

# CS-5630 / CS-6630 Visualization for Data Science Views

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HOW LONG CAN YOU WORK ON MAKING A ROUTINE TASK MORE  
EFFICIENT BEFORE YOU'RE SPENDING MORE TIME THAN YOU SAVE?  
(ACROSS FIVE YEARS)

		HOW OFTEN YOU DO THE TASK					
		50/DAY	5/DAY	DAILY	WEEKLY	MONTHLY	YEARLY
HOW MUCH TIME YOU SHAVE OFF	1 SECOND	1 DAY	2 HOURS	30 MINUTES	4 MINUTES	1 MINUTE	5 SECONDS
	5 SECONDS	5 DAYS	12 HOURS	2 HOURS	21 MINUTES	5 MINUTES	25 SECONDS
	30 SECONDS	4 WEEKS	3 DAYS	12 HOURS	2 HOURS	30 MINUTES	2 MINUTES
	1 MINUTE	8 WEEKS	6 DAYS	1 DAY	4 HOURS	1 HOUR	5 MINUTES
	5 MINUTES	9 MONTHS	4 WEEKS	6 DAYS	21 HOURS	5 HOURS	25 MINUTES
	30 MINUTES		6 MONTHS	5 WEEKS	5 DAYS	1 DAY	2 HOURS
	1 HOUR		10 MONTHS	2 MONTHS	10 DAYS	2 DAYS	5 HOURS
	6 HOURS				2 MONTHS	2 WEEKS	1 DAY
	1 DAY					8 WEEKS	5 DAYS

# Multiple Views

Eyes over Memory:

Trade-off of display space and  
working memory

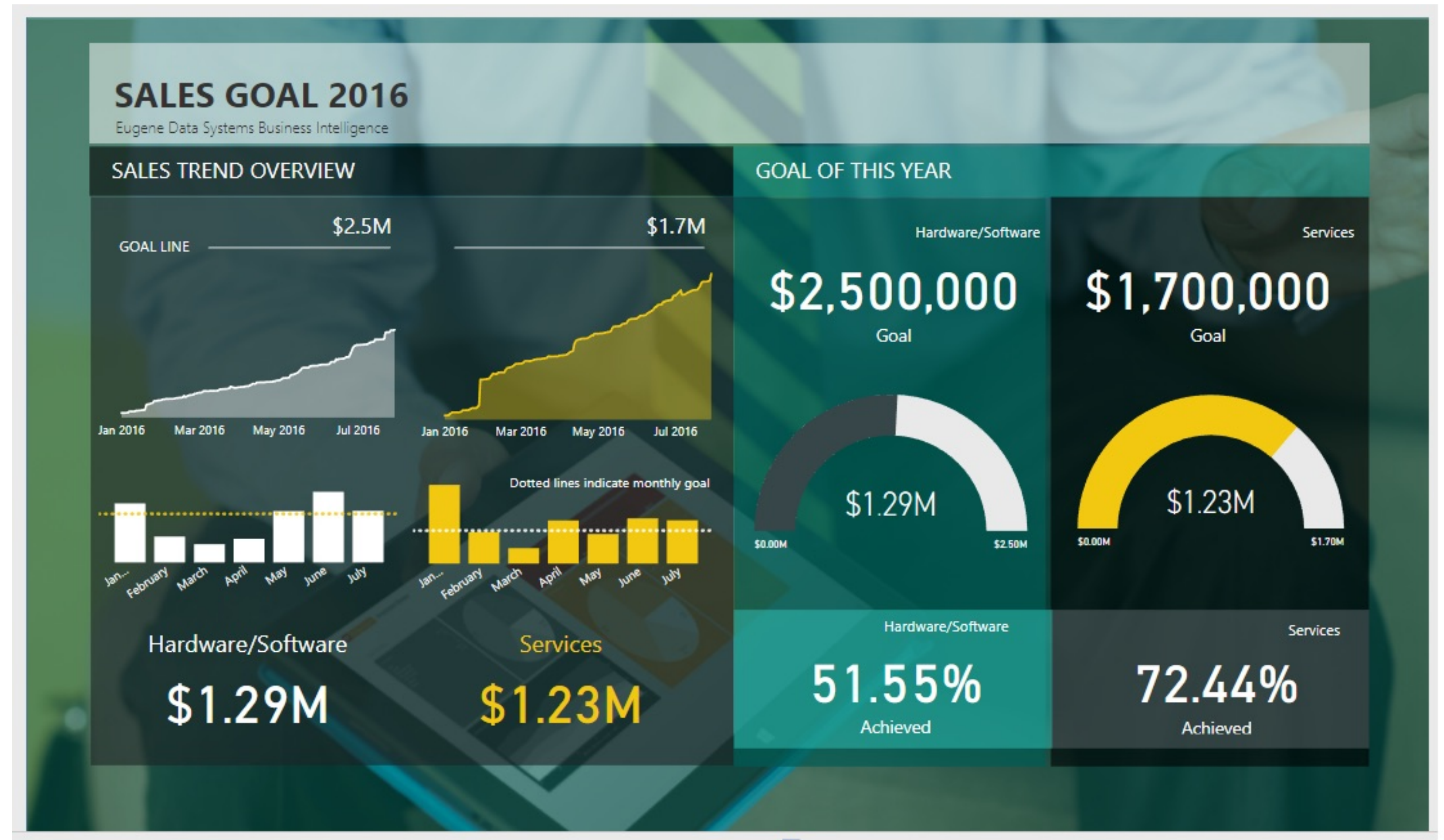
# Linked Views

Multiple Views that are simultaneously visible and linked together such that actions in one view affect the others.

# Dashboards

Multiple views for “data driven decision making”

“a visual display of data used to monitor conditions and/or facilitate understanding”





