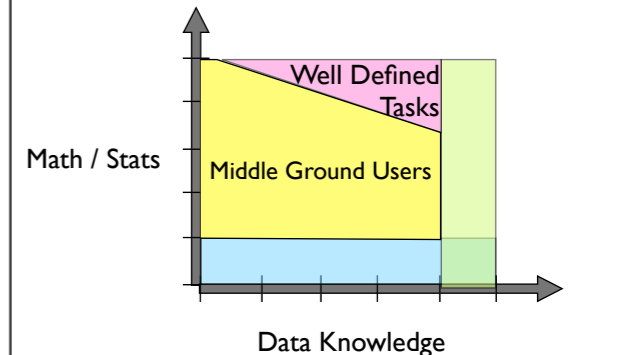
- Well Defined Tasks



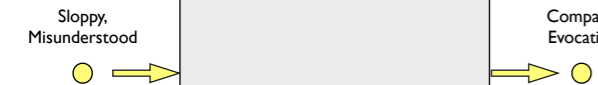
Who Might Use DR?

- middle ground users benefit from guidance

- Well Defined Tasks
- Middle Ground Users

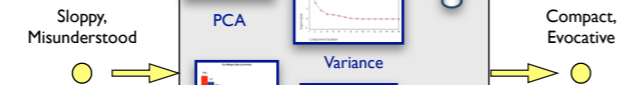


Global Guidance



Operator Space

Global Guidance



Operator Space

Global Guidance

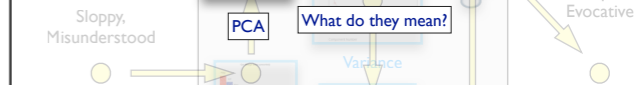
- which operations and in which order?



Operator Space

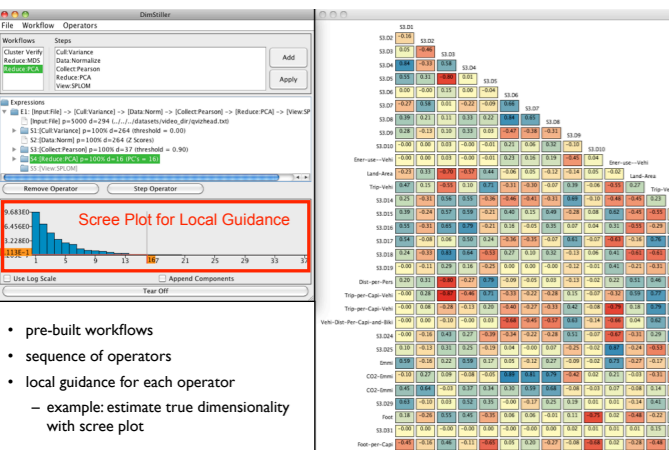
Local Guidance

- what to do with a given operator?



Operator Space

DimStiller



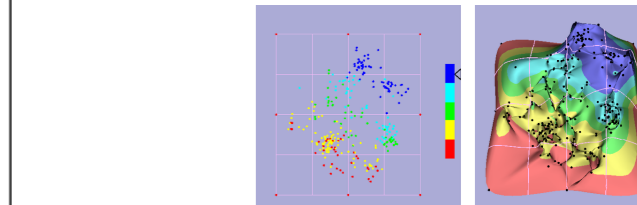
- pre-built workflows
- sequence of operators
- local guidance for each operator
 - example: estimate true dimensionality with scree plot

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

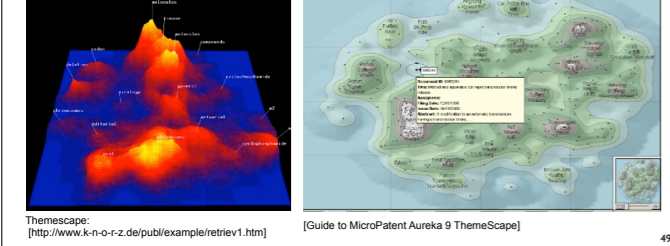
joint work with:
Melanie Tory, David W. Sprague, Fuqu Wu, Wing Yan So

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

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

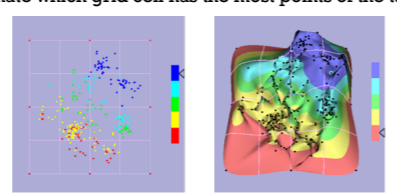
Information Landscapes

- 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



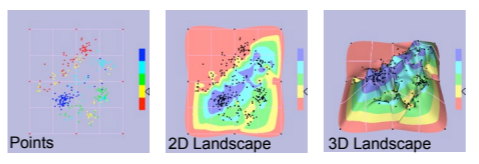
Understanding User Task

- 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 Sedlmair, Andrada Tatu, Melanie Tory

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

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

Cluster Separation

- simple idea

full overlap partial overlap adjacent separate distant

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
 - Good!
 - No!

User vs. Data Study

- user study
 - previous work on validating cluster measures
 - many users, few datasets
 - missing: 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
- evaluating the measures
 - metric aligns with human judgement?
 - if not: what are the reasons?

