Alexander Lex
@alexander_lex
http://alexander-lex.net

THE UNIVERSITY OF UTAH

Spatial Omics Visualizations:
Lessons Learned from Networks and Maps

visualization design lab

SCI
www.sci.utah.edu

EVERYBODY IS TALKING ABOUT SPATIAL OMICS!

FOCUS | TECHNOLOGY FEATURE

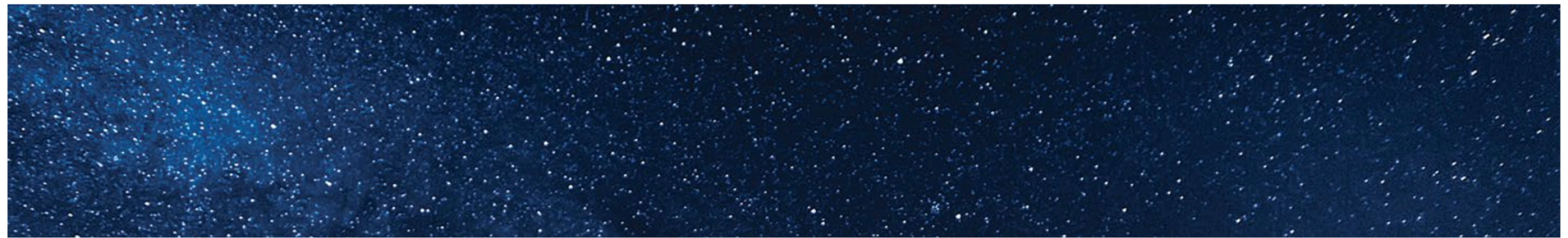
Check for updates

Method of the Year: spatially resolved transcriptomics

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

Vivien Marx

If a researcher is making a smoothie, it might be snack time. Or it could be the moment to prepare a sample for bulk RNA sequencing, in which tissue is homogenized and analyzed to yield



BIOVIS CHALLENGE: FROM IMAGES TO ANALYSIS

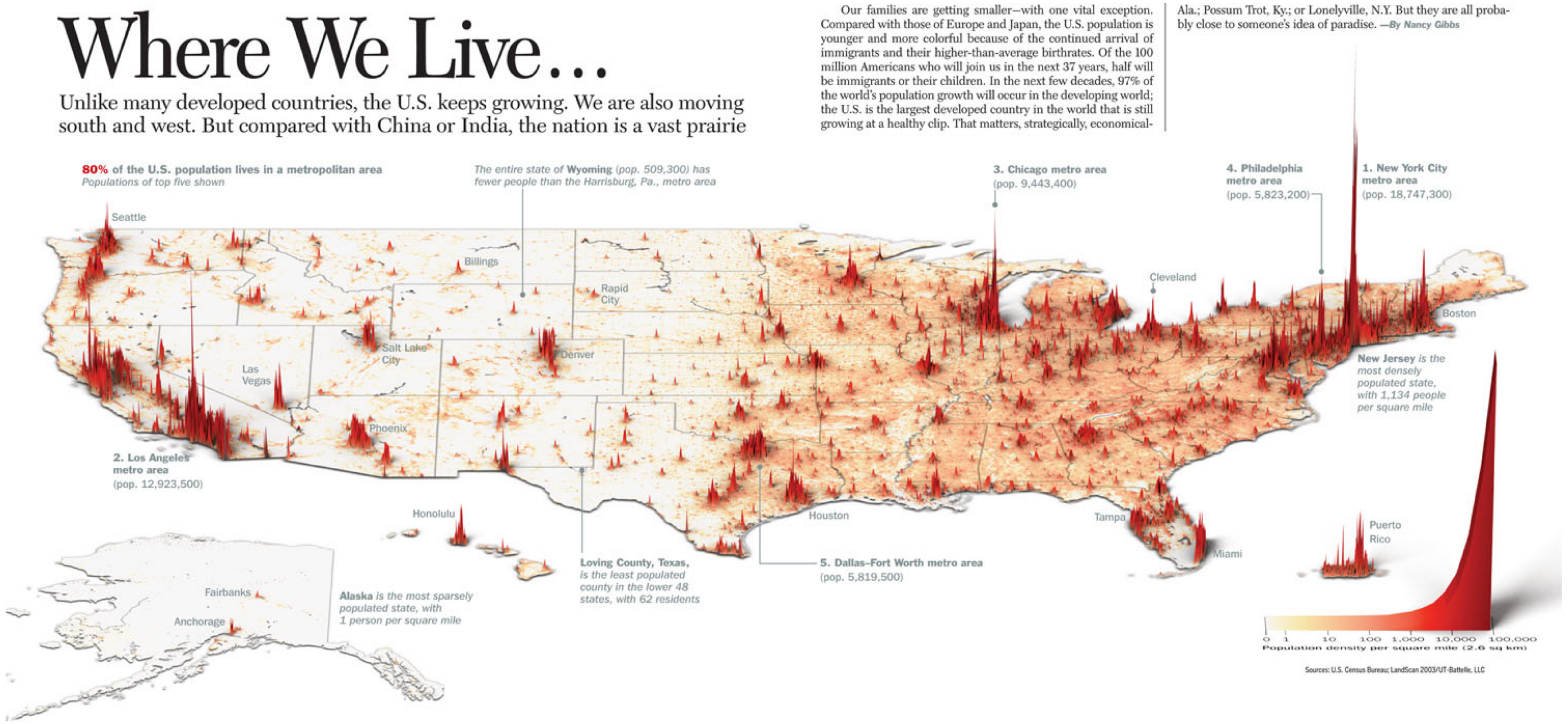
SPATIAL OMICS VISUALIZATION CHALLENGES

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

ANALOGY: MAPS!