# Mandatory Reading

## What Do We Talk About When We Talk About Dashboards?

Alper Sarikaya, Michael Correll, Lyn Bartram, Melanie Tory, and Danyel Fisher

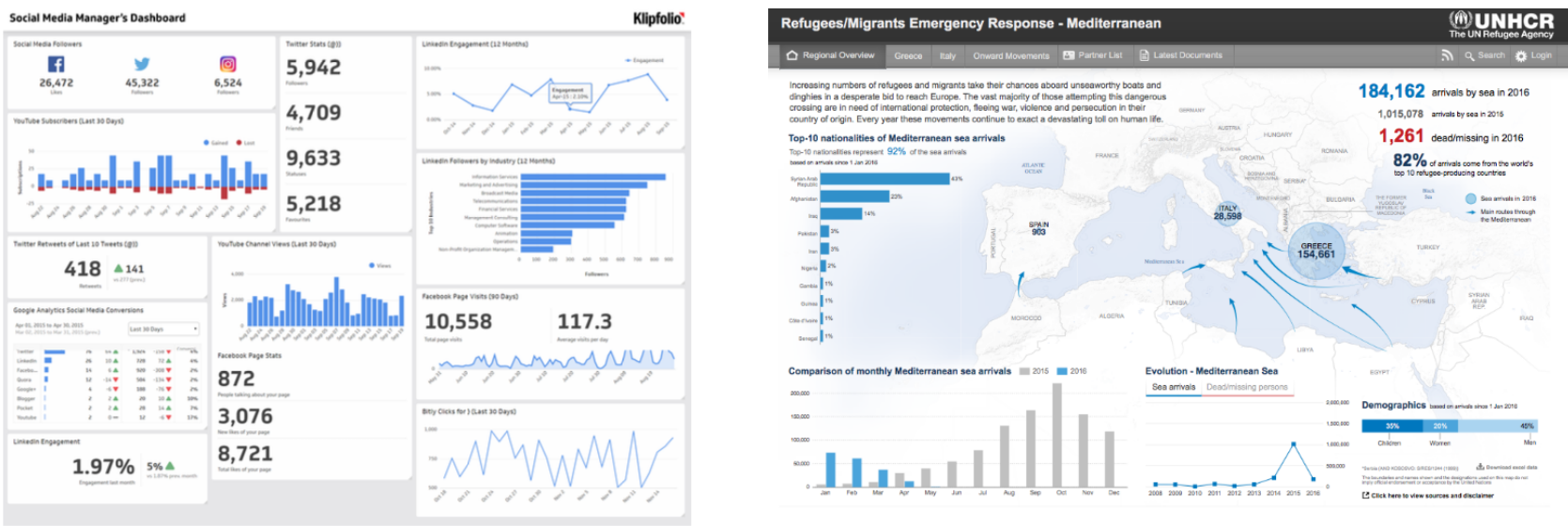


Fig. 1: Klipfolio's Social Media Manager Dashboard (DB065 from our example corpus, left) is a traditional dashboard, with large numbers representing key metrics, and tiled graphs of real-time data. The UNCHR Refugees/Migrants Emergency Response dashboard (DB117, right) also is a juxtaposition of key metrics and simple visualizations, but includes annotations and guided narrative elements. Are both dashboards? Do design principles meant for one transfer to the other?

**Abstract**—Dashboards are one of the most common use cases for data visualization, and their design and contexts of use are considerably different from exploratory visualization tools. In this paper, we look at the broad scope of how dashboards are used in practice through an analysis of dashboard examples and documentation about their use. We systematically review the literature surrounding dashboard use, construct a design space for dashboards, and identify major dashboard types. We characterize dashboards by their design goals, levels of interaction, and the practices around them. Our framework and literature review suggest a number of fruitful research directions to better support dashboard design, implementation, and use.

**Index Terms**—Dashboards, literature review, survey, design space, open coding

### 1 INTRODUCTION

Visualization dashboards are ubiquitous. They are built and employed by nearly every industry, non-profit, and service organization to support data-driven decision making. They are used by students to track learning, and by individuals to monitor energy consumption and personal health. Despite their prevalence, the visualization research community has rarely given dashboards their due consideration, with few exceptions [46]. Are dashboards simply an extension of known visualization design principles? Or is there more to their design and use?

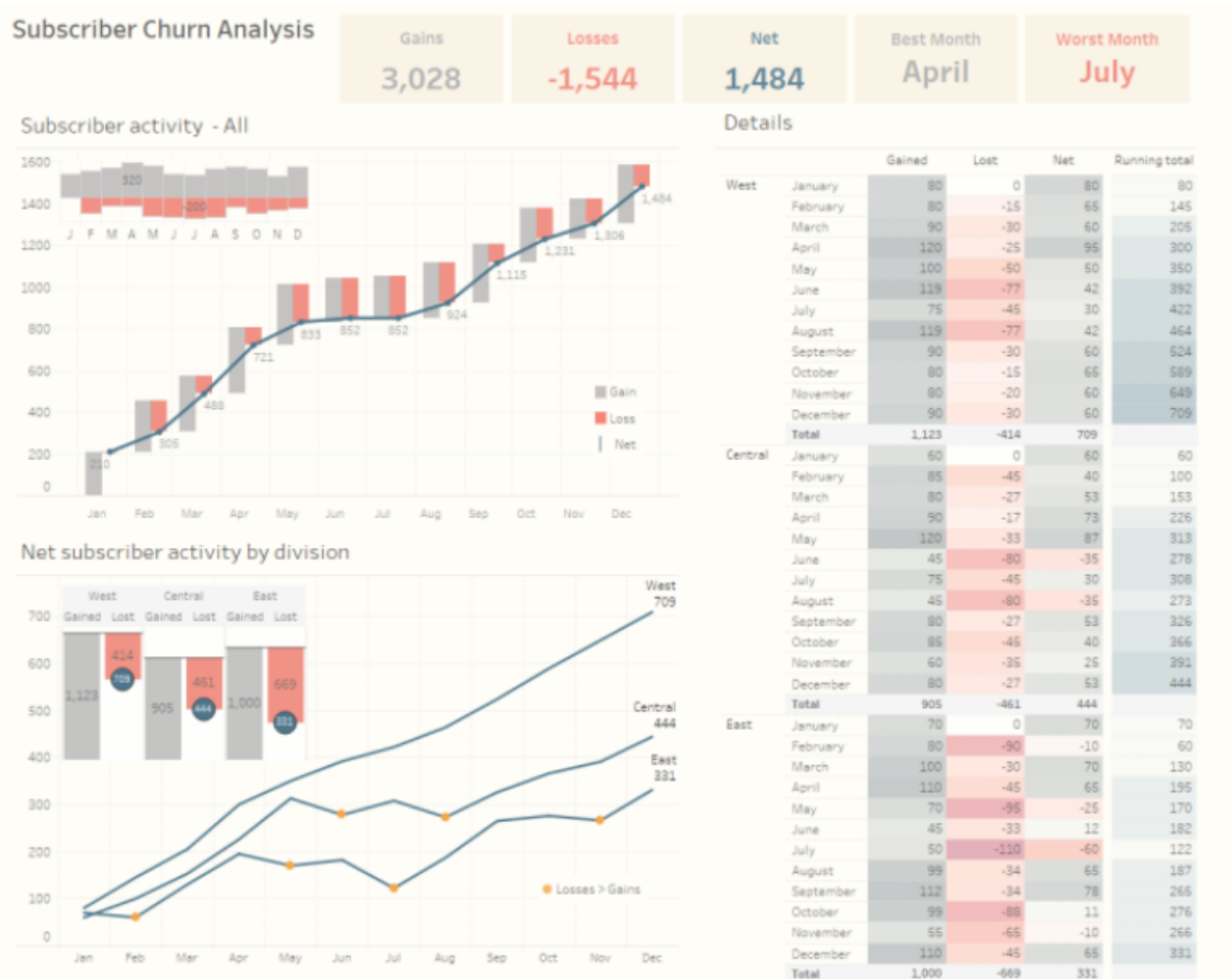
We argue that dashboards are worthy of discussion and research in

gle screen reports. Uniquely, compared to visualization modalities for presentation and exploration, dashboards bring together challenges of at-a-glance reading, coordinated views, tracking data and both private and shared awareness. Designers of dashboards must be mindful of literacy, contextually appropriate representations and visual language, and social framing. We identify dashboards as a distinct area of visualization that offers impactful directions for future research.

