# Advanced Data Visualization **CS 6965** Spring 2018 Prof. Bei Wang Phillips University of Utah



# Today

- a selection process if there are more than one team.
- Visual mapping perception evaluation
- View transformation

A project presentation by Prof. Melodie Weller from the School of Dentistry (a potential final project topic). Please contact the course instructor if your team is interested in the project; we will go through

Visual mapping: glyphs, pixel-oriented, hierarchy-based, animation



# Visual Mapping Continued

HD





# Visualization pipeline for HD data

## **Subspace Clustering** Dimension Space Exploration [47], [48], [49], Subset of Dimension [51], [53], Non-Axis-Parallel Subspace [56], [57], [58]

## **Regression Analysis**

Optimization & Design Steering [61], [62], [63], **Structural Summaries** [67], [68]

## **Topological Data Analysis** Morse-Smale Complex [166], [168], [169], [170], Reeb Graph [174], [175], [181] Contour Tree [179, 180], Topological Features [191], [192]

	<b>Pixel-Oriented</b>	<b>Hierarchy-Based</b>	Animation	Evalu
phs	Jigsaw Map [109],	Dimension	GGob i[119],	Scatterplot
	Pixel Bar Charts [108],	Hierarchy [113],	TripAdvisor <sup>ND</sup>	[122],
	Circle Segment [107]	Topology-Based	[52],	Parallel Co
phs	Value & Relation	Hierarchy [197], [198],	Rolling the	Effectiven
05]	Dispaly [110]	Others [115], [117]	Dice [120]	Animatic

## **Continuous Visual Representation**

Continuous Scatterplot [134], [135] Continuous Parallel Coordinates [136], Splatterplots [138], Splatting in Parallel Coordinates [136]

## **Accurate Color Blending**

Hue-Preserving Blending [140], Weaving vs. Blending [141]

## **Image Space Metrics**

**Clutter Reduction** [142], [143], Pargnostics [144], Pixnostic [145]

[LiuMaljovecWang2017]









# Visual mapping continued...

GlyphS

# Glyphs: small graphical symbol

0 ම Ì 1 ۵Ö ම 6 Ō 2|5 18794 211 207 96527 203 18816 20142 **@** 65 65 0.0 0.0 214 206 45544 210 20380 202 79984 14829 0,0 <u>,</u>  $\odot$ 0,0 213 209 205 12003 77583 201 10617 63333 <u>,</u> 0.0 <u>,</u> 0 00 212 62992 208 12894 204 11980 200 21172 15329

## Using shape, color, opacity, size, location to encode high-dim info

## 2. FACES FOR 53 GEOLOGICAL SPECIMENS OF EXAMPLE 2



# Chernoff faces

- One of the first attempts to map a high-dim data point to a single glyph Mapping different facial features to a separate dimension Each point in k-dimensional space (k<18) is represented by a cartoon of a face</p> whose features, such as length of nose and curvature of mouth, correspond to components of the point.
- People grow up studying and reacting to faces all of the time. Small and barely
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   In the studying and reacting to faces all of the time. Small and barely
   In the studying and reacting to faces all of the time. measurable differences are easily detected and evoke emotional reactions from a long catalogue buried in the memory. ...human mind subconsciously operates as a high-speed computer, filtering out insignificant visual phenomena and focusing on the potentially important... It is this flexibility which is lacking in standard computer programs.









## Chernoff faces



2. FACES FOR 53 GEOLOGICAL SPECIMENS OF EXAMPLE 2

# Why glyphs?

- Enhancing the user's ability to detect and comprehend important phenomena.
- Serving as a mnemonic device for remembering major conclusions Communicating major conclusions to others.
- Providing the facility for doing relatively accurate calculations informally.
- Recent efforts: provide statistical and sensitivity information to present trends in data

# Generalizing scatterplot



Fig. 1. Visualization of two variables of the Wine data set [47], where points are color coded by class. (a) Traditional scatterplots suffer from overlap and different classes may appear to mix in arbitrary ways. (b) a FBS [10] reveals a positively correlated trend, but misrepresents the trend of the points in blue. (c) a GSS on a 3D subspace represents better the trends of points belonging to different classes; class 3 is distinguishable from others. (d) A star glyph plot summarizes the GSS across multiple 3D subspaces, where all of the three classes stand out distinctly, as evidenced by the shape and size of the glyphs.

By utilizing local linear regression to compute partial derivatives around sampled data points and representing the information in terms of glyph shape, sensitivity information can be encoded into scatterplots [ChanCorreaMa2013]





# Flow-based scatterplot

Computing the sensitivity of one variable w.r.t. the other variable with respect to another. neighborhood of N points:  $\frac{\partial y}{\partial x}$ 



- Sensitivity can be approximated by the partial derivative of one
- Approximate the partial derivative for point (x0,y0) in a

$$\frac{y}{x} \approx \frac{\sum_{i=0}^{N} (y_i - y_0) (x_i - x_0)}{\sum_{i=0}^{N} (x_i - x_0)^2}$$



Fig. 1. DICON is a dynamic icon-based visualization technique that helps users understand, evaluate, and adjust complex multidimensional clusters. It provides visual cues describing the quality of a cluster as well as its multiple attributes, and can be embedded within many kinds of visualizations such as maps, scatter plots, and graphs.