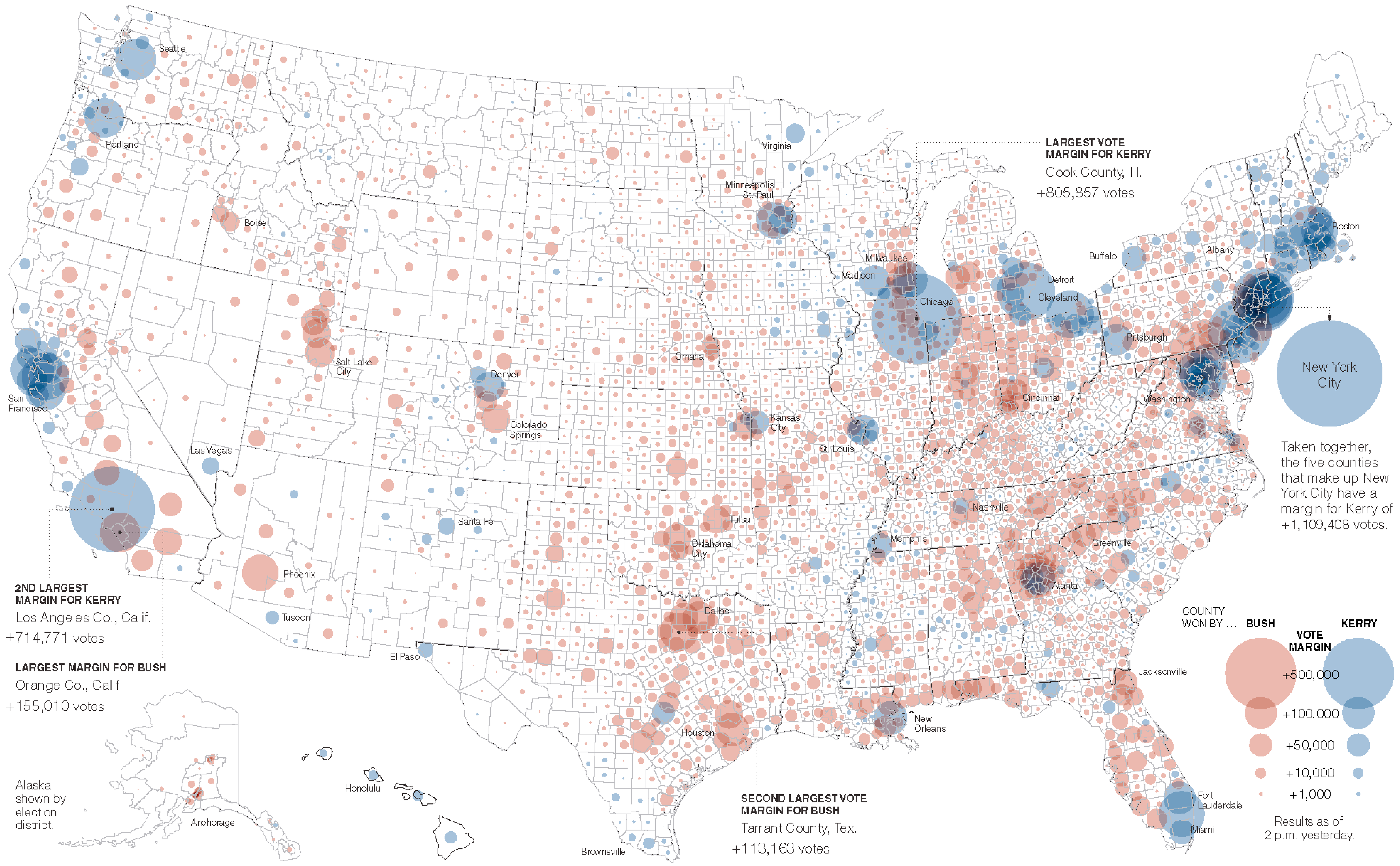
Fixed location

Potentially high-D vector for each location



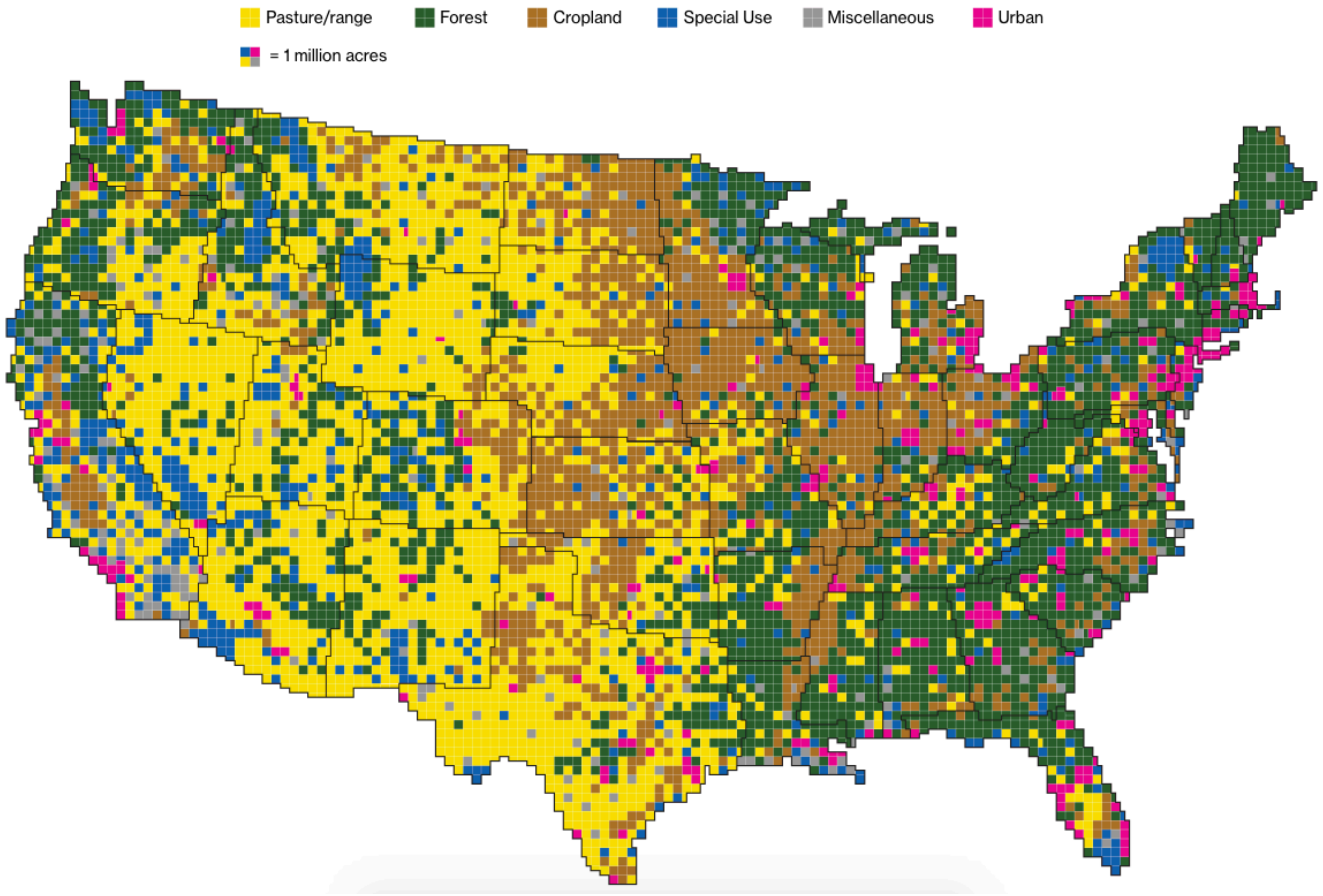
SINGLE DATA VALUE + SPATIAL LOCATION

Glyphs – Size



Matthew Ericson, NY Times

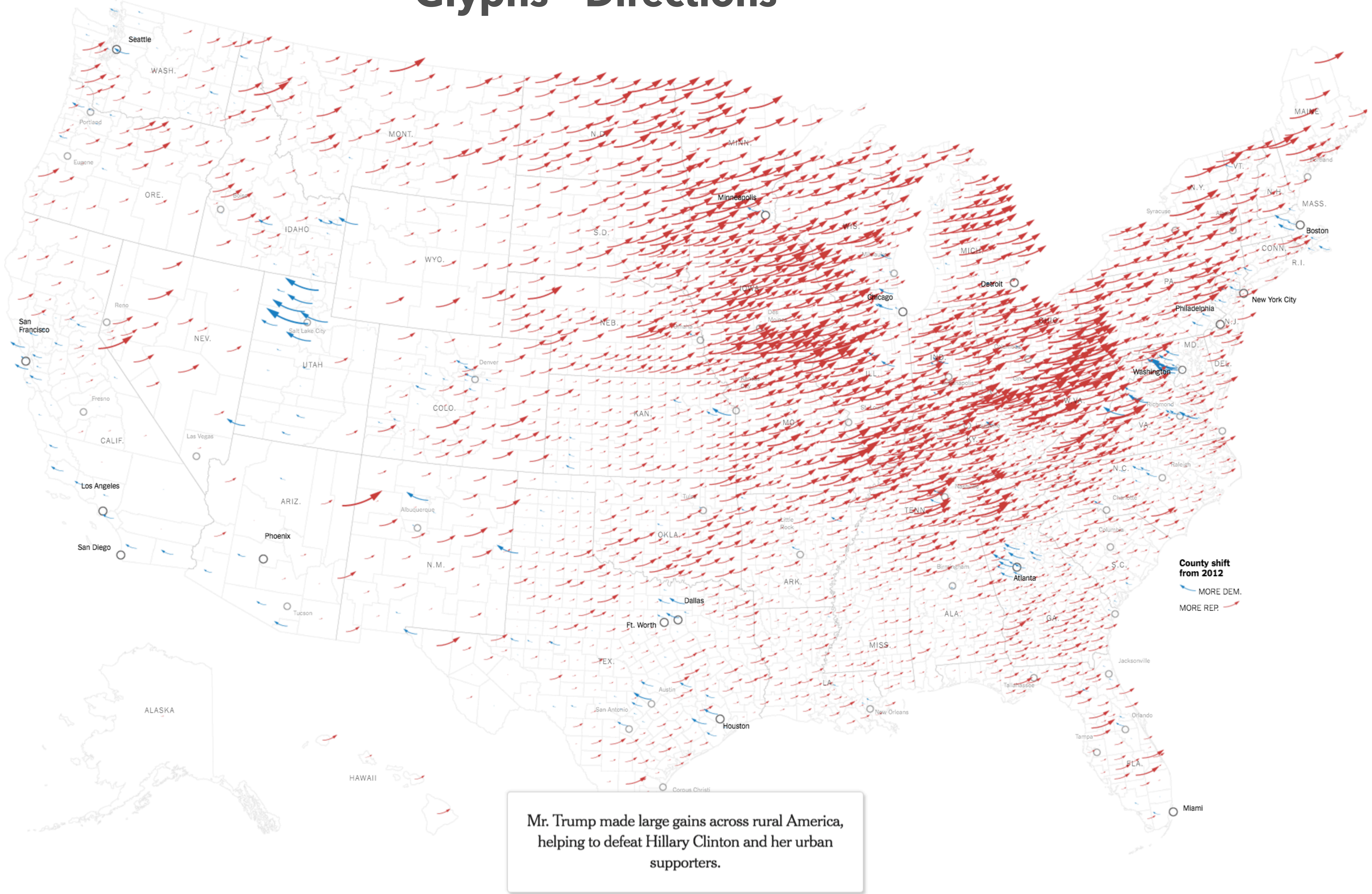
Color



Blomberg

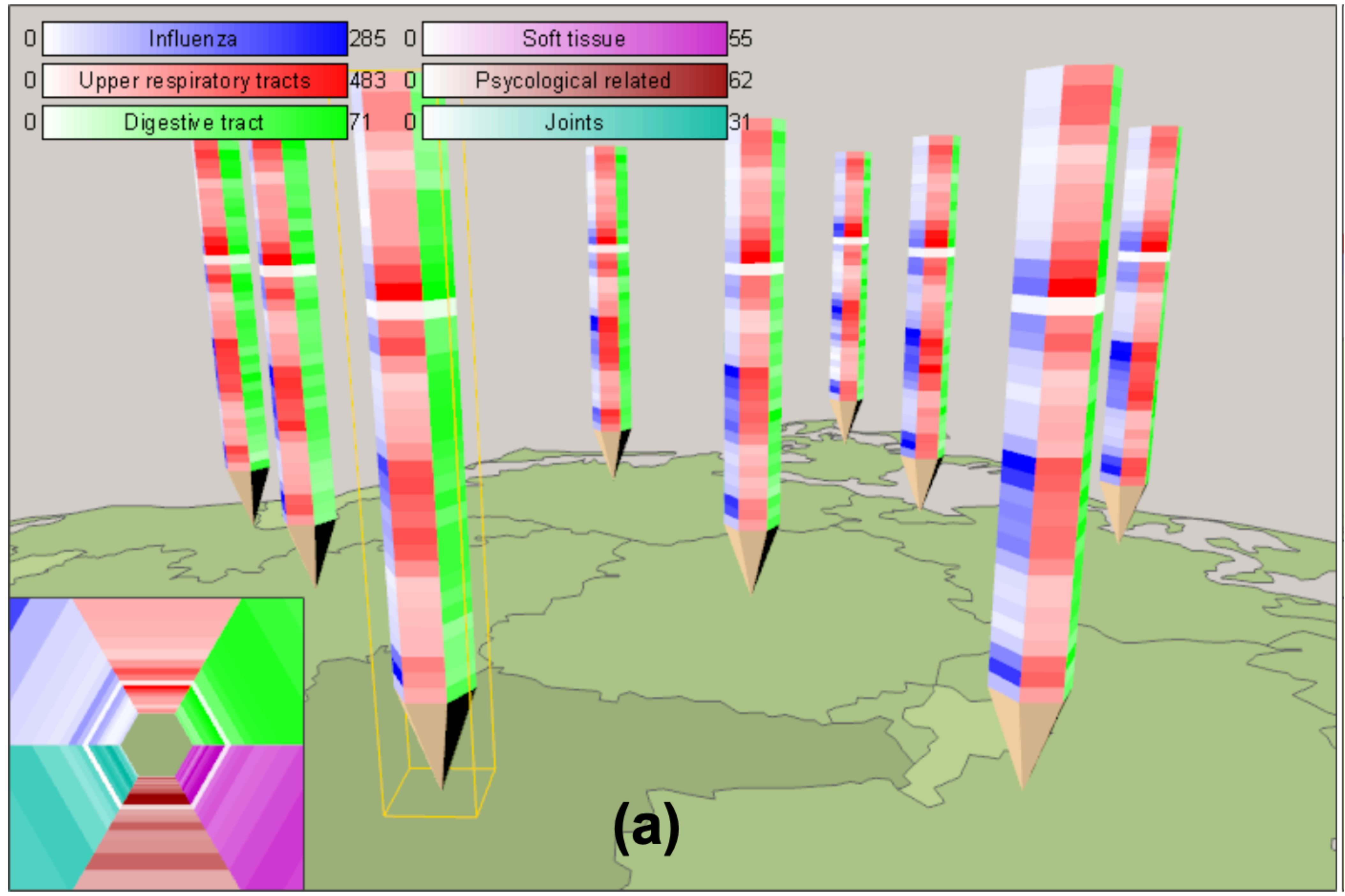
SINGLE DATA VALUE + SPATIAL LOCATION

Glyphs – Directions



BUT WHAT IF YOU HAVE MORE THAN ONE DATA VALUE?

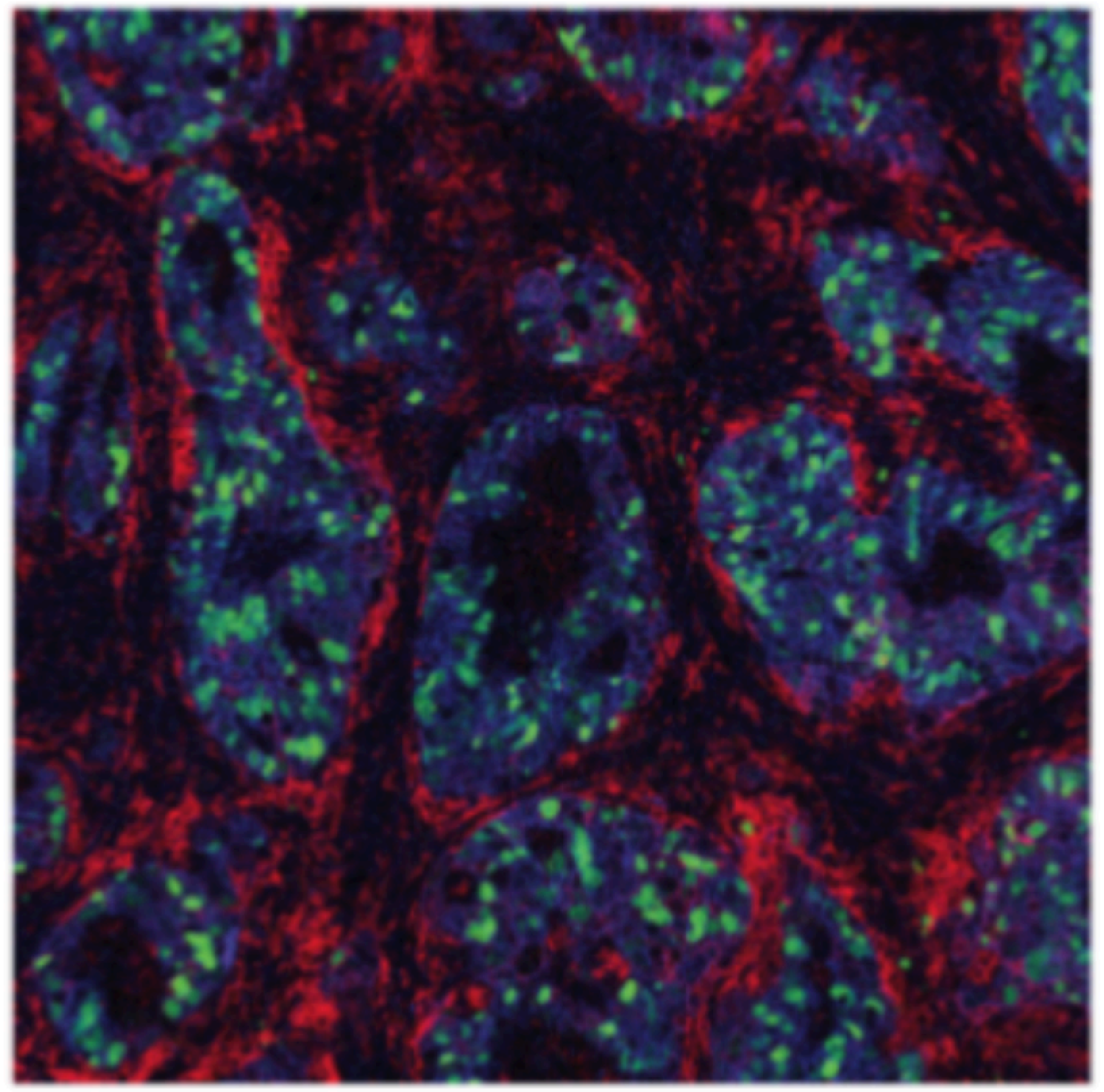
Glyphs?



Scalability?

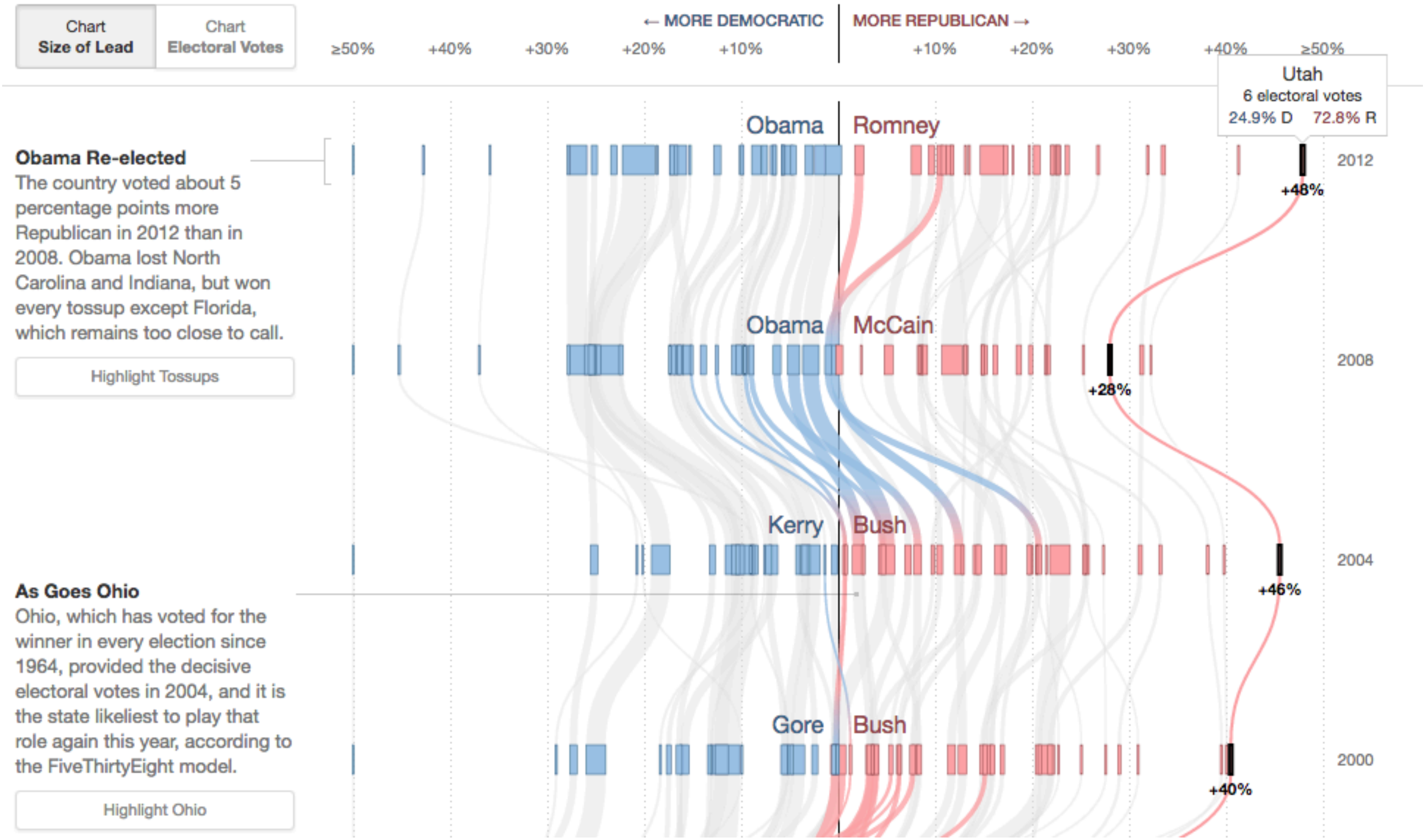
[Tominski]

Don’t treat color channels as separate visual channels



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

DO WE REALLY NEED A MAP?



