# Visualization Highlights

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Amore Reading Group, Mar 24 2017

http://www.cs.ubc.ca/~tmm/talks.html#amore17

#### · terrain of visualization venues

- names, scopes, relative strengths

Visualization highlights

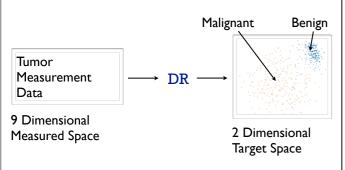
- · a few recent interesting papers
- dimensionality reduction for visual data analysis
  - Probing Projections https://uclab.fh-botsdam.de/projects/probing-projections/
- visualization to understand deep learning
- Towards Better Analysis of Deep Convolutional Neural Networks http://www.shixialiu.com/publications/cnnvis/paper.pdf
- Visualizing the Hidden Activity of Artificial Neural Networks http://www.cs.rug.nl/~alext/PAPERS/VAST16/paper.pdf
- visualization incorporating ideas from ML
- Surprise! Bayesian Weighting for De-Biasing Thematic Maps https://idl.cs.washington.edu/papers/surprise-maps
- scalable algorithms
- Nanocubes http://www.nanocubes.net/
- Hashedcubes https://cscheid.net/static/papers/infovis hashed cubes 2016.pdf

Dimensionality reduction: Background, our past work

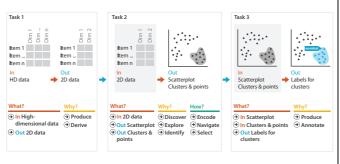
## **Dimensionality Reduction**

- 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

### DR Example: Tumor Malignancy



### DR Example: Large Document Collections



#### **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 Sedlmair, Matthew Brehmer, Stephen Ingram

Visualizing Dimensionally-Reduced Data Interviews with Analysts and a Characterization of Task Sequences

Brehmer, Sedlmair, Ingram, and Munzner

### Two-Year Cross-Domain Qualitative Study

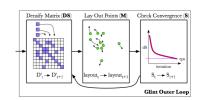
- · interviewed two dozen high-dim data analysts
- how are they using DR?
- does it match up with assumptions?
- in the wild: HCl term for field work with real users
- · five abstract tasks
- naming synthesized dimensions
- mapping synthesized dimension to original dimensions
- verifying clusters
- naming clusters
- matching clusters and classes



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
- -limitations: quality for very high dimensional sparse data
- · distance scaling: minimize stress
- -nonlinear optimization: O(N2)
- 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



## Glint

An MDS Framework for Costly Distance Functions

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**

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 EuroVis 2013), Volume 150 Part B, p 557-569, 2015.