Lecture 10: Attribute Reduction Methods

Information Visualization
CPSC 533C, Fall 2011

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Required Readings

Chapter 8: Attribute Reduction Methods

Glimmer: Multilevel MDS on the GPU. Stephen Ingram, Tamara Munzner and Marc Olano. IEEE TVCG, 15(2):249-261, Mar/Apr 2009.

Further Reading

HyperSlice: Visualization of scalar functions of many variables. Jarke J. van Wijk and Robert van Liere. Proc. IEEE Visualization 1993, p 119-125.

Interactive Hierarchical Dimension Ordering, Spacing and Filtering for Exploration Of High Dimensional Datasets. Jing Yang, Wei Peng, Matthew O. Ward and Elke A. Rundensteiner. Proc. InfoVis 2003.

A Data-Driven Reflectance Model. Wojciech Matusik, Hanspeter Pfister, Matt Brand and Leonard McMillan. Proc. SIGGRAPH 2003

Data Reduction

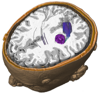
- how to reduce amount of stuff to draw?
  - crosscuts view composition considerations
- item reduction
  - **last** time
  - rows of table
- attribute reduction
  - **this** time
  - columns of table
- methods for both
  - filtering, aggregation, ordering

Attribute Reduction Methods

- camera metaphors
  - slicing, cutting, projection
- filtering, ordering, aggregation
  - for attributes as opposed to items
- dimensionality reduction
  - uncovering hidden structure
  - estimating true dimensionality
  - generating synthetic dimensions
    - linear mappings
    - nonlinear mappings
  - displaying low-dimensional spaces
    - scatterplots, SPLOMS, landscapes

Slicing/Cutting: Spatial Data

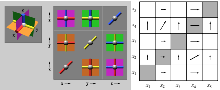
- easy to understand: spatial data, 3D to 2D, axis aligned



[Fig 0. Rieder et al. Interactive Visualization of Multimodal Volume Data for Neurosurgical Tumor Treatment. Computer Graphics Forum (Proc. EuroVis 2008) 27(3):1055–1062, 2008.

Slicing: High-Dimensional Functions

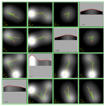
- HyperSlice: matrix of orthogonal 2D slices
  - each panel is display and control: drag to change slice
  - simple 3D example



[Fig 1, 2. van Wijk and van Liere. HyperSlice: Visualization of scalar functions of many variables. Proc. IEEE Visualization 1993]

Slicing: HyperSlice

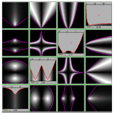
- 4D function $\sum_{i=0}^{3} w_i/(1+|x-p_i|^2)$
  - diagonals = standard graph



[Fig 4. van Wijk and van Liere. HyperSlice: Visualization of scalar functions of many variables. Proc. IEEE Visualization 1993]

Slicing: HyperSlice

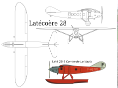
- satellite orbit eccentricity: x pos, y pos, x vel, grav const



[Fig 4. van Liere and van Wijk. Visualization of Multi-Dimensional Scalar Functions Using HyperSlice. CWI Quarterly, 7(2), June 1994, 147-158.]

Projections

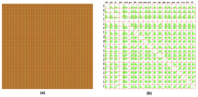
- orthographic: remove all information about filtered dims
  - hypercube: 3D to 2D, 4D to 3D (video)
- perspective: some info about filtered dims remains



[http://en.wikipedia.org/wiki/File:Lat%C3%A9co%C3%A8re_28.svg,
http://en.wikipedia.org/wiki/File:Railroad-Tracks-Perspective.jpg]

Attribute Filtering

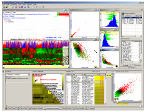
- filtering, but for attributes rather than items
  - unfiltered vs filtered SPLOM



[Fig 4. Yang et al. Interactive Hierarchical Dimension Ordering, Spacing and Filtering for Exploration Of High Dimensional Datasets. Proc. InfoVis 2003]

Attribute Ordering

- ordering, but for attributes rather than items
  - Hierarchical Clustering Explorer



[Fig 1. Seo and Shneiderman. A Rank-by-Feature Framework for Unsupervised Multidimensional Data Exploration Using Low Dimensional Projections. Proc. IEEE InfoVis 2004, p 65-72.]

Dimensionality vs Attribute Reduction

- vocab use in field not consistent
  - dimension/attribute
- attribute reduction: reduce set with filtering
  - includes orthographic projection
- dimensionality reduction: create smaller set of new dims
  - set size is smaller than original, new dims completely synthetic
  - **clarification:** includes dimensional aggregation
  - includes some projections (but not all)
    - vocab: projection/mapping

Uncovering Hidden Structure

- measurements indirect not direct
  - real-world sensor limitations
- measurements made in sprawling space
  - documents, images
- DR only suitable if (almost) all information could be conveyed with fewer dimensions
  - how do you know? need to estimate true dimensionality to check if different than original!