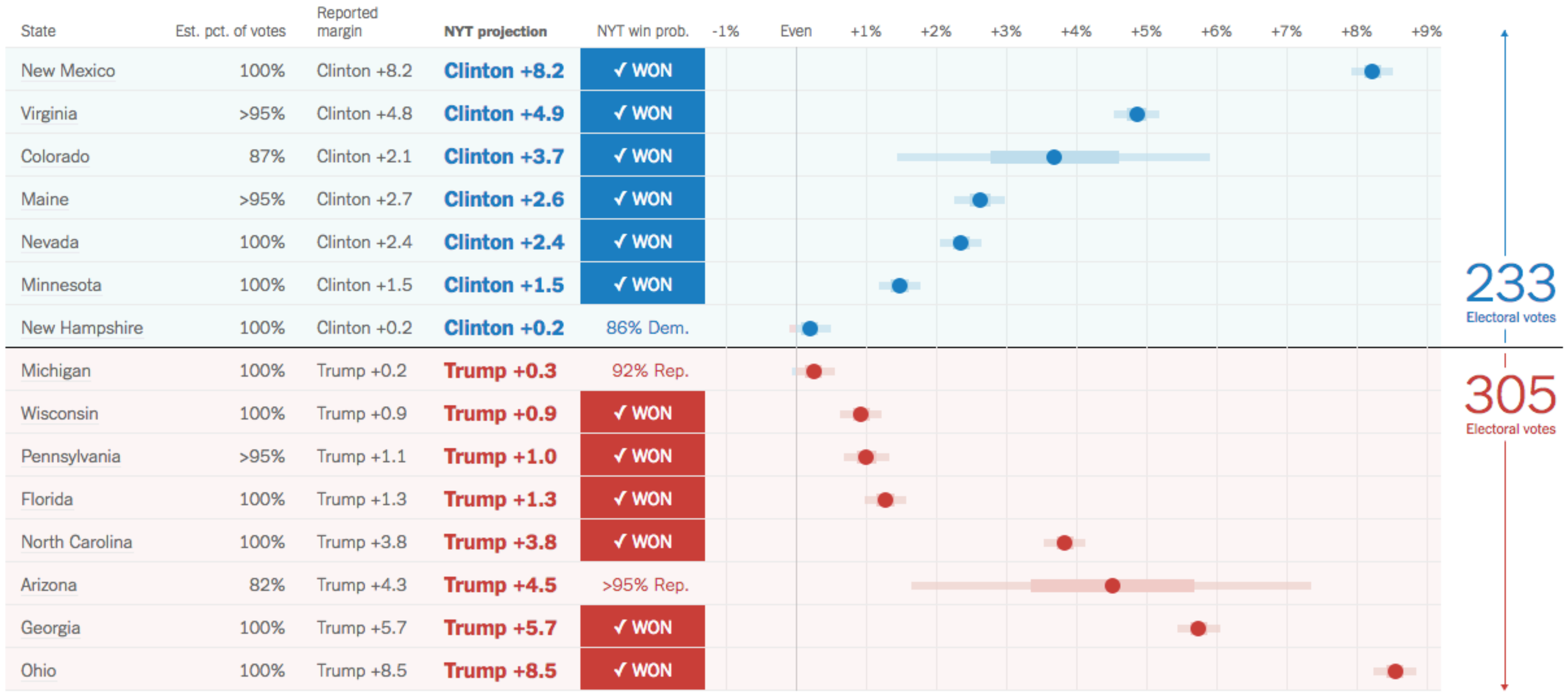
Mike Bostok, NY Times

DO WE REALLY NEED A MAP?

It’s hard to do more complex things with maps

Is the spatial context paramount?

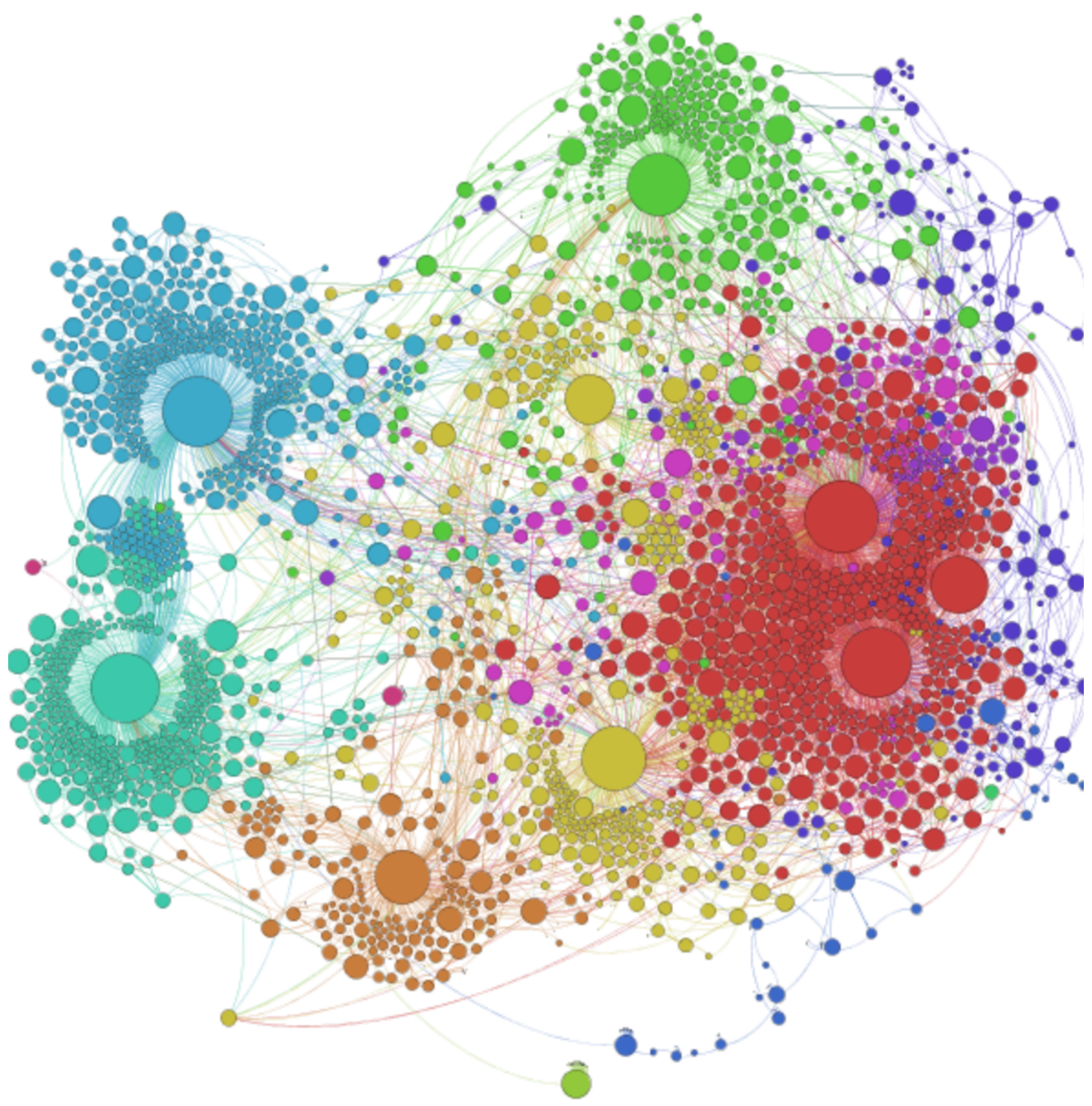
Is the spatial context a proxy for something?



State	Est. pct. of votes	Reported margin	NYT projection	NYT win prob.
New Mexico	100%	Clinton +8.2	Clinton +8.2	✓ WON
Virginia	>95%	Clinton +4.8	Clinton +4.9	✓ WON
Colorado	87%	Clinton +2.1	Clinton +3.7	✓ WON
Maine	>95%	Clinton +2.7	Clinton +2.6	✓ WON
Nevada	100%	Clinton +2.4	Clinton +2.4	✓ WON
Minnesota	100%	Clinton +1.5	Clinton +1.5	✓ WON
New Hampshire	100%	Clinton +0.2	Clinton +0.2	86% Dem.
Michigan	100%	Trump +0.2	Trump +0.3	92% Rep.
Wisconsin	100%	Trump +0.9	Trump +0.9	✓ WON
Pennsylvania	>95%	Trump +1.1	Trump +1.0	✓ WON
Florida	100%	Trump +1.3	Trump +1.3	✓ WON
North Carolina	100%	Trump +3.8	Trump +3.8	✓ WON
Arizona	82%	Trump +4.3	Trump +4.5	>95% Rep.
Georgia	100%	Trump +5.7	Trump +5.7	✓ WON
Ohio	100%	Trump +8.5	Trump +8.5	✓ WON

ANALOGY: MULTIVARIATE NETWORKS

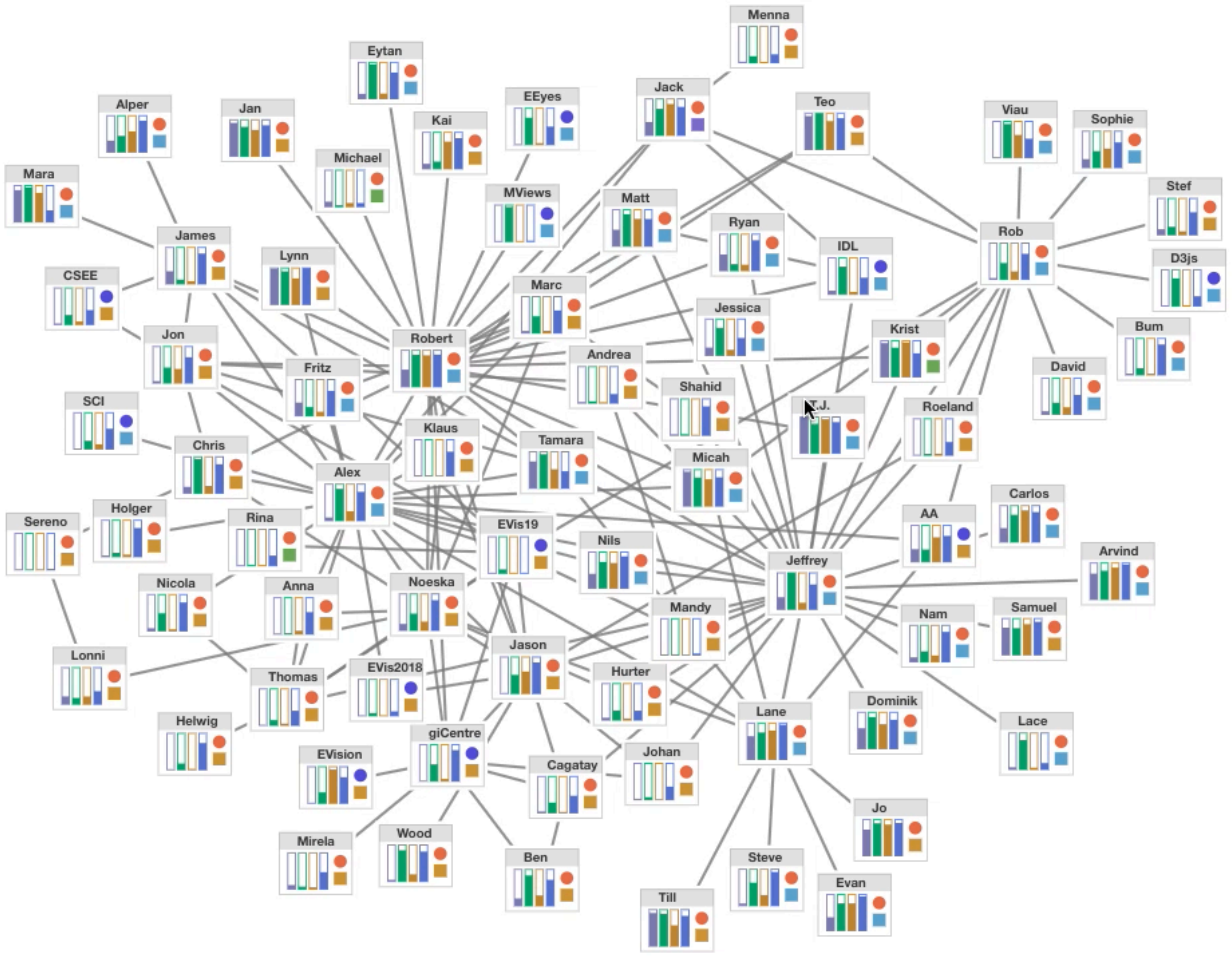
- Lots of attributes for nodes and edges
- Location doesn't matter, but connectivity does
  - Can't choose location freely



ON-NODE ENCODING?