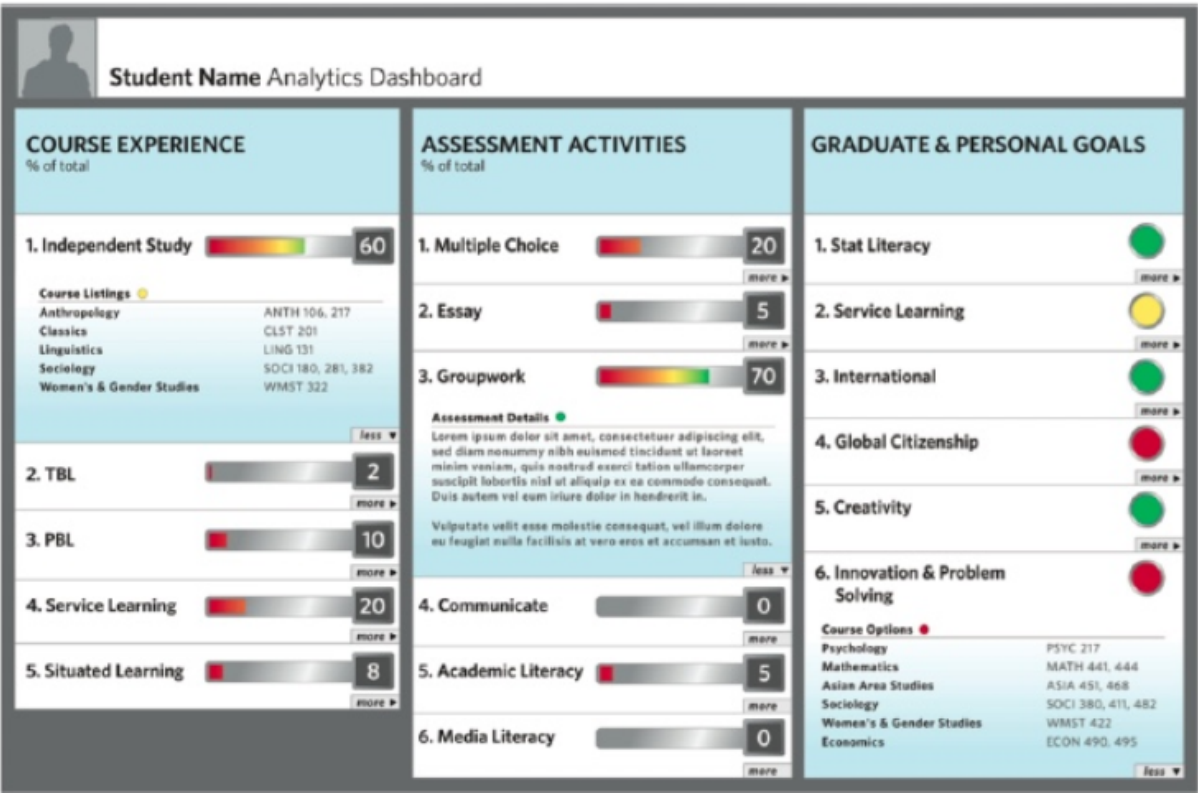
We took a two-pronged approach to understanding practices around dashboard design and use. We conducted an exploratory survey of



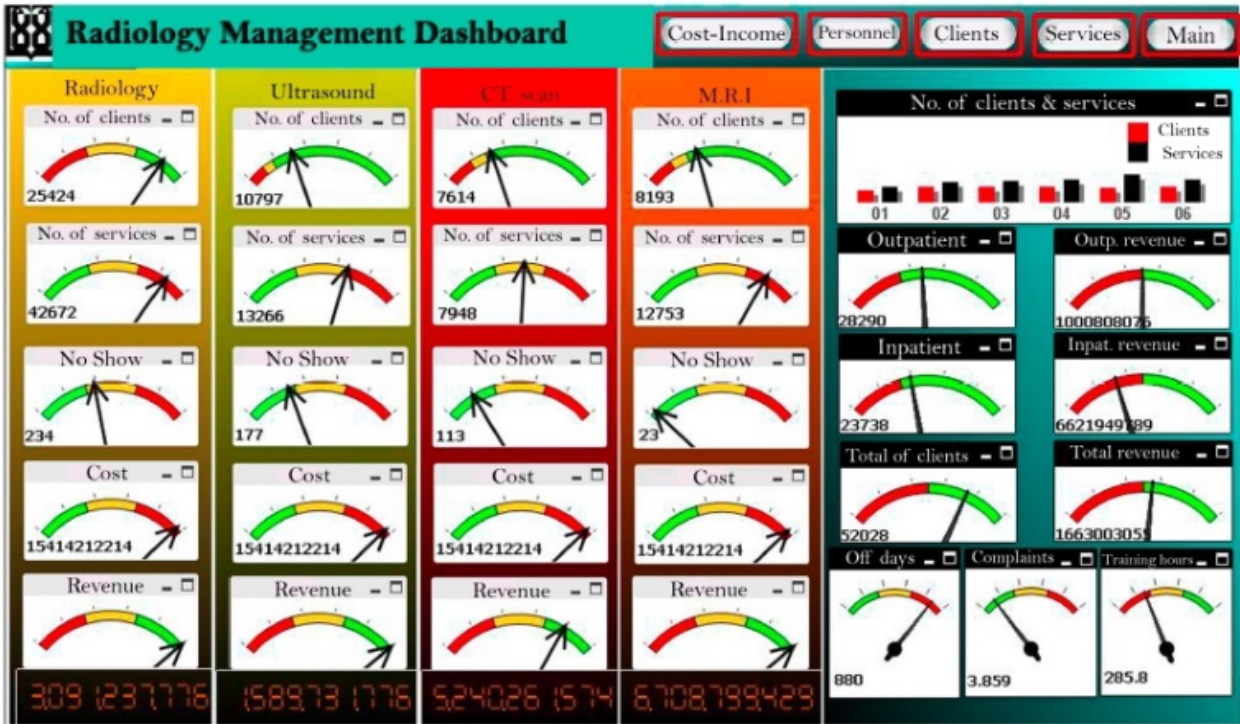
# Types of Dashboards



(a) Strategic Dashboard (DB001)



(b) Tactical Dashboard (DB106)



(c) Operational Dashboard (DB102)



(d) Social Dashboard (DB028)



# Dashboard Design Elements

## Key Performance Indicators (KPIs)

Often shown as numbers

## Gauge

Numerical value + context / reference point

what is the goal?