Estimating True Dimensionality

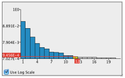
- error for low-dim projection vs high-dim original
- no single correct answer; many metrics proposed
  - cumulative variance that is not accounted for
  - strain: match variations in distance (vs actual distance values)
  - stress: difference between interpoint distances in high and low dimensions

$$stress(D,\Delta)=\sqrt{\frac{\sum_{ij}(d_{ij}-\delta_{ij})^2}{\sum_{ij}\delta_{ij}^2}}$$

- D: matrix of lowD distances
- Δ: matrix of hiD distances δ_{ij}

Showing Dimensionality Estimates

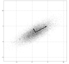
- scree plots as simple way: error against # dims
  - original dataset: 294 dims
  - estimate: almost all variance preserved with < 20 dims



[Fig 2. Ingram et al. DimStiller: Workows for dimensional analysis and reduction. Proc. VAST 2010, p 3-10]

Linear Dimensionality Reduction: PCA

- principal components analysis
  - describe location of each point as linear combination of weights for each axis
  - finding axes: first with most variance, second with next most, ...



[http://en.wikipedia.org/wiki/File:GaussianScatterPCA.png]

Nonlinear Dimensionality Reduction

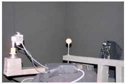
- many techniques proposed
  - MDS, charting, Isomap, LLE, TSNE,...
  - optimization problem
- pro: can handle curved rather than linear structure
- con: lose all ties to original dimensions
  - new dimensions cannot be easily related to originals

DR in Visualization: Tasks

- find/verify new/synthetic dimensions
  - are the new dimensions believable?
  - ex: data-driven reflectance model
- find/verify clusters
  - is there clear cluster structure in the new low-dim space?
  - does it match a conjectured clustering (color-coded)?
  - ex: glimmer

Example: DR for CG Reflectance Model

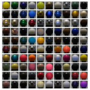
- goal: simulate how light bounces off materials to make realistic pictures
  - computer graphics: BRDF (reflectance)
- idea: measure what light does with real materials



[Fig 2. Matusik et al. A Data-Driven Reflectance Model. SIGGRAPH 2003]

Capturing Material Reflectance

- measurement: interaction of light with real materials (spheres)
- result: 104 high-res images of material
  - each image 4M pixels



[Fig 5. Matusik et al. A Data-Driven Reflectance Model. SIGGRAPH 2003]

Goal: Image Synthesis

- step 1: create new renderings with CG objects that look like captured materials
  - CG teapot looks just like real hematite

- step 2: simulate completely new materials
  - rusty, greasy, ...

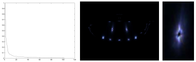
[Fig 6, 1. Matusik et al. A Data-Driven Reflectance Model. SIGGRAPH 2003]

Need For Low-Dimensional Model

- how to do step 2 simulation of new materials?
  - 104 materials * 4M pixels = 400 million dimensions
  - model much too hi-dim to be useful
- goal: much more concise model that humans can understand/use to generate computer graphics images
  - allow users to tweak meaningful knobs: how shiny, how greasy, how metallic, what color...
- dimensionality reduction to the rescue

Dimensionality Reduction: Linear

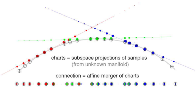
- first try: PCA, linear DR technique
- result: error falls off sharply
- good results for step 1 around 45 dims
  - step 2 problem: physically impossible intermediate points when simulating new materials
  - specular highlights cannot have holes!



[Fig 7, 9. Matusik et al. A Data-Driven Reflectance Model. SIGGRAPH 2003]

Dimensionality Reduction: Nonlinear

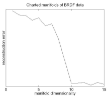
- second try: charting, nonlinear DR
  - better if data embedding is curved not flat



[Fig 10. Matusik et al. A Data-Driven Reflectance Model. SIGGRAPH 2003]

Dimensionality Reduction: Nonlinear

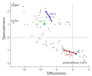
- second try: charting, nonlinear DR
  - scree plot suggests 10-15 dims
  - note that dim estimate depends on technique used!



[Fig 11. Matusik et al. A Data-Driven Reflectance Model. SIGGRAPH 2003]

Finding Semantics for Synthetic Dimensions

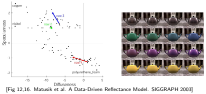
- look for meaning in scatterplots
  - each synthetic dimension named by people, not by algorithm
  - points represent real-world images (spheres)
  - people inspect images corresponding to points to decide if axis could have a meaningful name



[Fig 12. Matusik et al. A Data-Driven Reflectance Model. SIGGRAPH 2003]

Understanding Synthetic Dimensions

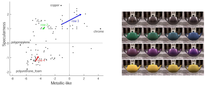
- crosscheck meaning
  - arrows show simulated images (teapots) made from model
  - check if those match dimension semantics