Maybe if you zoom in

Still limited



EUROVIS 2019
R. S. Laramee, S. Oeltze, and M. Sedlmair
(Guest Editors)

Volume 38 (2019), Number 3
STAR – State of The Art Report

The State of the Art in Visualizing Multivariate Networks

C. Nobre[1], M. Meyer[1], M. Streit[2], and A. Lex[1]

[1]University of Utah, Utah, USA
[2]Johannes Kepler University Linz, Austria

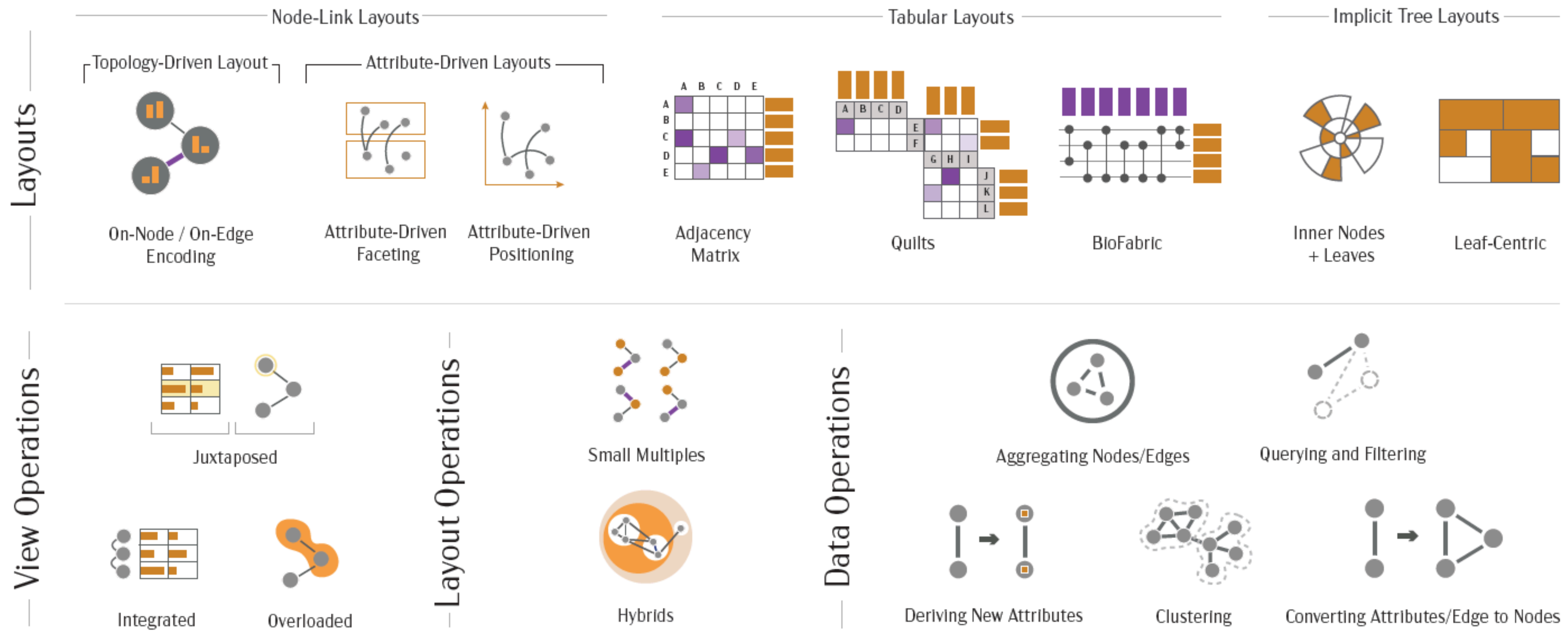


Figure 1: *A typology of operations and layouts used in multivariate network visualization.* ***Layouts*** *describe the fundamental choices for encoding multivariate networks.* ***View Operations*** *capture how topology and attribute focused visualizations can be combined.* ***Layout Operations*** *are applied to basic layouts to create specific visualization techniques.* ***Data Operations*** *are used to transform a network or derive attributes before visualizations. The colors reflect node attributes (orange), edge attributes (purple), and topology (grey).*

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.


Layouts
Node-Link Layouts
Topology-Driven Layout
Attribute-Driven Layouts
On-Node / On-Edge Encoding
Attribute-Driven Faceting
Attribute-Driven Positioning
Tabular Layouts
Adjacency Matrix
Quilts
BioFabric
Implicit Tree Layouts
Inner Nodes + Leaves
Leaf-Centric
View Operations
Juxtaposed
Integrated
Overloaded
Layout Operations
Small Multiples
Hybrids
Data Operations
Aggregating Nodes/Edges
Querying and Filtering
Deriving New Attributes
Clustering
Converting Attributes/Edge to Nodes

SO WHAT ELSE CAN YOU DO?

INTERACTION!

Two Paths:

1. Select regions to show
2. Select / derive data to show

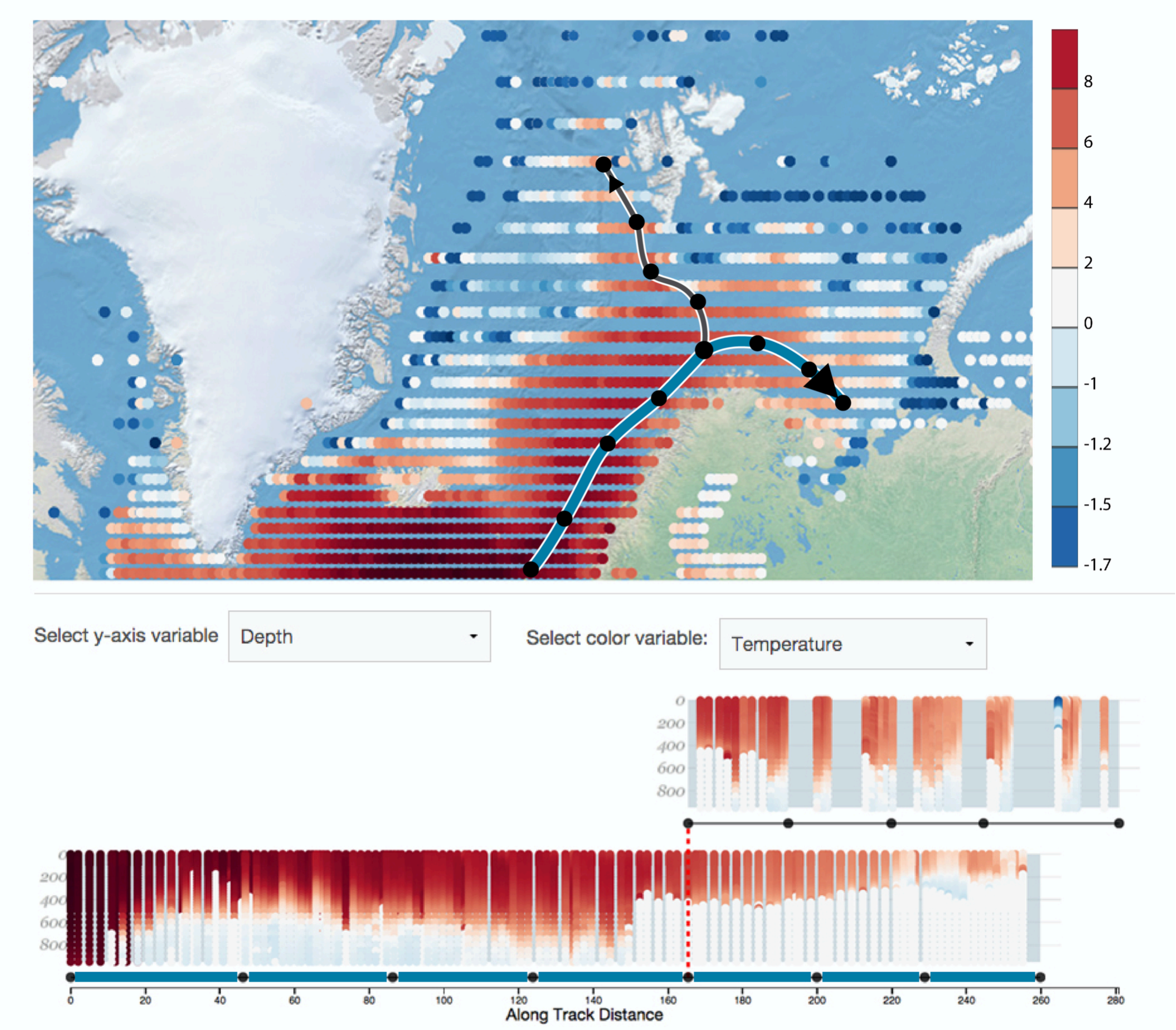
SELECTING REGIONS TO SHOW

PRINCIPLE

Select one or multiple items/regions

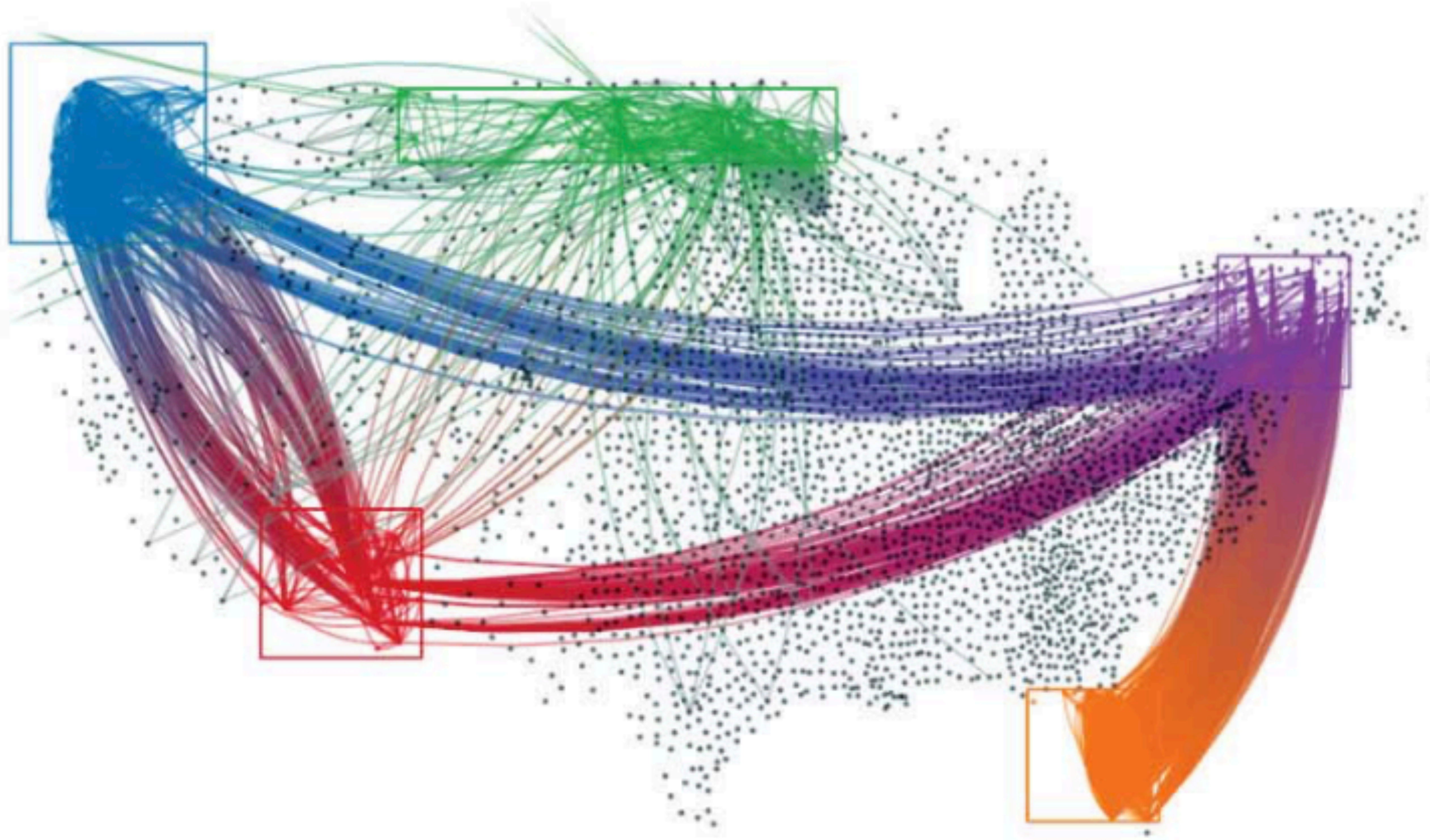
Show rich data about them in separate view

