Spatial Omics Visualizations: Lessons Learned from Networks and Maps

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EVERYBODY IS TALKING ABOUT SPATIAL OMICS!

Method of the Year: spatially resolved transcriptomics

*Nature Methods* has crowned spatially resolved transcriptomics Method of the Year 2020.

Vivien Marx
BIOVIS CHALLENGE: FROM IMAGES TO ANALYSIS

Stack of images, each corresponding to one protein, i.e., one channel of the multi-dimensional measurement

Basic visualization e.g., overlaying 3 proteins as RGB

Segmentation mask. Cells indicated by random color

Downstream data analysis
Spatial Omics Visualization Challenges

High dimensional data
Similar to “classical” omics data (except for scale)
Spatial location / proximity is important
NOT encountered in “classical” omics data.
Fixed location
Potentially high-D vector for each location

ANALOGY: MAPS!
SINGLE DATA VALUE + SPATIAL LOCATION

Glyphs - Size

Color

- Pasture/Range
- Forest
- Cropland
- Special Use
- Miscellaneous
- Urban

Matthew Ericson, NY Times

Bloomberg
SINGLE DATA VALUE + SPATIAL LOCATION

Glyphs – Directions

Mc: Trump made huge gains across rural America, helping to defeat Hillary Clinton and her urban supporters.
BUT WHAT IF YOU HAVE MORE THAN ONE DATA VALUE?

Glyphs?

Don’t treat color channels as separate visual channels

Scalability? [Tominski]
DO WE REALLY NEED A MAP?

Mike Bostok, NY Times
DO WE REALLY NEED A MAP?

It’s hard to do more complex things with maps
Is the spatial context paramount?
Is the spatial context a proxy for something?
Lots of attributes for nodes and edges
Location doesn’t matter, but connectivity does
Can’t choose location freely
ON-NODE ENCODING?

Maybe if you zoom in
Still limited
The State of the Art in Visualizing Multivariate Networks

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Abstract
Multivariate networks are made up of nodes and their relationships (links), but also data about those nodes and links as attributes. Most real-world networks are associated with several attributes, and many analysis tasks depend on analyzing both relationships and attributes. Visualization of multivariate networks, however, is challenging, especially when both the topology of the network and the attributes need to be considered concurrently. In this state-of-the-art report, we analyze current practices and classify techniques along four axes: layouts, view operations, layout operations, and data operations. We also provide an analysis of tasks specific to multivariate networks and give recommendations for which technique to use in which scenario. Finally, we survey application areas and evaluation methodologies.
INTERACTION!

Two Paths:
1. Select regions to show
2. Select / derive data to show
SELECTING REGIONS TO SHOW
Select one or multiple items/regions
Show rich data about them in separate view
SELECT A PATH IN A MAP

Carolina Nobre, Alexander Lex
OceanPaths: Visualizing Multivariate Oceanography Data
ENROUTE – PATH SELECTION
SELECT / DERIVE DATA TO SHOW
But do you need to?
Show average expression (etc)
Show average expression for pathway of interest
Filter out uninteresting items
Create domain specific scores
Create clusters/archetypes
...

SHOWING RAW DATA IS HOPELESS!
APPROACH: USE A PRIOR, SHOW DIFFERENCE.

(a) The Event Density of “mischief” in Canada.

(b) The per-capita Event Rate of mischief.

(c) The Surprise Map of mischief.

model of population density + accounting for variability when analyzing small numbers
HAVE A HANDFUL OF SCORES? VIS FEASIBLE!

[Barsky et al., Cerebral, 2008]
CLUSTERGRAMMER JUST EARLIER AT BIOVIS:
DYNAMIC FILTERS
Miriah Meyer, Tamara Munzner, Angela DePace, Hanspeter Pfister
MulteeSum: A Tool for Comparative Spatial and Temporal Gene Expression Data
Assessing co-localization

- We were interested in TLS-sites enriched for both B and T-cells; these have relevance for prognosis and understanding of the cancer.
- Our immunologist wanted to relate this co-localization to the morphology.
- Solution: transform to single metric (co-localization score) and show

Sample from breast cancer patient (HER2-positive)
USA and Japan Fertility Over Time

Creator: Stephen Holman
Source: Human Fertility Database

USA: 3.16
Japan: 4.57

http://www.randalolson.com/2015/08/23/small-multiples-vs-animated-gifs-for-showing-changes-in-fertility-rates-over-time/

Randal S. Olson
EYES BEAT MEMORY: SMALL MULTIPLES
EYES BEAT MEMORY: SMALL MULTIPLES

Fertility in USA and Japan, 1947 - 2010

Data source: Human Fertility Database (humanfertility.org)
Author: Randy Elam (randyelam.com) (@randy_elam)
Total fertility rate in USA and Japan, 1947 - 2010

Average age when giving birth in USA and Japan, 1947 - 2010

Data source: Human Fertility Database (humanfertility.org)
Author: Randy Olson (randololson.com / @randololson)
You can’t show all the data!
But you can show what’s important about the data.
Build tools that give analysts the ability to show that!
Thanks to: Carolina Nobre, Kiran Gadhave, Jen Rogers, Haihan Lin, Dylan Wootton, Jochen Görtler, Oliver Deussen, Miriah Meyer, Jeff Phillips, Samuel Gratzl, Holger Stitz, Marc Streit, Nils Gehlenborg, Hilary Coon, Lane Harrison, Hendrik Strobelt, Romain Vuillemot, Hanspeter Pfister, and many Others!