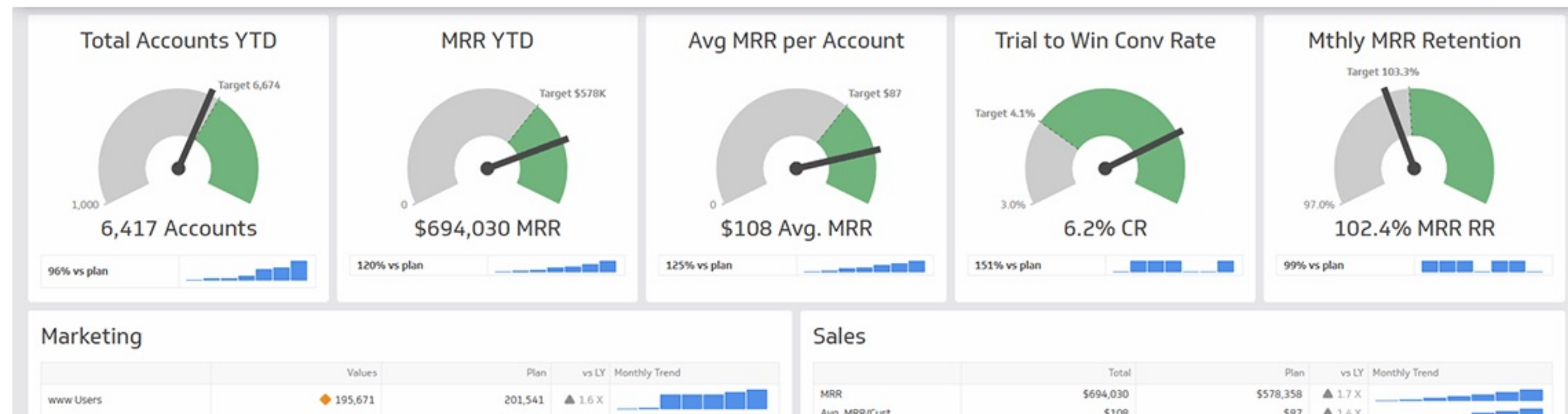
are we in “danger zone”?

what's the minimum?



KVO Executive Reporting Dashboard

Klipfolio





# COVID-19 Dashboards

## Overview of COVID-19 Surveillance

Data are updated weekly on Thursdays. Most of the tables, charts, and maps in this report are interactive. Tables can be sorted by clicking on column headings. Maps and charts can be sorted, zoomed, selected, etc. using the mouse cursor and data will appear when hovering or clicking the mouse cursor. Controls will appear at the top right corner of charts when the mouse cursor is placed on the chart. The data used to create the charts on this dashboard are also available for [download](#). Case and laboratory data that can be queried is available on [IBIS](#).

Weekly Report Date: October 20, 2022.

1,043,353  
COVID-19 Cases

38,937  
COVID-19 Hospitalizations

5,047  
COVID-19 Deaths

20.6%  
Wastewater Sites Elevated or Increasing

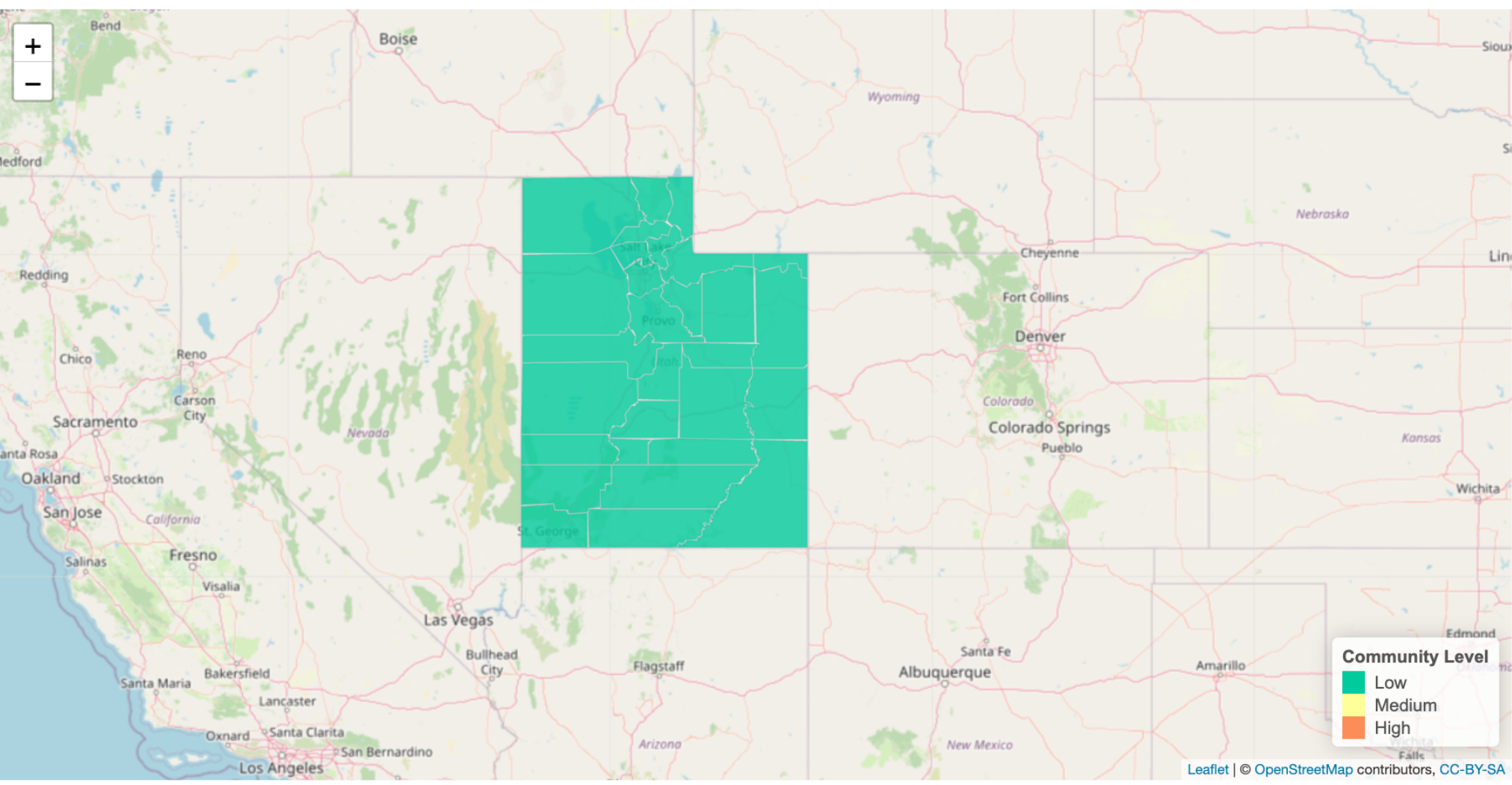
1.79%  
7-day Emergency Room Visits with COVID-19