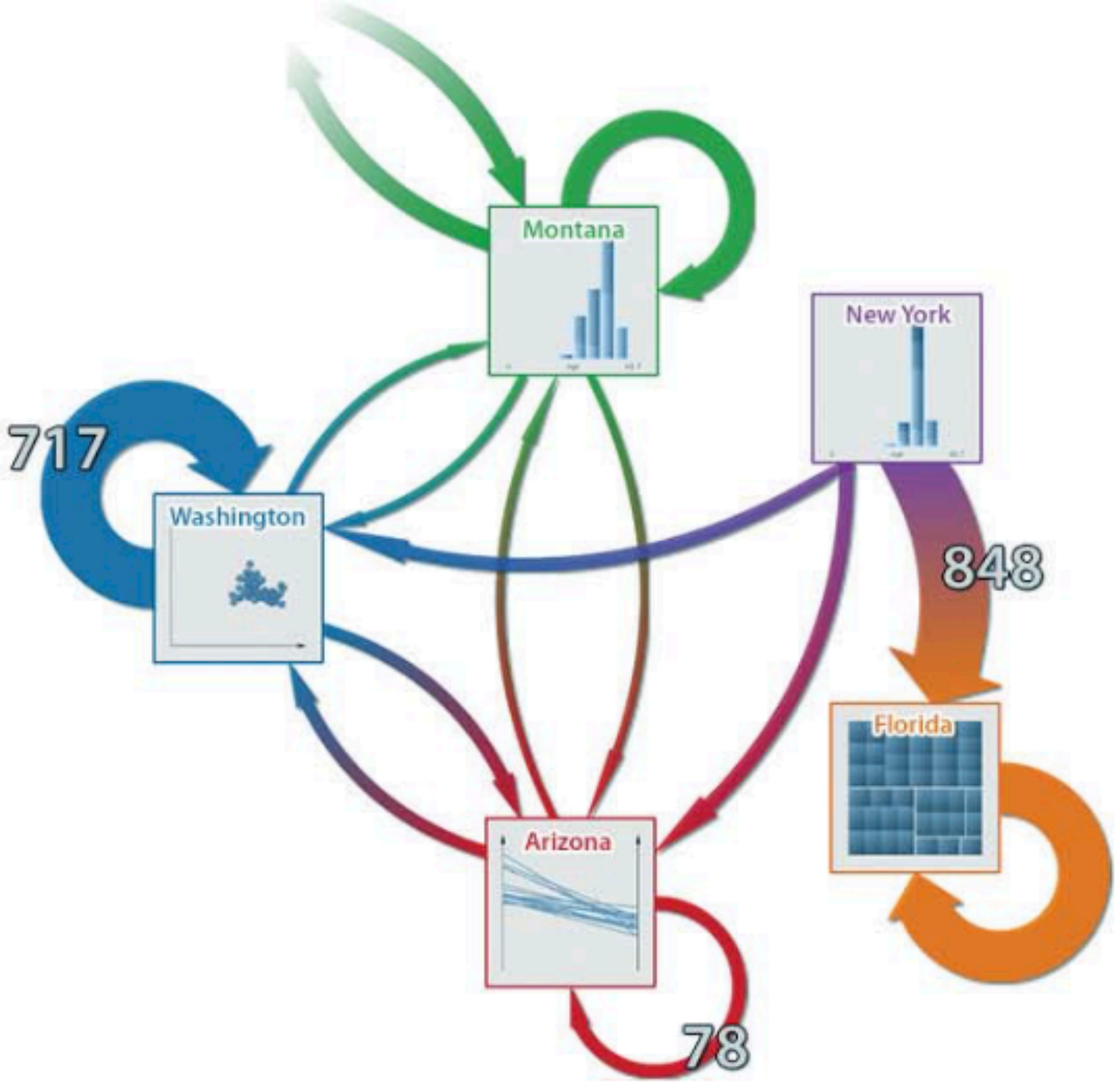
SELECT A PATH IN A MAP



Carolina Nobre, Alexander Lex
OceanPaths: Visualizing Multivariate Oceanography Data
Proceedings of the Eurographics Conference on Visualization (EuroVis '15) - Short Papers, doi:10.2312/eurovisshort.20151124, 2015.

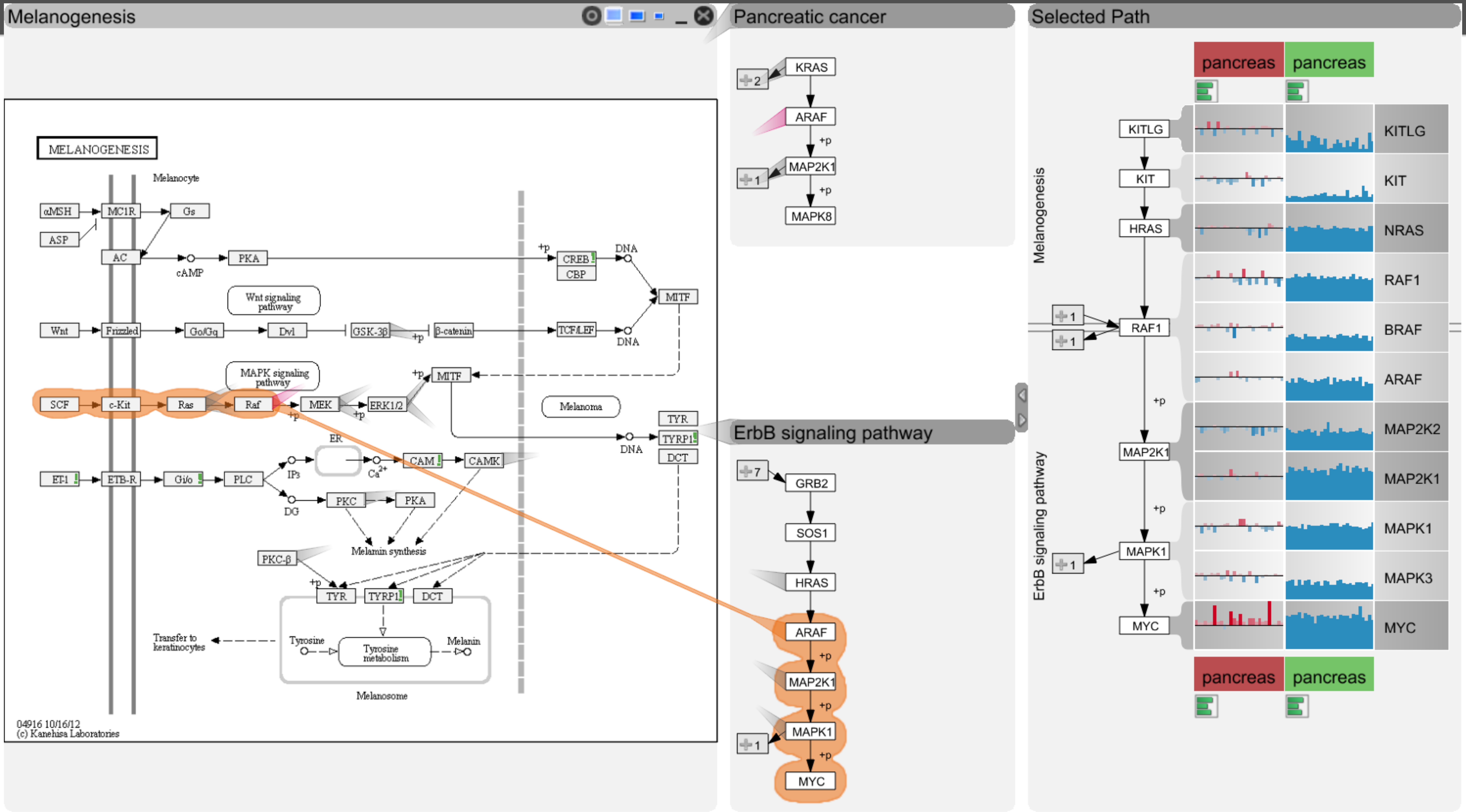
SELECT A REGION AND AGGREGATE!





S. van den Elzen and J. J. van Wijk, “Multivariate Network Exploration and Presentation: From Detail to Overview via Selections and Aggregations,” IEEE Transactions on Visualization and Computer Graphics (InfoVis ’14), vol. 20, no. 12, pp. 2310–2319, 2014, doi: 10.1109/TVCG.2014.2346441.

ENROUTE – PATH SELECTION



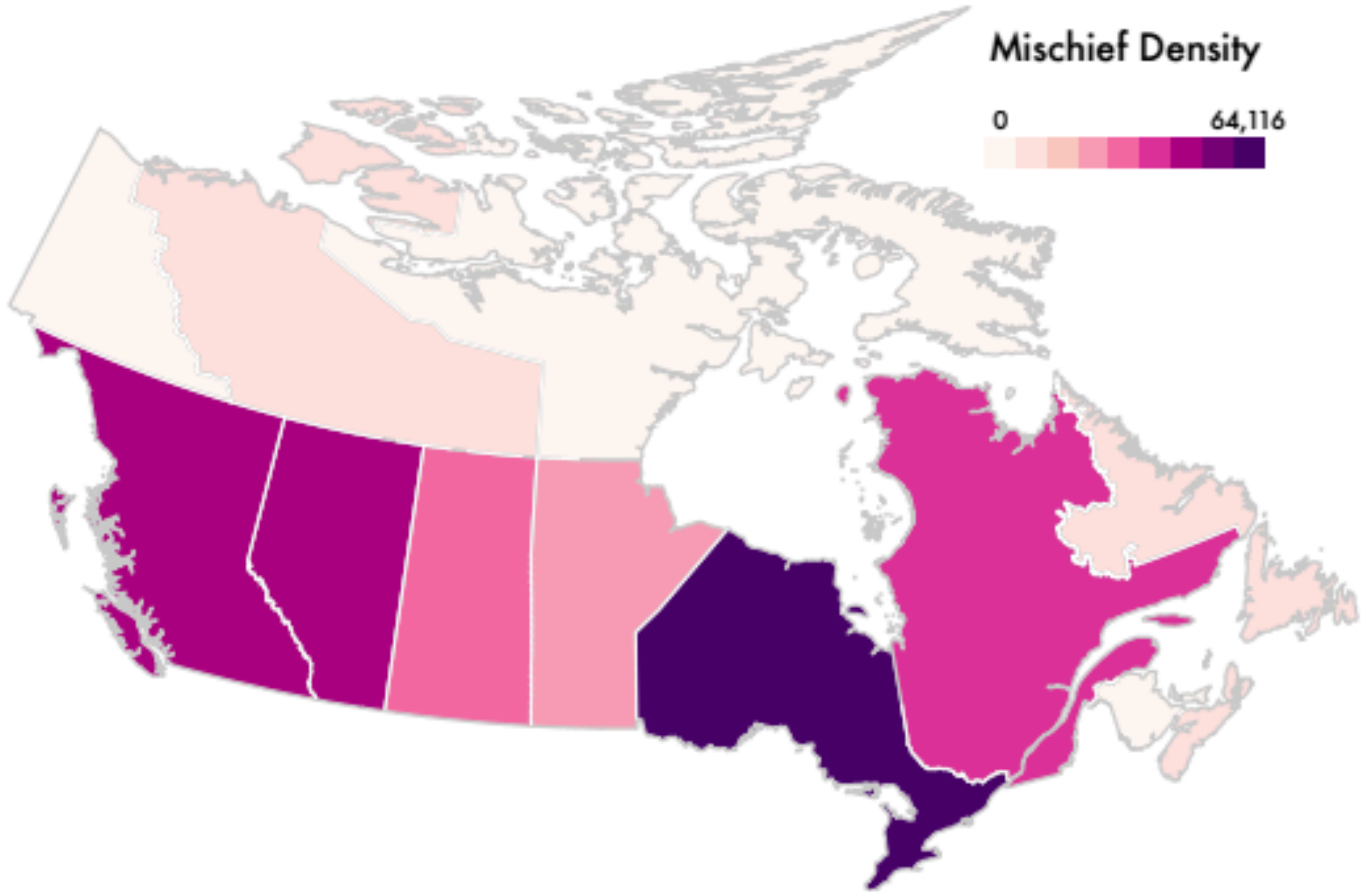
SELECT / DERIVE DATA TO SHOW

SHOWING RAW DATA IS HOPELESS!

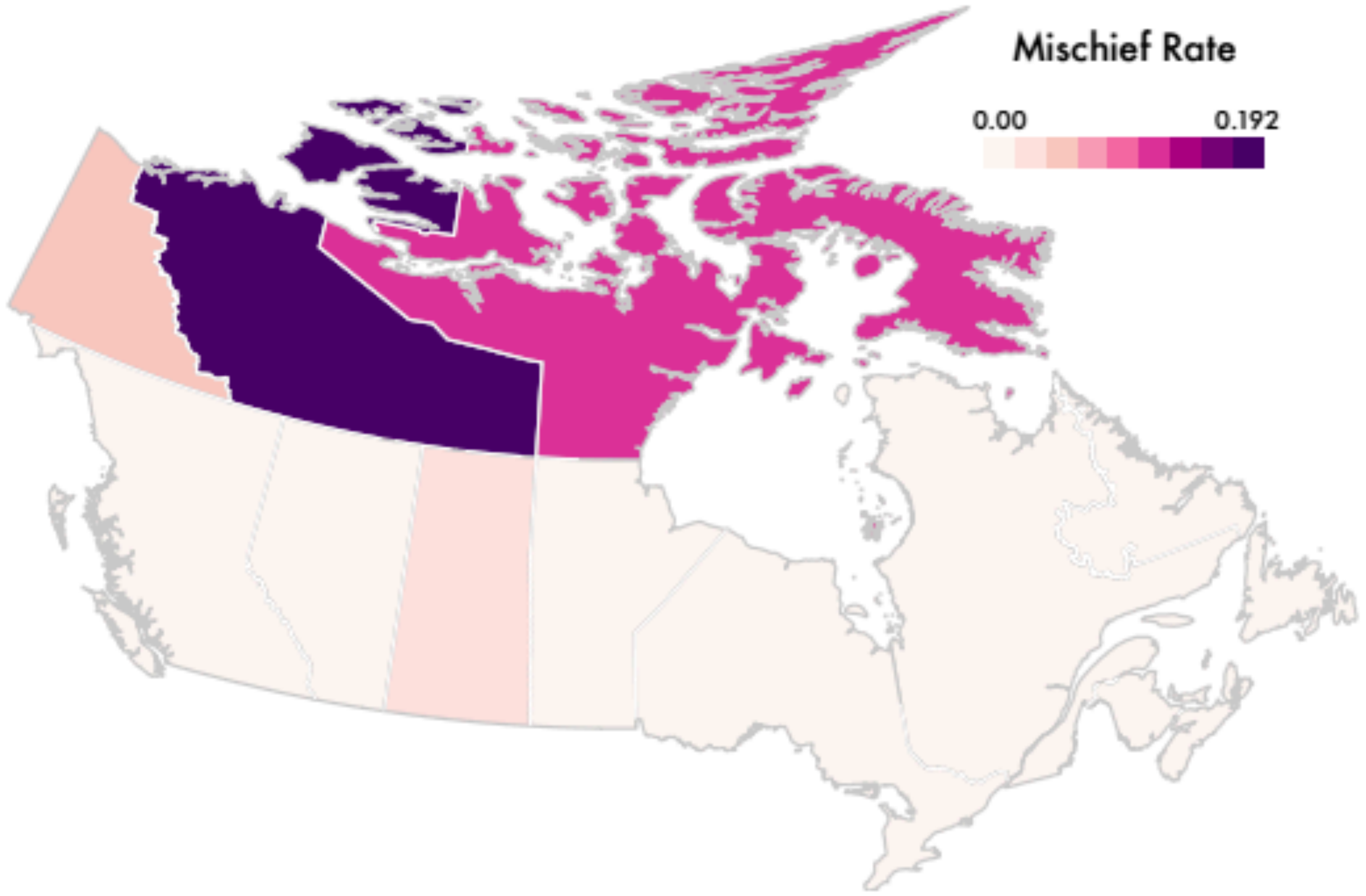
But do you need to?