[Fig 12,16. Matusik et al. A Data-Driven Reflectance Model. SIGGRAPH 2003]

Understanding Synthetic Dimensions

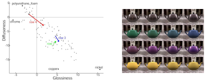
- Specular-Metallic



[Fig 13,16. Matusik et al. A Data-Driven Reflectance Model. SIGGRAPH 2003]

Understanding Synthetic Dimensions

- Diffuseness-Glossiness



[Fig 14,16. Matusik et al. A Data-Driven Reflectance Model. SIGGRAPH 2003]

Nonlinear Dimensionality Reduction

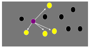
- MDS: multidimensional scaling
- confusingly, large family of things all called MDS
  - some linear, some nonlinear!
- classical: minimize strain
  - early formulation equivalent to PCA (linear)
  - spectral methods: approximate eigenvectors
- distance scaling: minimize stress
  - nonlinear optimization
  - force simulation (mass-spring)

Spring-Based MDS: Naive

- repeat for all points
  - compute spring force to all other points
  - difference between high dim, low dim distance
  - move to better location using computed forces
- compute distances between all points
  - $O(n^2)$ iteration, $O(n^3)$ algorithm

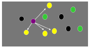
Faster Spring Model: Stochastic

- compare distances only with a few points
  - maintain small local neighborhood set



Faster Spring Model: Stochastic

- compare distances only with a few points
  - maintain small local neighborhood set
  - each time pick some randoms, swap in if closer



Faster Spring Model: Stochastic

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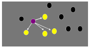
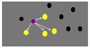


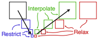
Faster Spring Model: Stochastic

- compare distances only with a few points
  - maintain small local neighborhood set
  - each time pick some randoms, swap in if closer
- small constant: 6 locals, 3 randoms typical
  - $O(n)$ iteration, $O(n^2)$ algorithm

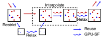


Glimmer Algorithm

- multilevel to avoid local minima, designed to exploit GPU



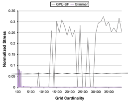
- restriction to decimate
- relaxation as core computation
- relaxation to interpolate up to next level



[Fig 1. Ingram, Munzner, and Olano. Glimmer: Multilevel MDS on the GPU. IEEE TVCG, 15(2):249-261, Mar/Apr 2009.]

Glimmer vs Stochastic Alone

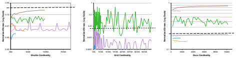
- GPU version of stochastic as relaxation subsystem
  - poor convergence properties if run alone
  - only obvious when scalability allows thorough testing



[Fig 2,4. Ingram, Munzner, and Olano. Glimmer: Multilevel MDS on the GPU. IEEE TVCG, 15(2):249-261, Mar/Apr 2009.]

Stochastic Termination

- how do you know when it's done?
  - no absolute threshold, depends on dataset
  - interactive click to stop does not work for subsystem



- sparse normalized stress approximation
  - minimal overhead to compute (vs. full stress)
  - low pass filter

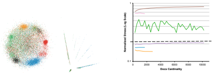
[Fig 9. Ingram, Munzner, and Olano. Glimmer: Multilevel MDS on the GPU. IEEE TVCG, 15(2):249-261, Mar/Apr 2009.]

GPUs

- characteristics
  - small set of localized texture accesses
  - output at predetermined locations
  - no variable length looping
  - avoid conditionals: all floating point units execute same instr at same time
- mapping problems to GPU
  - arrays become textures
  - inner loops become fragment shader code
  - program execution becomes rendering

Finding/Verifying Clusters

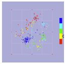
- sparse document dataset: 28K dims, 28K points
- Glimmer (distance) vs PivotMDS (classical)
  - speed improvement so distance as fast as classical
  - major quality difference for sparse datasets

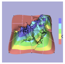


[Fig 8,9. Ingram, Munzner, and Olano. Glimmer: Multilevel MDS on the GPU. IEEE TVCG, 15(2):249-261, Mar/Apr 2009.]

Showing DR Data

- scatterplot showing points
  - only works if true dimensionality is 2 (... or 3)
  - need to drill down to see what points represent
- SPLOM
  - safe choice
- landscapes
  - avoid! studies show worse than just using points





Reading For Next Time

Hierarchical Parallel Coordinates for Exploration of Large Datasets
Ying-Huey Fua, Matthew O. Ward, and Elke A. Rundensteiner,
IEEE Visualization '99.

Parallel sets: visual analysis of categorical data. Fabien Bendix, Robert Kosara, and Helwig Hauser. Proc. InfoVis 2005, p 133-140.

Metric-Based Network Exploration and Multiscale Scatterplot.
Yves Chiricota, Fabien Jourdan, Guy Melancon. Proc. InfoVis 04, pages 135-142.

Reminders

- Project meetings due 10/19
  - one week from today
- Office hours today after class (5-6)
  - or schedule specific meeting time by email
- No class Oct 24/26