2,331,857  
People Received at Least One Vaccine

Total Number of Lab-Confirmed COVID-19 Cases in Utah Residents

Jurisdiction	Cases	Hospitalizations	Deaths
Bear River	56,270	2,313	261
Central Utah	22,103	1,019	173
Davis County	113,795	3,303	430
San Juan	4,668	244	50
Salt Lake County	392,045	16,486	1,740
Southeast Utah	11,393	360	90
Southwest Utah	69,484	3,439	680
Summit County	15,340	370	27
Tooele County	24,025	805	111
TriCounty	14,382	1,253	116
Utah County	219,619	5,900	846
Wasatch County	11,761	208	37
Weber-Morgan	84,293	3,182	479
Under Investigation	4,175	55	7
State Total	1,043,353	38,937	5,047

COVID-19 Community Levels by County - CDC\*\*

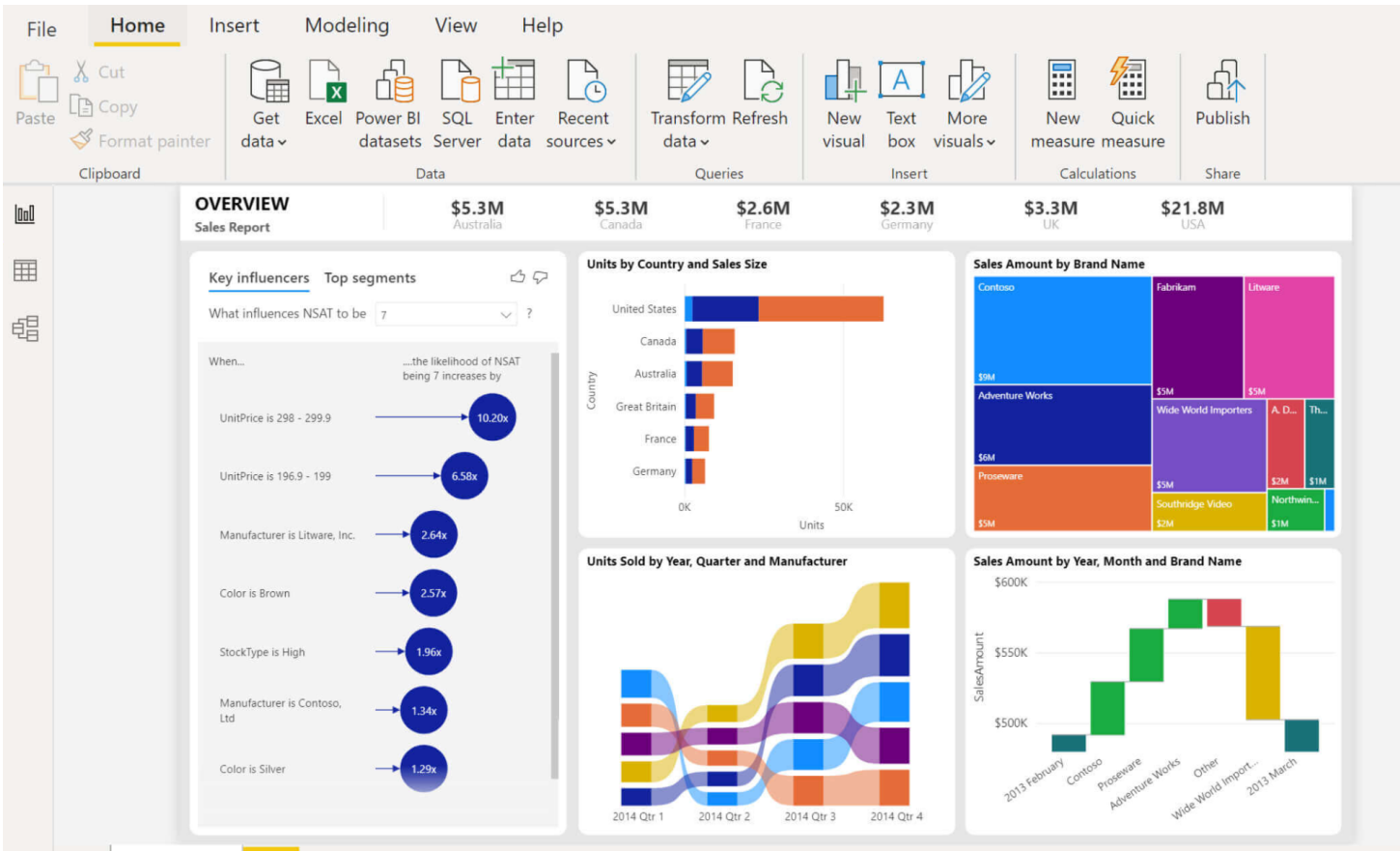


Cases Reported by Indian Health Service and Tribal Nations (these cases are also reflected in case counts by health district)

Reporting Jurisdiction	Cases
Navajo Nation Reservation (Utah) - Utah Navajo Health System	2,359
Uintah and Ouray Reservation: Uintah & Ouray Indian Health Services (IHS)	992
State Total	1,043,353