- Show average expression (etc)
- Show average expression for pathway of interest
- Filter out uninteresting items
- Create domain specific scores
- Create clusters/archetypes
- …

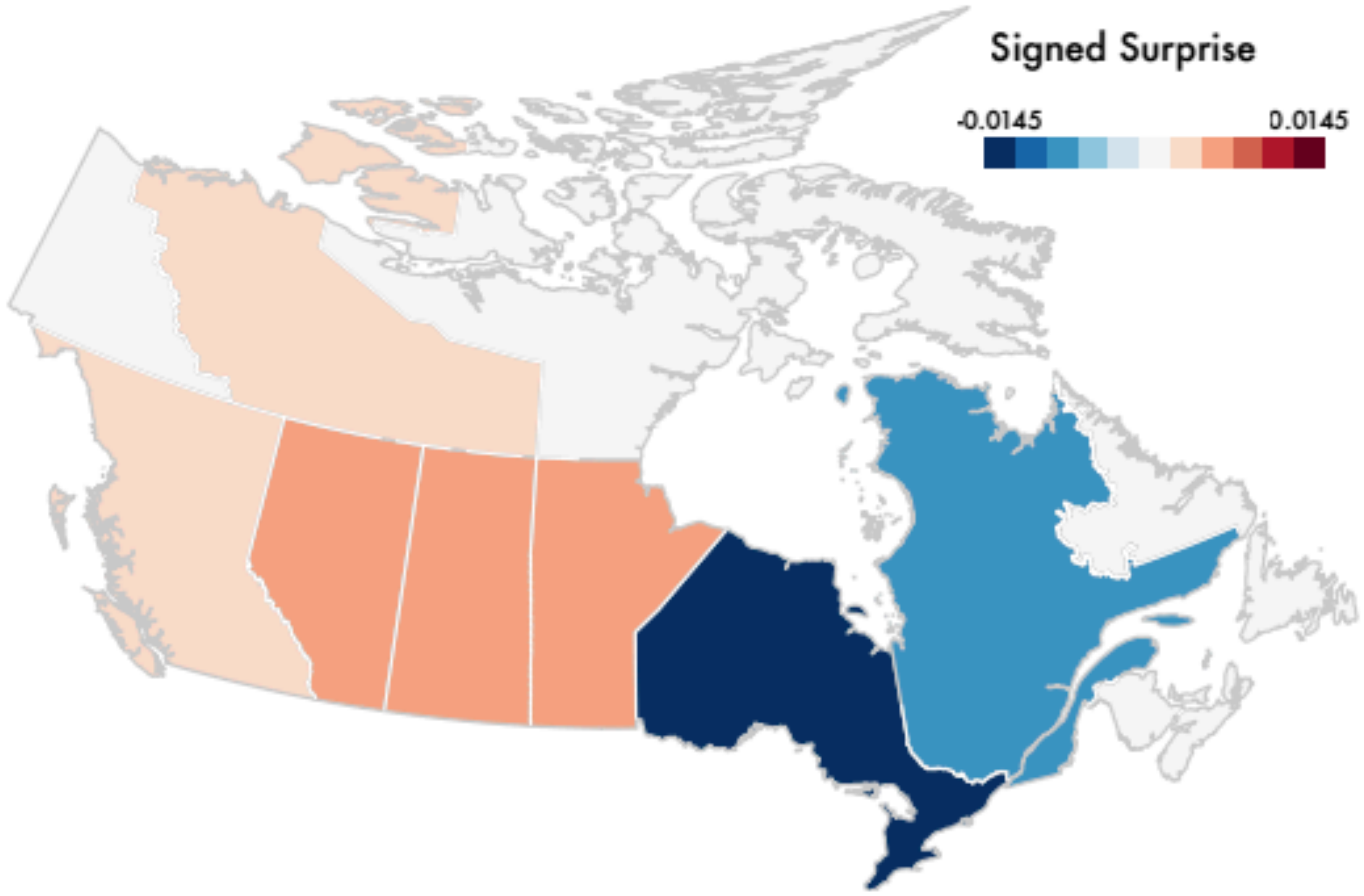
APPROACH: USE A PRIOR, SHOW DIFFERENCE.



(a) The **Event Density** of "mischief" in Canada.



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

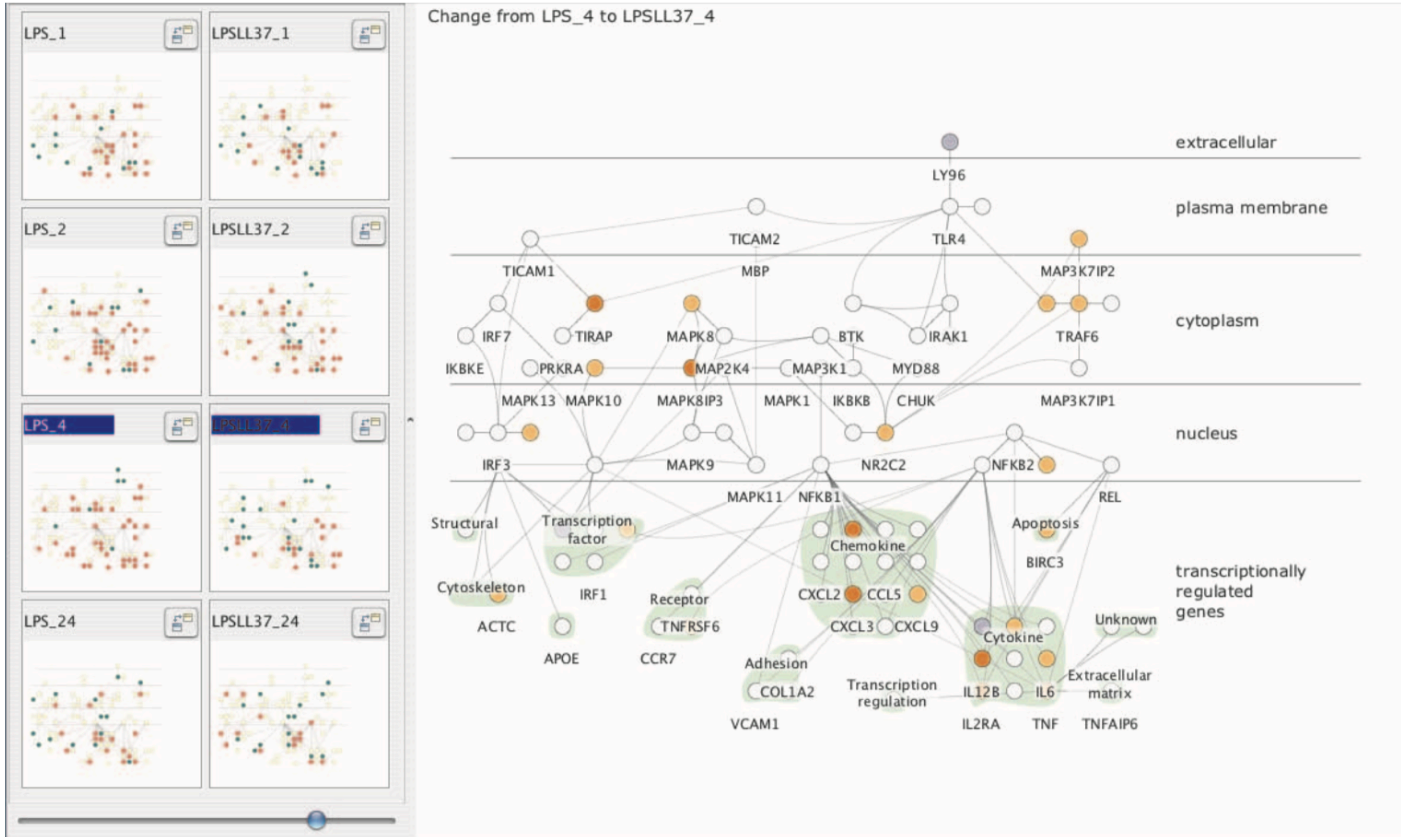


(c) The **Surprise Map** of mischief.

model of population density + accounting for variability when analyzing small numbers

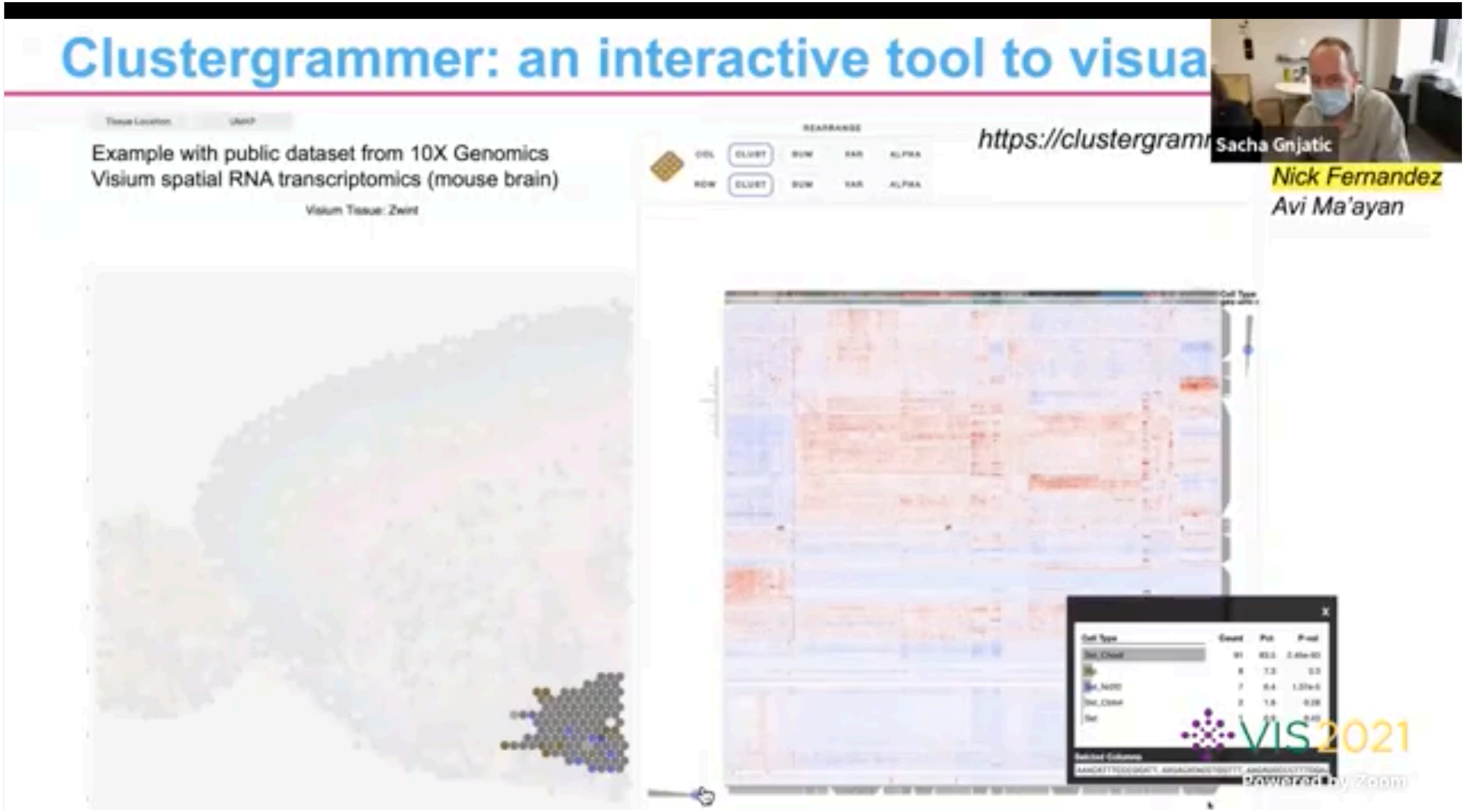
[Corell 2016]

HAVE A HANDFUL OF SCORES? VIS FEASIBLE!