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

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

Qualitative Analysis I: Cluster Separation Factors

outlier shape split equidistant points

Analysis Approach

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

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

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

A Taxonomy of Cluster Separation Factors

High-Level Results

■ Failure cases ■ Ok

All (816)

Centroid: 49% Failure cases, 51% Ok

Grid: 51% Failure cases, 49% Ok

Only real (296)

Centroid: 68% Failure cases, 32% Ok

Grid: 65% Failure cases, 35% Ok

All failure cases

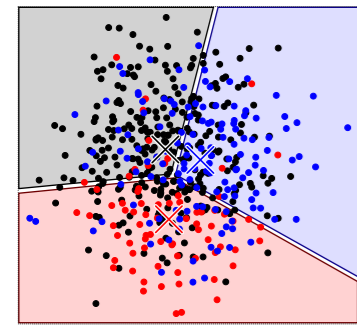
Centroid: 68% False Positives, 32% False Negatives

Grid: 85% False Positives, 15% False Negatives

Centroid Failure Example

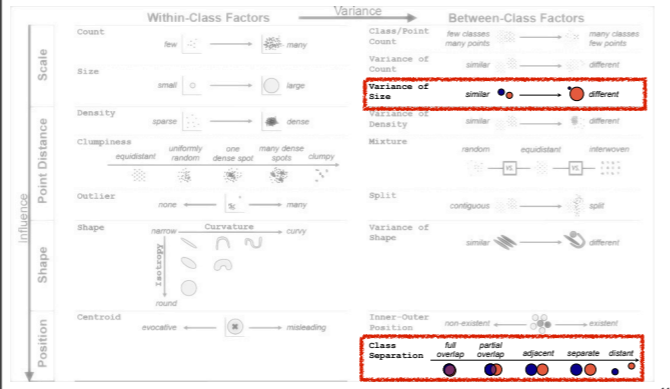


- big classes overspread small ones



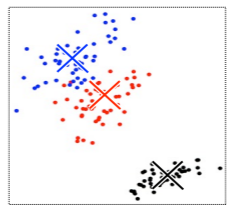
Red: **77 (Good)**
 Problem: **FP**
 Data: Gaussian, synthetic
 DR: MDS

Relevant Taxonomy Factors



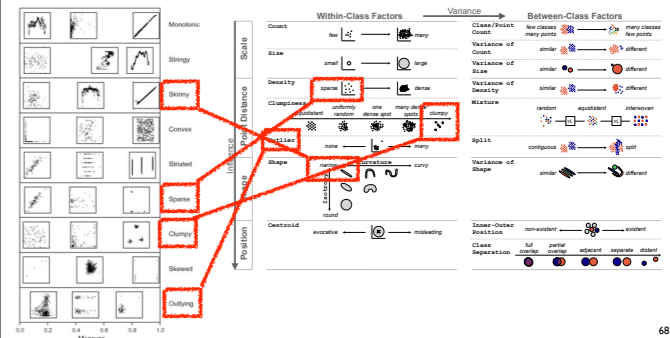
Centroid: Mapping Assumptions Into Taxonomy

- 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 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

Design Study Methodology

Reflections from the Trenches and from the Stacks

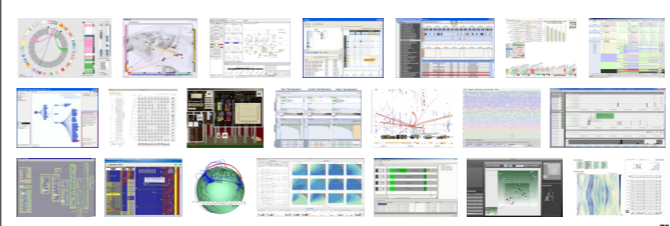
joint work with:
 Michael Sedlmair, Miriah Meyer

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

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

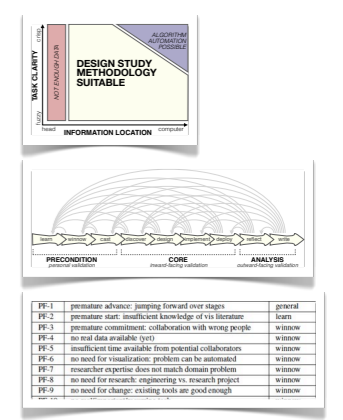
Design Studies

- 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



Pitfall Example: Premature Publishing

technique-driven vs. problem-driven

Must be first! (with image of a horse race)

Am I ready? (with image of a concert)

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!

Work in Progress

- DR in the Wild
 - end point: stay tuned
- DR for journalism
 - Overview project <http://overview.ap.org>
 - funded by Knight Foundation, collaboration with Stray@AP
 - starting point: Glimmer meets WikiLeaks
 - led us to identify and address more unmet real-world analysis needs
 - iterative rounds of development, deployment, adoption
 - end point: stay tuned
 - Pulitzer Prize finalist story used Overview for data analysis (Adam Playford, Newsday, For Their Eyes Only)

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

- further info

- <http://www.cs.ubc.ca/~tmm/talks.html#linz14>

- <http://www.cs.ubc.ca/group/infovis>

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- feedback on this talk

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