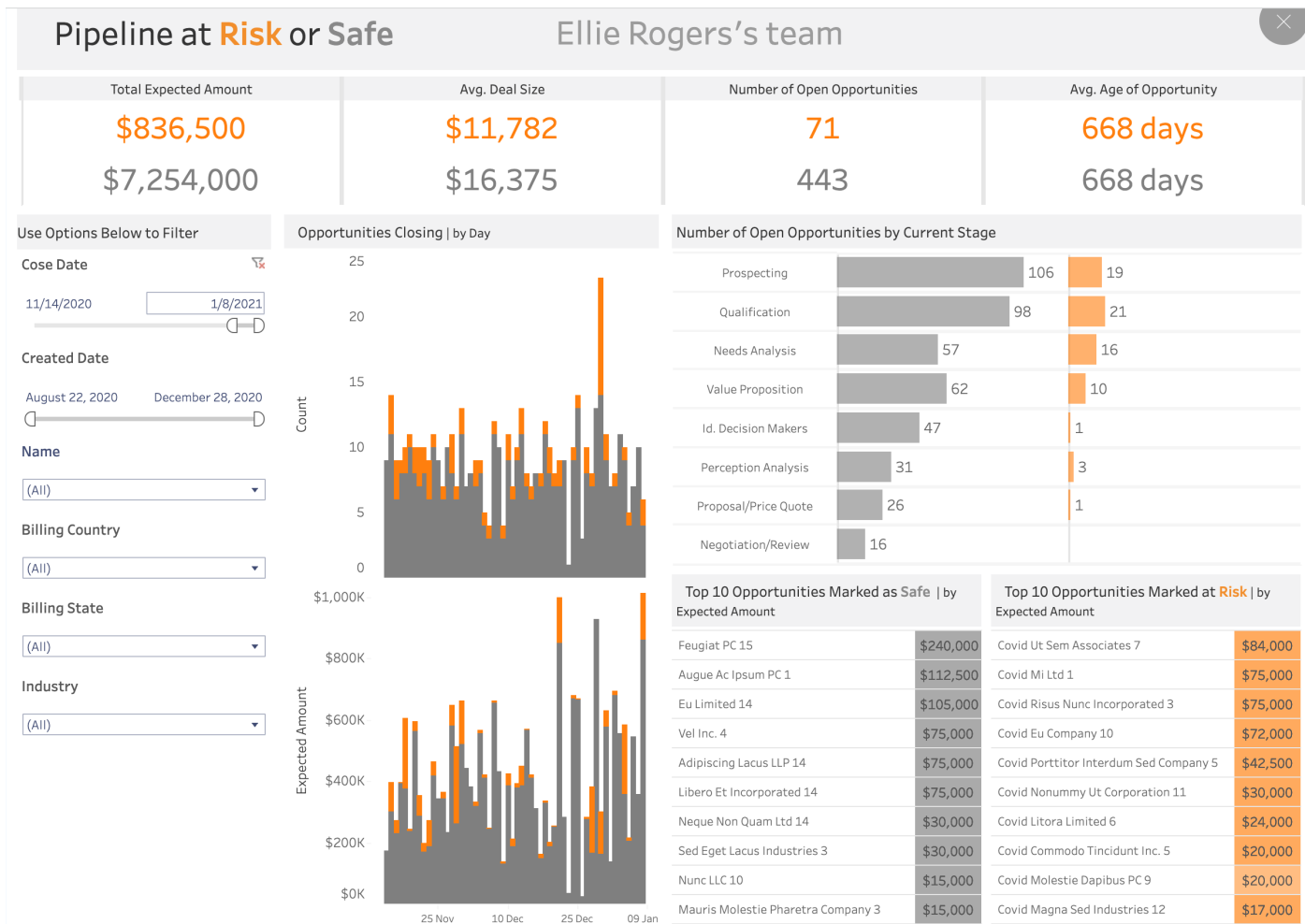
# Dashboarding Tools



Microsoft Power BI



Plot.ly



Tableau



Datawrapper

# Dashboards vs Analytical Multiple Views (MVs)

Exploratory vs Overview  
on current state

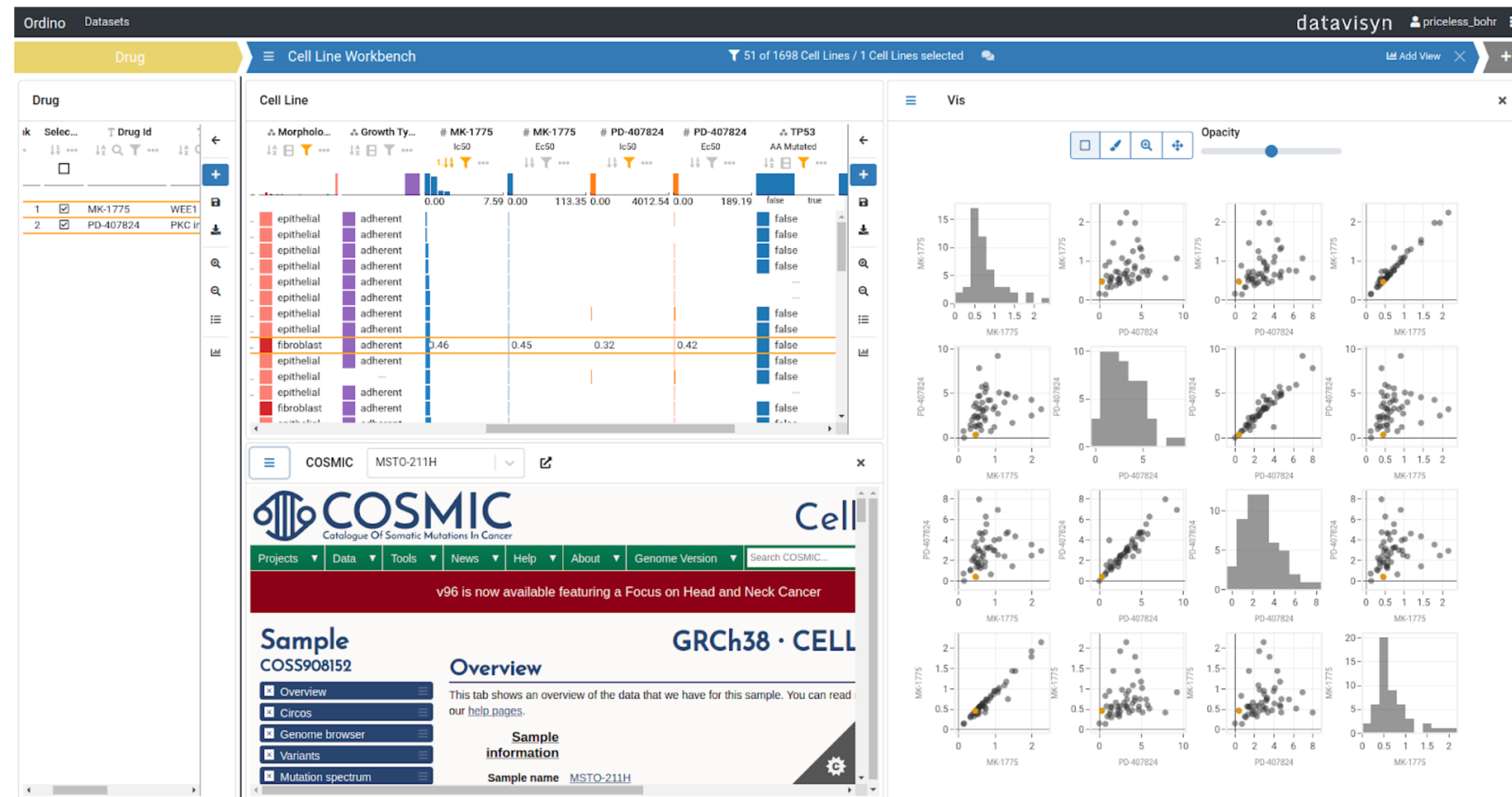
MVs have flexibility and  
complexity

Choose view composition

Choose data

Choose visualization

Custom Filters, etc.



Example of an Analytical Multiple Views (MVs) by datavisyn

# Systematic Analysis

Shared Encoding?

Shared Data?

All or Subset?

Shared Navigation?