# **Icon-based** visualization



[CaoGotzSun2011]

# Pixel-Oriented Approaches

- Encode maximal amount of information (?)
- Dense pixel displays
- Encode data values as individual pixels and creating separate
   displays or subwindows for each dimension

## Pixel based visualization

## **Pixel bar charts**

## • Use the pixels within the bars to present the detailed information of the data records.



Figure 2: A Pixel Bar Chart

[KeimHaoLadisch2001]

## Pixel bar charts



## a) Equal-Width Bar Chart

Regular bar chart

## a) Equal-Width Pixel Bar Chart

[KeimHaoLadisch2001]



# Treemap



20 40 60 80 100 0 No. of Urban Ecology studies

Fig 3.

0 2 4 6 8 10 No. of Urban Ecology studies

# Hierarchy-Based Approaches

# **Dimension hierarchies**

Group similar clusters of dimensions together in a hierarchy Key: using a similarity measure of dimensions



YangPengWard2003

# Focus+context: hierarchical graphs





(b)

## [KreuselerSchumann2002]



Animation

# Rolling the Dice Transition between any pair of scatterplots in a SPLOM Connecting a series of 3D transitions between scatterplots



## Rolling the Dice: Scatterplot Matrix Navigation https://www.youtube.com/watch?v=E1birsp9iYk

# Other Examples

# Dynamic projection, continuou TripAdvisor-ND

Operation of the second sec

# **Perception Evaluation**

- Obsigue of the provide the second user through visual perception
- Observation Determining the effectiveness of the overall visualization
- Some existing conclusions

# Evaluation

# Evaluate scatterplots and DR

- An empirical data study.
- scatterplot techniques.
- terms of their separability from other classes.

Two human coders manually inspected a broad set of 816 scatterplots derived from 75 datasets, 4 DR techniques, and the 3

Each coder scored all color-coded classes in each scatterplot in

[SedImairMunznerTory2013]

# Verifying cluster separation



[SedImairMunznerTory2013]

# Some Conclusions

- O 2D scatterplots are often 'good enough', that is, neither SPLOM nor
   O interactive 3D adds notably more cluster separability with the chosen DR technique.
- If 2D is not good enough, the most promising approach is to use an alternative DR technique in 2D.
- SPLOM occasionally adds additional value, and interactive 3D rarely helps but often hurts in terms of poorer class separation and usability.

[SedImairMunznerTory2013]

# **Perception evaluation of DR**



Fig. 1. Instances of task stimuli: (a) Estimate number of clusters, (b) estimate number of subclusters of red group, (c) estimate number of outliers, (d) determine whether green or blue cluster is closer to red object, (e) determine whether green or blue cluster is closer to red cluster, (f) find five closest objects to red object, (g) rank red, green, and blue clusters by density, and (h) estimate number of objects in red group.

[EtemadpourMottaPaiva2015]





# **Perception evaluation of DR**

	#Clu	#SClu	#Out	fCluClu	fCluObj	rKnn	rDens	#Obj
Glimmer	3.67	2.80	4.31	3.13	3.65	3.17	3.30	4.31
Isomap	3.58	3.19	3.72	3.10	3.23	3.53	3.57	3.72
LSP	3.12	3.23	3.57	3.4	3.58	3.45	3.78	3.57
PCA	3.61	3.63	3.10	2.77	3.12	2.81	3.75	3.10
Tree	2.91	3.31	3.74	3.26	3.84	3.17	3.61	3.74

Fig. 4. Confidence: Comparing mean confidence values for completing tasks with different projection methods. Colors indicate groups of no significant pairwise differences in form of winners shown in dark red, loser in white, and the ones in between in light red.

[EtemadpourMottaPaiva2015]

# **Evaluating PCP**



Figure 1: Scatter plots embedded into a PCP. Red arrows denote the direction of the al axis in each visualization.

- Evaluation of cluster identification performance for different PCP variants
- Conclusion: A fair number of the seemingly valid improvements, with the exception of scatter plots embedded into PCPs, do not result in significant performance gains.



[HoltenWijk2010]



# Thanks! Any questions?

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## CREDITS

Special thanks to all people who made and share these awesome resources for free:

- Vector Icons by Matthew Skiles

Presentation template designed by <u>Slidesmash</u>

Photographs by <u>unsplash.com</u> and <u>pexels.com</u>

## **Presentation Design**

This presentation uses the following typographies and colors:

## Free Fonts used:

http://www.1001fonts.com/oswald-font.html

https://www.fontsquirrel.com/fonts/open-sans

## **Colors** used