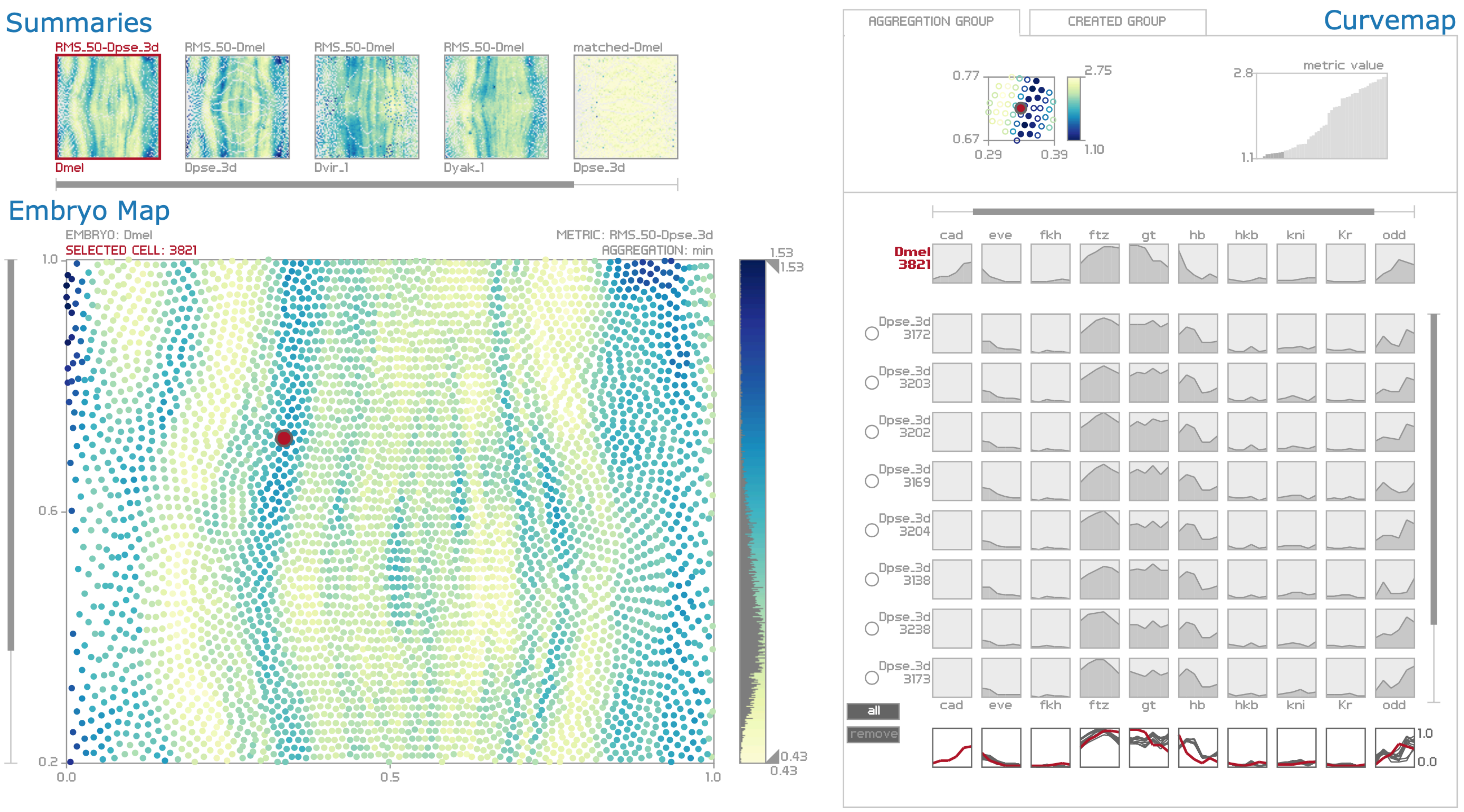


[Barsky et al., Cerebral, 2008]

CLUSTERGRAMMER JUST EARLIER AT BIOVIS: DYNAMIC FILTERS



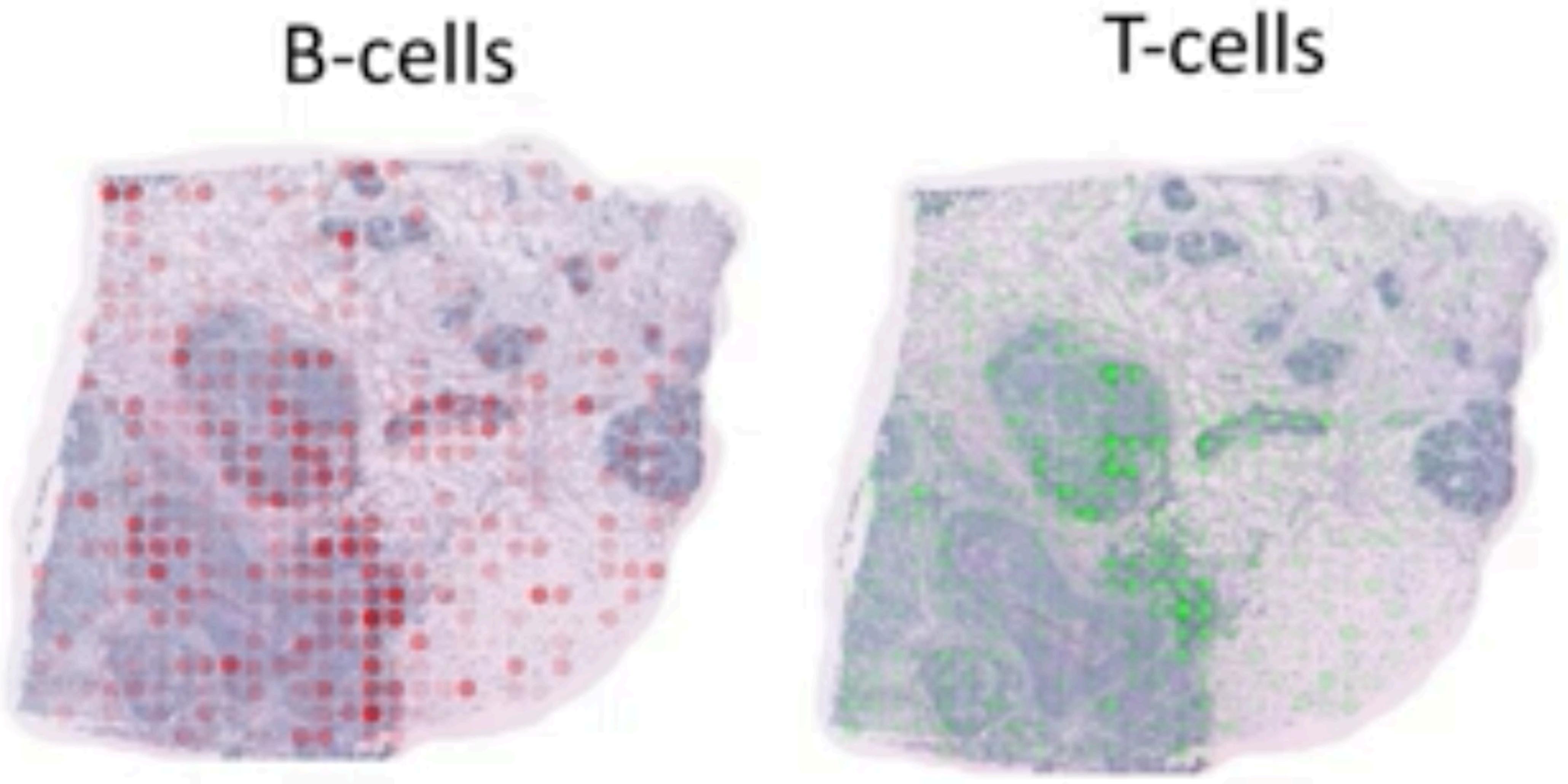
EXAMPLE: DOMAIN SPECIFIC SCORE



Miriah Meyer, Tamara Munzner, Angela DePace, Hanspeter Pfister
MulteeSum: A Tool for Comparative Spatial and Temporal Gene Expression Data
IEEE Transactions on Visualization and Computer Graphics (InfoVis), 16(6): 908--917, doi:10.1109/TVCG.2010.137, 2010.

USING SCORES @ BIOVIS BY ALMA ANDERSON

Assessing co-localization

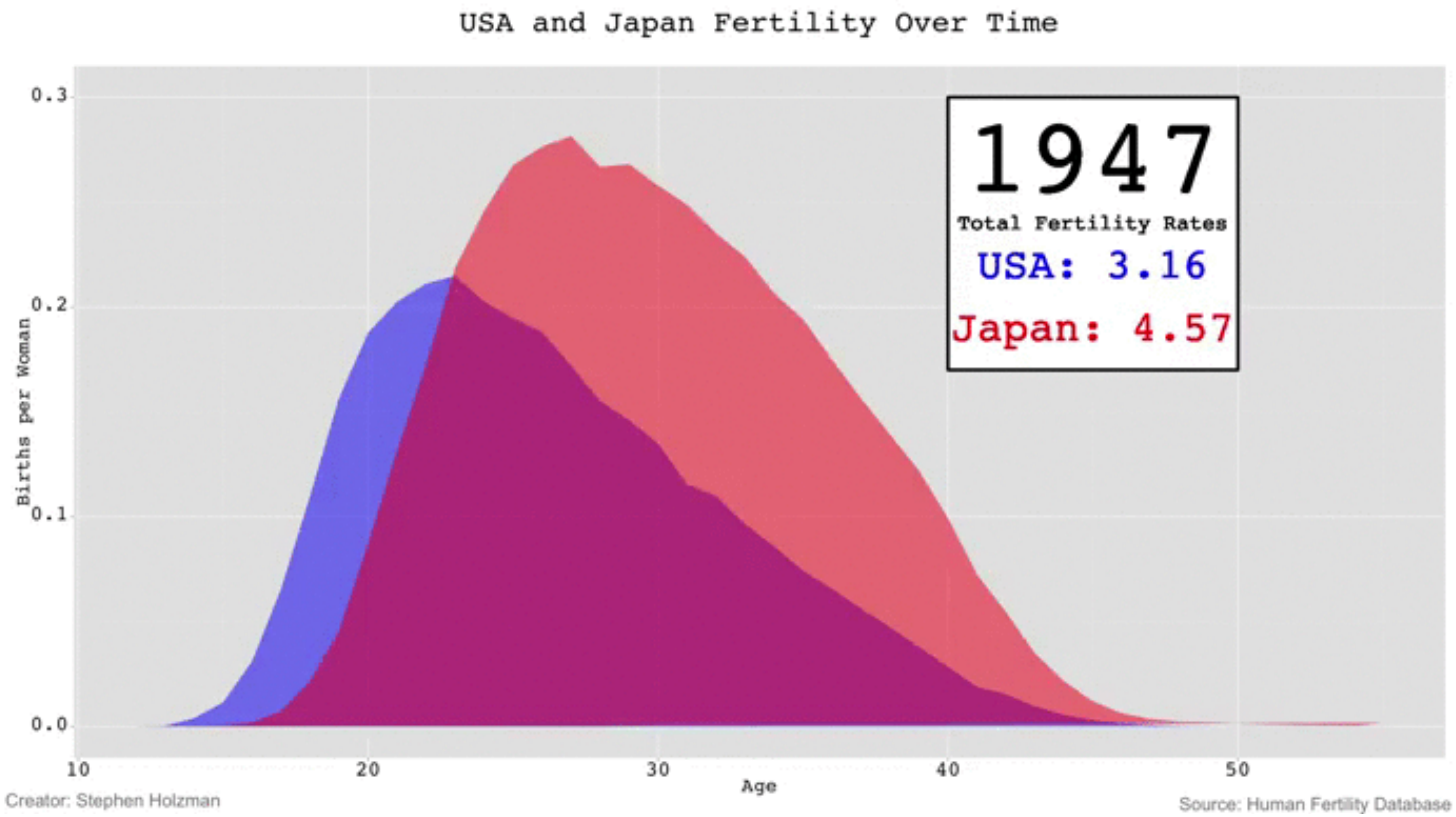


Sample from breast cancer patient (HER2-positive)