→ Share Encoding: Same/Different

→ *Linked Highlighting*



→ Share Data: All/Subset/None



→ Share Navigation



		Data		
		All	Subset	None
Encoding	Same	Redundant	Overview/ Detail	Small Multiples
	Different	Multiform	Multiform, Overview/ Detail	No Linkage

# Linked Views Options

highlighting: to link, or not

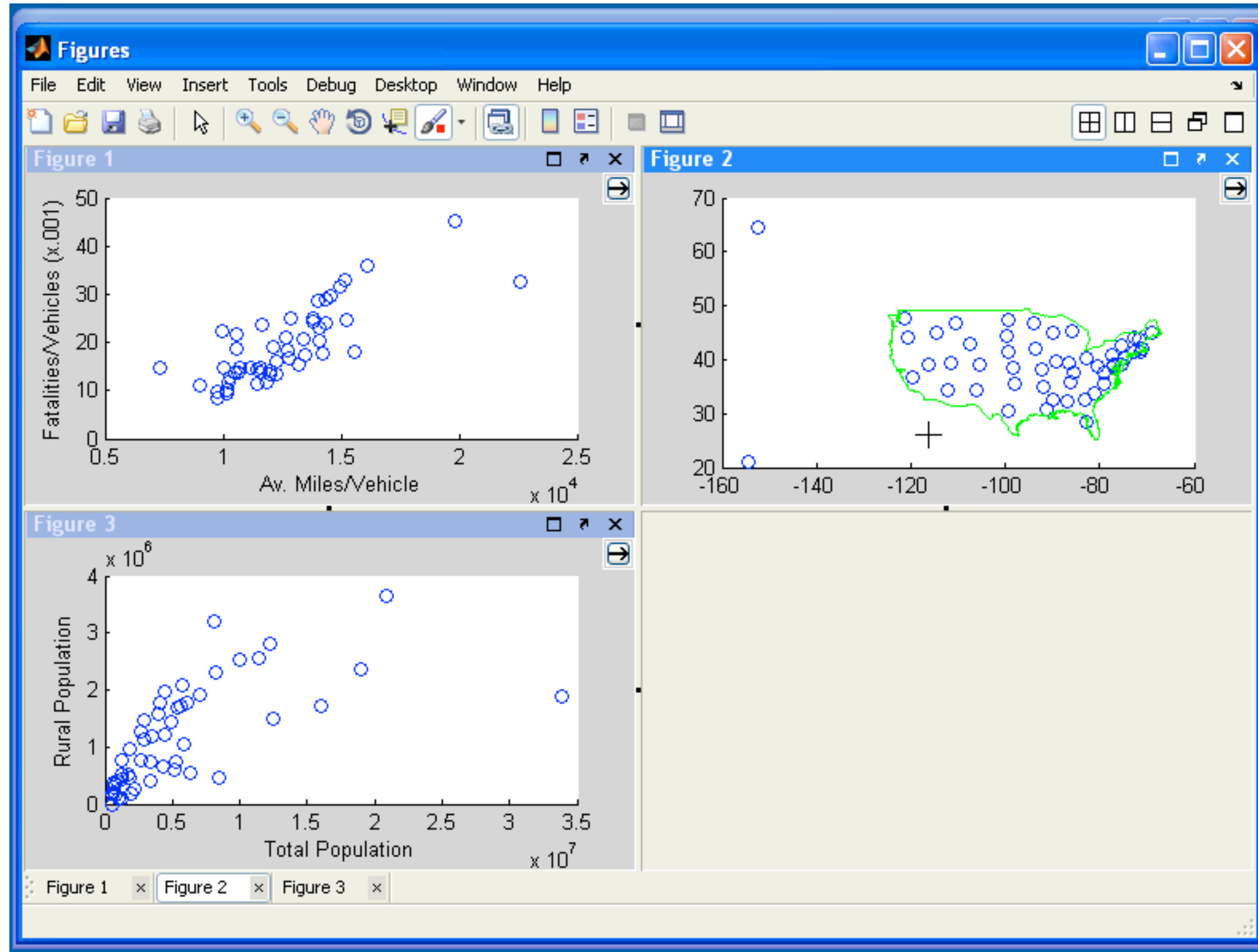
navigation: to share, or not

encoding: same or multiform

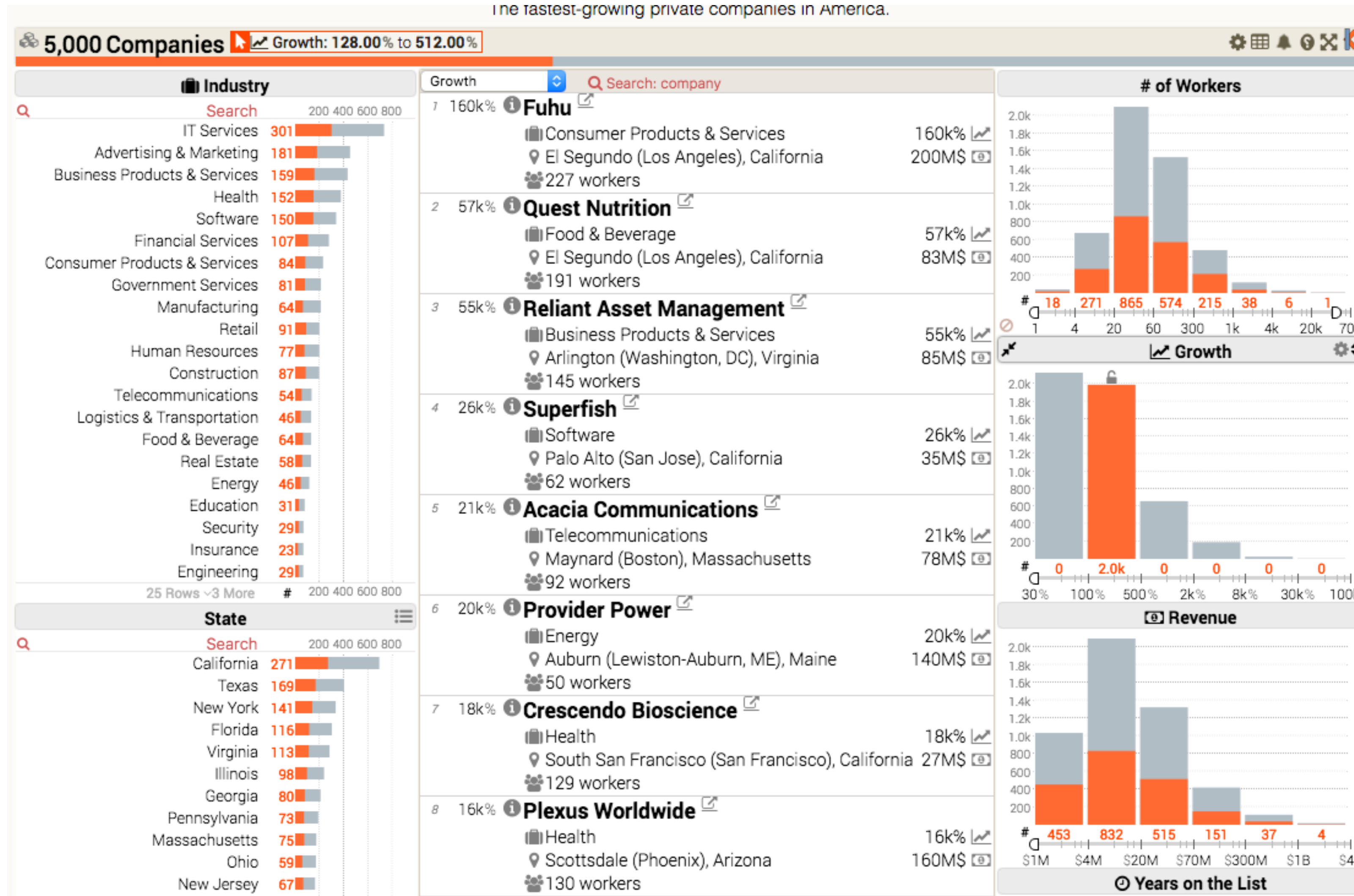
dataset: share all, subset, or none



# Linked Highlighting



# Linked Highlighting



# Multiform Views

different visual encodings are used between the views

