Reading

Hyperdimensional Data Analysis Using Parallel Coordinates
Edward J. Wegman. Journal of the American Statistical Association,

Fast Multidimensional Scaling through Sampling, Springs and Interpolation
Alistair Morrison, Greg Ross, Matthew Chalmers,
Information Visualization 2(1) March 2003, pp. 68–77.

Cluster Stability and the Use of Noise in Interpretation of Clustering

Interactive Hierarchical Dimension Ordering, Spacing and Filtering for Exploration Of High
Dimensional Datasets

Optional:
• Visualizing the non-visual: spatial analysis and interaction with information from text
• Hierarchical Parallel Coordinates for Visualizing Large Multivariate Data Sets
• Parallel Coordinates: A Tool for Visualizing Multi-Dimensional Geometry.
  Alfred Inselberg and Bernard Dimsdale, IEEE Visualization '90.
Parallel Coordinates

only 2 orthogonal axes in the plane instead, use parallel axes!

PC: Correlation

Figure 3. Parallel Coordinate Plot of Six-Dimensional Data Illustrating Correlations of $p = 1, .8, .2, 0, -.2, -.8,$ and $-1.$

PC: Duality

rotate–translate
point–line

- pencil: set of lines coincident at one point
- not critical to understand projective plane details!

[Parallel Coordinates: A Tool for Visualizing Multi-Dimensional Geometry. Alfred Inselberg and Bernard Dimsdale, IEEE Visualization '90.]
PC: Axis Ordering

geometric interpretations
  · hyperplane, hypersphere
  · points do have intrinsic order

infovis
  · no intrinsic order, what to do?
  · indeterminate/arbitrary order
     weakness of many techniques
     downside: human-powered search
     upside: powerful interaction technique
  · most implementations
     user can interactively swap axes

Automated Multidimensional Detective
  · [Inselberg 99]
  · machine learning approach
Hierarchical Parallel Coords: LOD

[Hierarchical Parallel Coordinates for Visualizing Large Multivariate Data Sets. Ying-Huey Fua, Matthew O. Ward, and Elke A. Rundensteiner. IEEE Visualization '99]
Hierarchical Clustering

proximity-based coloring

[Hierarchical Parallel Coordinates for Visualizing Large Multivariate Data Sets. Ying-Huey Fua, Matthew O. Ward, and Elke A. Rundensteiner, IEEE Visualization ’99.]

interaction lecture later:
· structure-based brushing
· extent scaling
Dimensionality Reduction

mapping multidimensional space into space of fewer dimensions

- typically 2D for infovis
- keep/explain as much variance as possible
- show underlying dataset structure
- multidimensional scaling (MDS)

minimize differences between interpoint distances in high and low dimensions
Dimensionality Reduction: Isomap

4096 D: pixels in image
2D: wrist rotation, fingers extension

Naive Spring Model

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 [Chalmers 96]

compare distances only with a few points
  · maintain small local neighborhood set
Faster Spring Model [Chalmers 96]

- compare distances only with a few points
- maintain small local neighborhood set
- each time pick some randoms, swap in if closer
Faster Spring Model [Chalmers 96]

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**Faster Spring Model [Chalmers 96]**

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
Parent Finding [Morrison 02, 03]

lay out a root(n) subset with [Chalmers 96] for all remaining points
  · find “parent”: laid-out point closest in high D
  · place point close to this parent

$O(n^{5/4})$ algorithm
True Dimensionality: Linear

how many dimensions is enough? > 2 or 3?
  · knee in error curve
example: measured materials from graphics linear PCA: 25
  · can get physically impossible intermediate points

True Dimensionality: Nonlinear

nonlinear MDS: 10–15
  · all intermediate points possible
categorizable by people
  · red, green, blue, specular, diffuse, glossy, metallic,
  · plastic-y, roughness, rubbery, greasiness, dustiness...

[A Data–Driven Reflectance Model, SIGGRAPH 2003, W Matusik, H. Pfister
H. Pfister et al. H. Pfister et al.]
Themeescapes / Galaxies

MDS output: beyond just drawing points
  - galaxies: aggregation

- themescapes: terrain/landscapes
Cluster Stability

display
  · also terrain metaphor

underlying computation
  · energy minimization (springs) vs. MDS
  · weighted edges

do same clusters form with different random start points?

"ordination"
  · spatial layout of graph nodes
Approach

- normalize within each column
- similarity metric
  - discussion: Pearson's correlation coefficient
- threshold value for marking as similar
  - discussion: finding critical value
Graph Layout

criteria
  • distance in layout matching graph-theoretic distance
    vertices one hop away close
    vertices many hops away far
  • insensitive to random starting positions
    major problem with previous work!
  • tractable computation

force-directed placement
  • discussion: energy minimization
  • others: gradient descent, etc
  • discussion: termination criteria
Barrier Jumping

same idea as simulated annealing
  · but compute directly
  · just ignore repulsion for fraction of vertices
solves start position sensitivity problem
Results

efficiency
  · naive approach: $O(V^2)$
  · approximate density field: $O(V)$

good stability
  · rotation/reflection can occur

different random start  adding noise
Critique

real data
  · suggest check against subsequent publication!

give criteria, then discuss why solution fits

visual + numerical results
  · convincing images plus benchmark graphs

detailed discussion of alternatives at each stage

specific prescriptive advice in conclusion
Dimension Ordering

in NP, like most interesting infovis problems
  · heuristic

divide and conquer
  · iterative hierarchical clustering
  · representative dimensions

choices
  · similarity metrics
  · importance metrics
    variance
  · ordering algorithms
    optimal
    random swap
    simple depth-first traversal
Spacing, Filtering

same idea: automatic support

interaction

· manual intervention

· structure-based brushing
· focus+context, next week
Results: InterRing

raw, order, distort, rollup (filter)
Results: Parallel Coordinates

raw, order/space, zoom, filter
Results: Star Glyphs

raw, order/space, distort, filter
Results: Scatterplot Matrices

raw, filter
Critique

pro

approach on multiple techniques, real data!

con

always show order then space then filter
  · hard to tell which is effective
  · show ordered vs. unordered after zoom/filter?
Software, Data Resources

www.cs.ubc.ca/~tmm/courses/cpsc533c-04-fall/resources.html