- 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

SciLifeLab

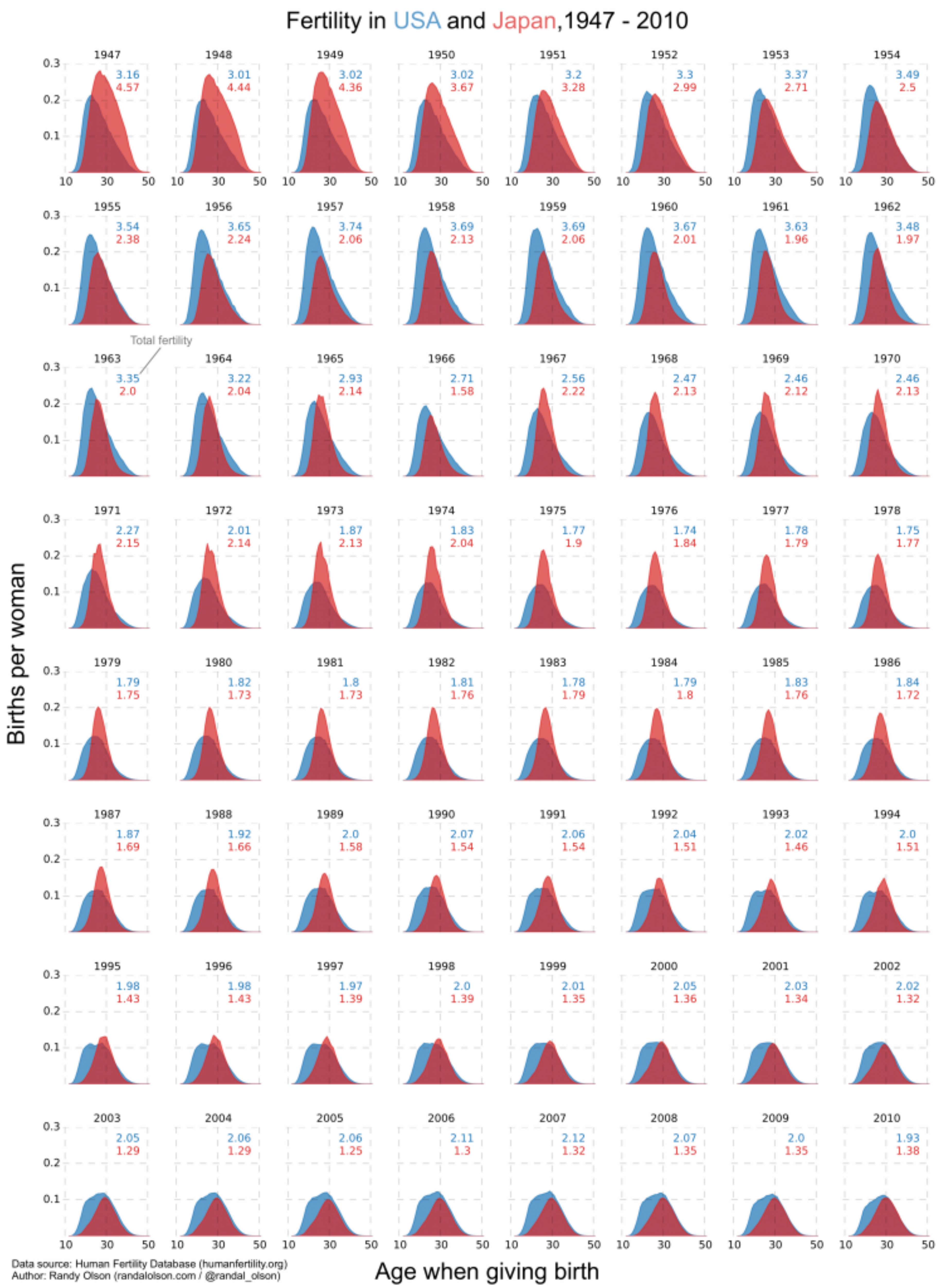
REDESIGN EXAMPLE



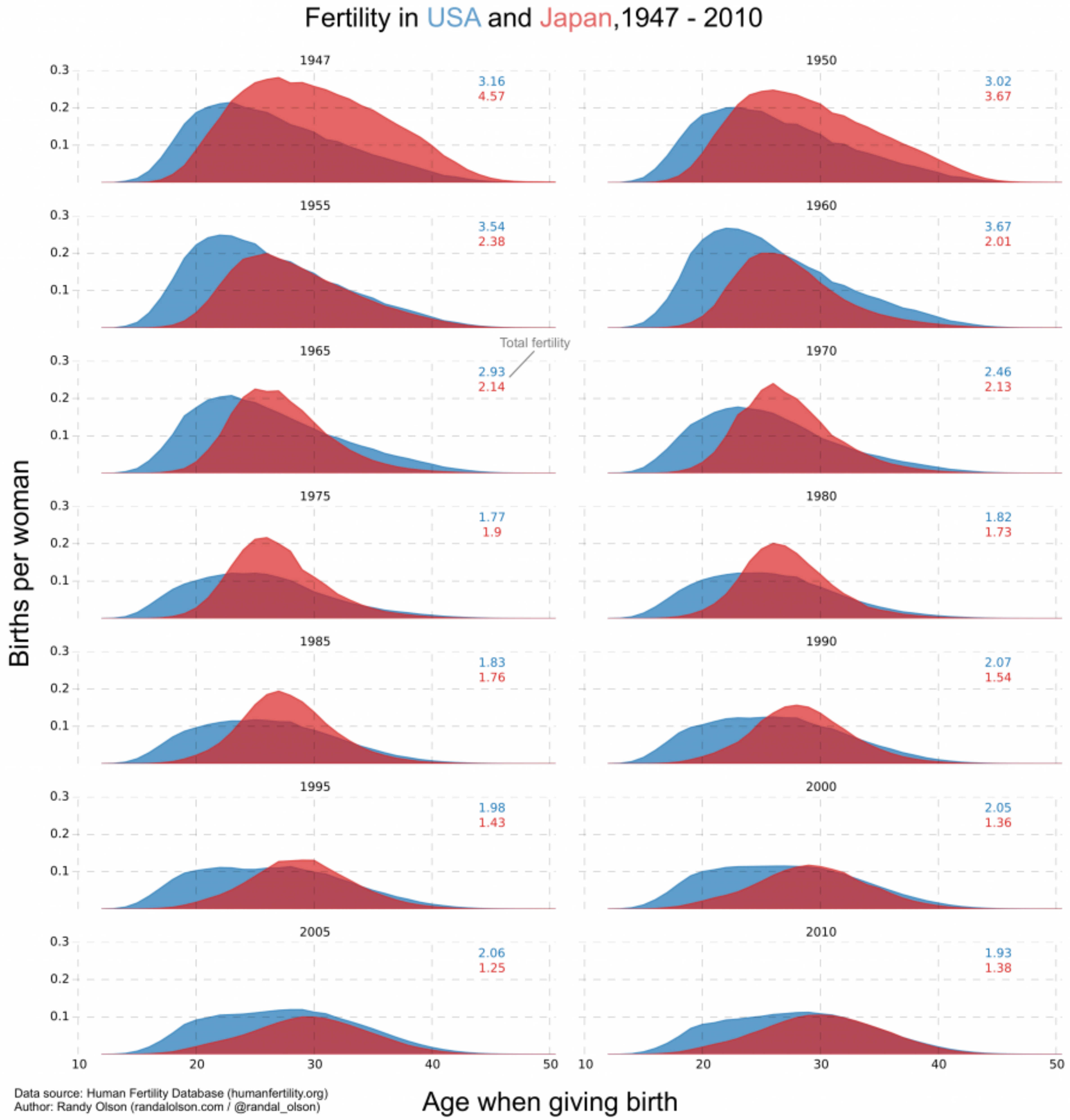
Randal S. Olson

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

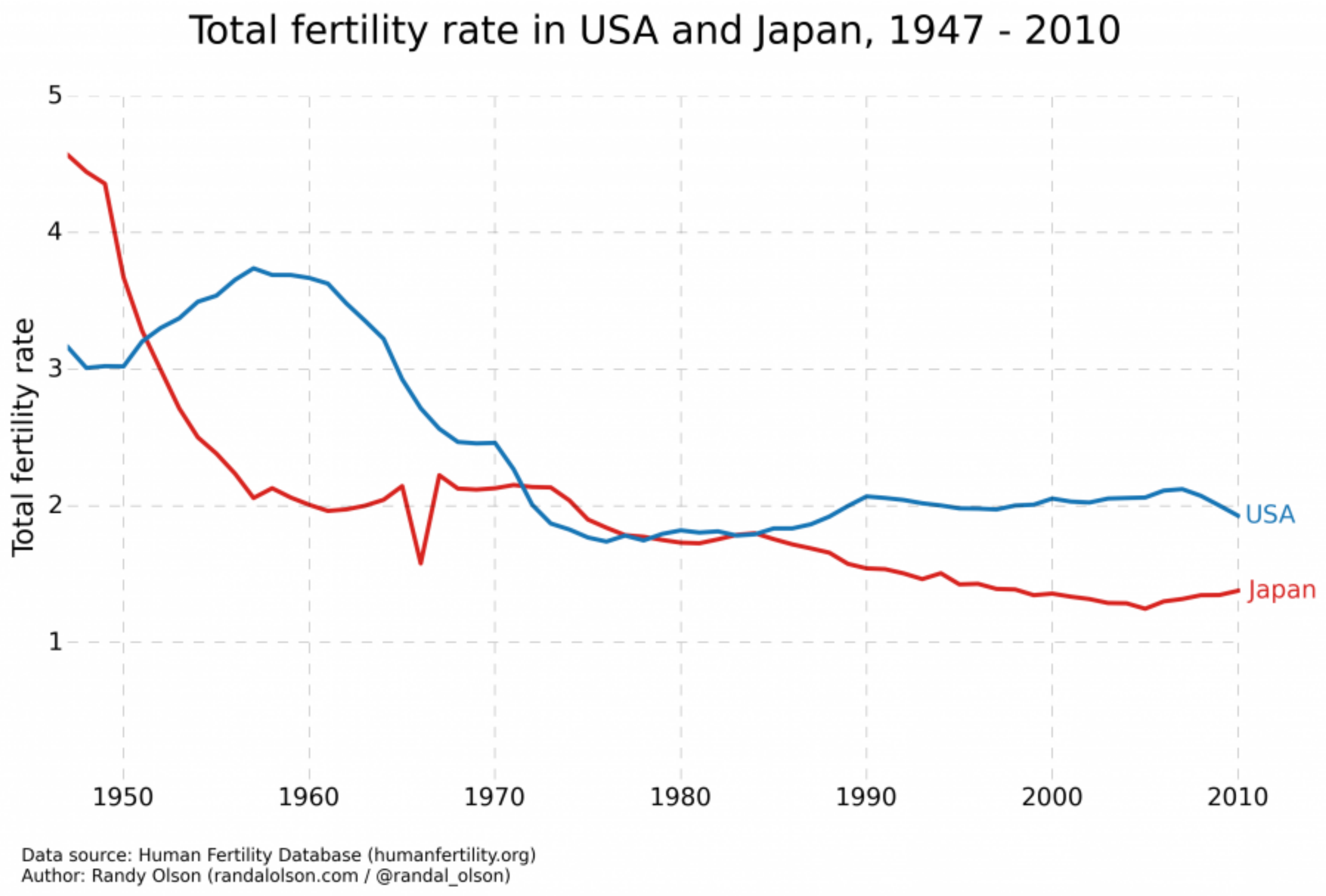
EYES BEAT MEMORY: SMALL MULTIPLES



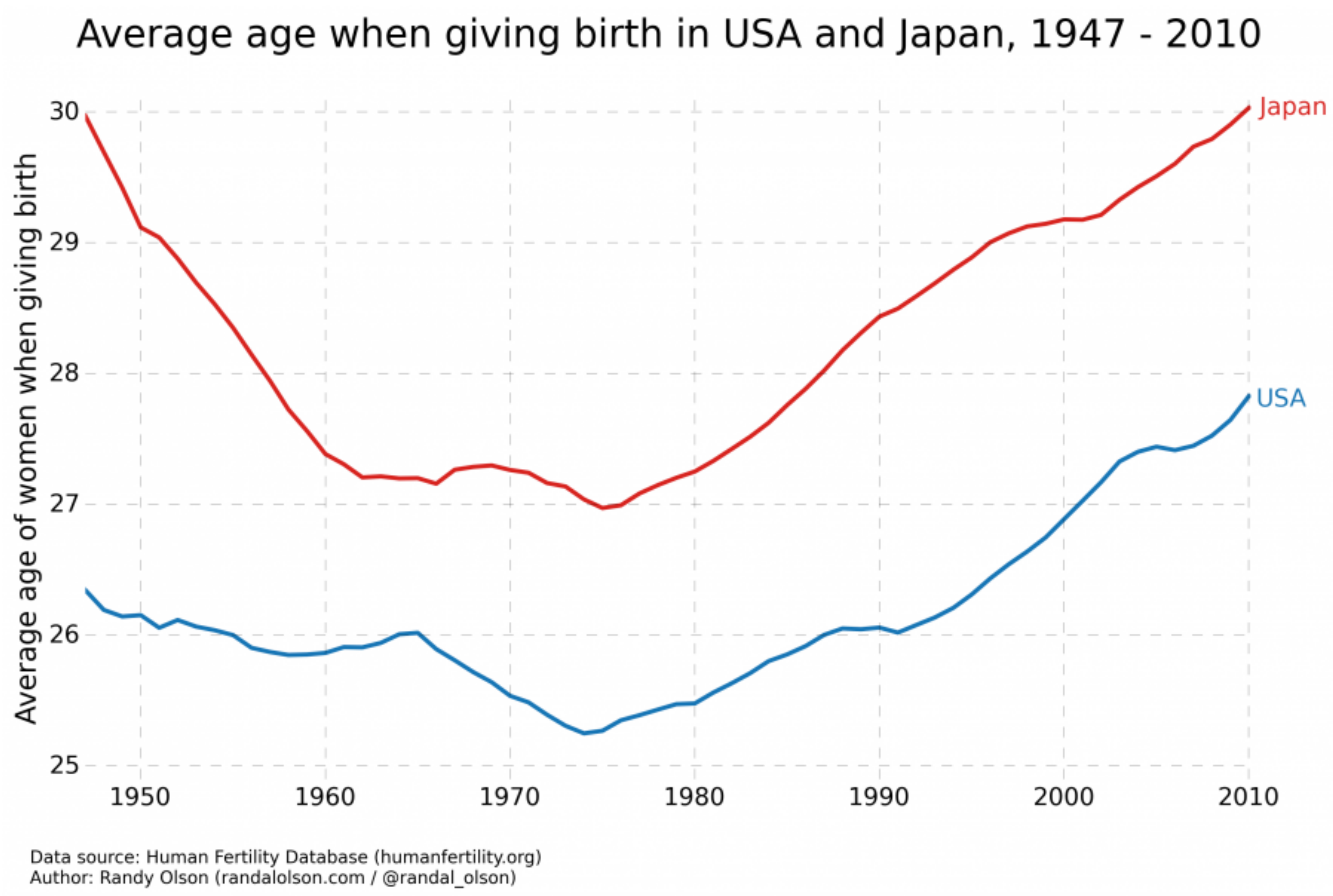
EYES BEAT MEMORY: SMALL MULTIPLES



SIMPLIFY!



Total fertility rate in USA and Japan, 1947 - 2010
Total fertility rate
5
4
3
2
1
1950
1960
1970
1980
1990
2000
2010
USA
Japan
Data source: Human Fertility Database (humanfertility.org)
Author: Randy Olson (randalolson.com / @randal_olson)



Average age when giving birth in USA and Japan, 1947 - 2010
Average age of women when giving birth
30
29
28
27
26
25
1950
1960
1970
1980
1990
2000
2010
Japan
USA
Data source: Human Fertility Database (humanfertility.org)
Author: Randy Olson (randalolson.com / @randal_olson)

CONCLUSION

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!

Alexander Lex
@alexander_lex
http://alexander-lex.net

THE UNIVERSITY OF UTAH

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!

visualization design lab

SCI www.sci.utah.edu