- implies shared data

- either all data

- or subset of data (overview + detail)

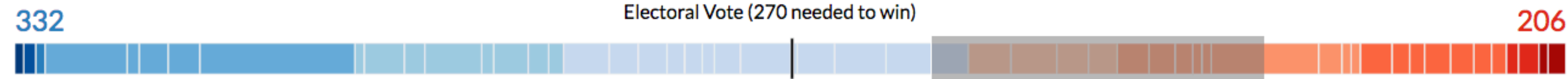
**rational:**

single, monolithic view has strong limits on the number of attributes that can be shown simultaneously

different views support different tasks

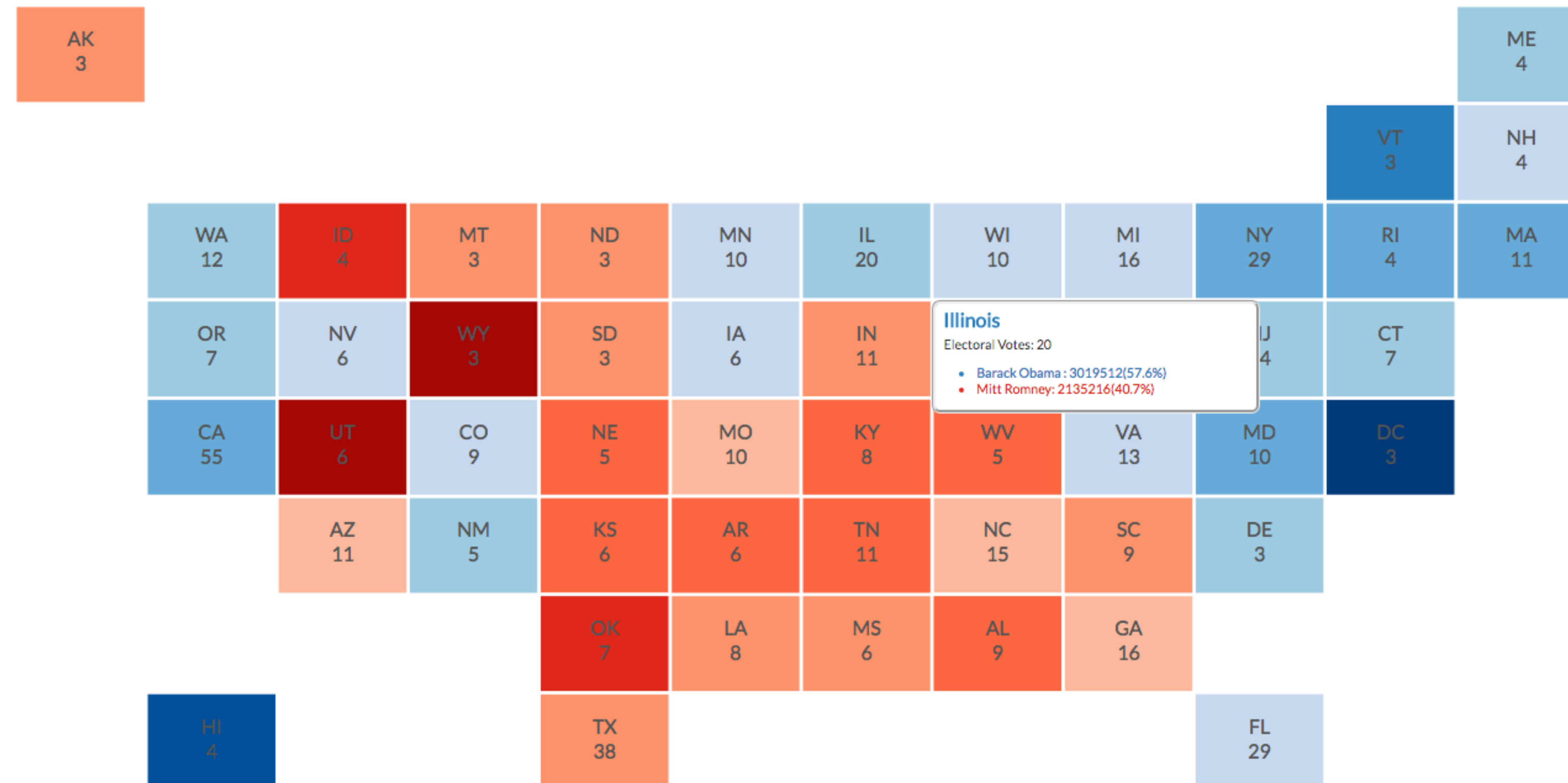
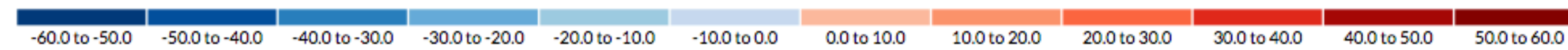
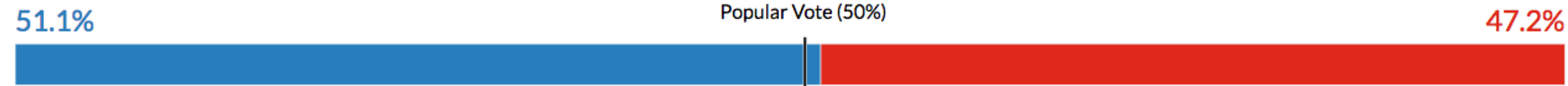
# US Presidential Elections from 1940 to 2012

Name: Your Name; E-Mail: Your E-Mail; UID: Your UID



Barack Obama

Mitt Romney



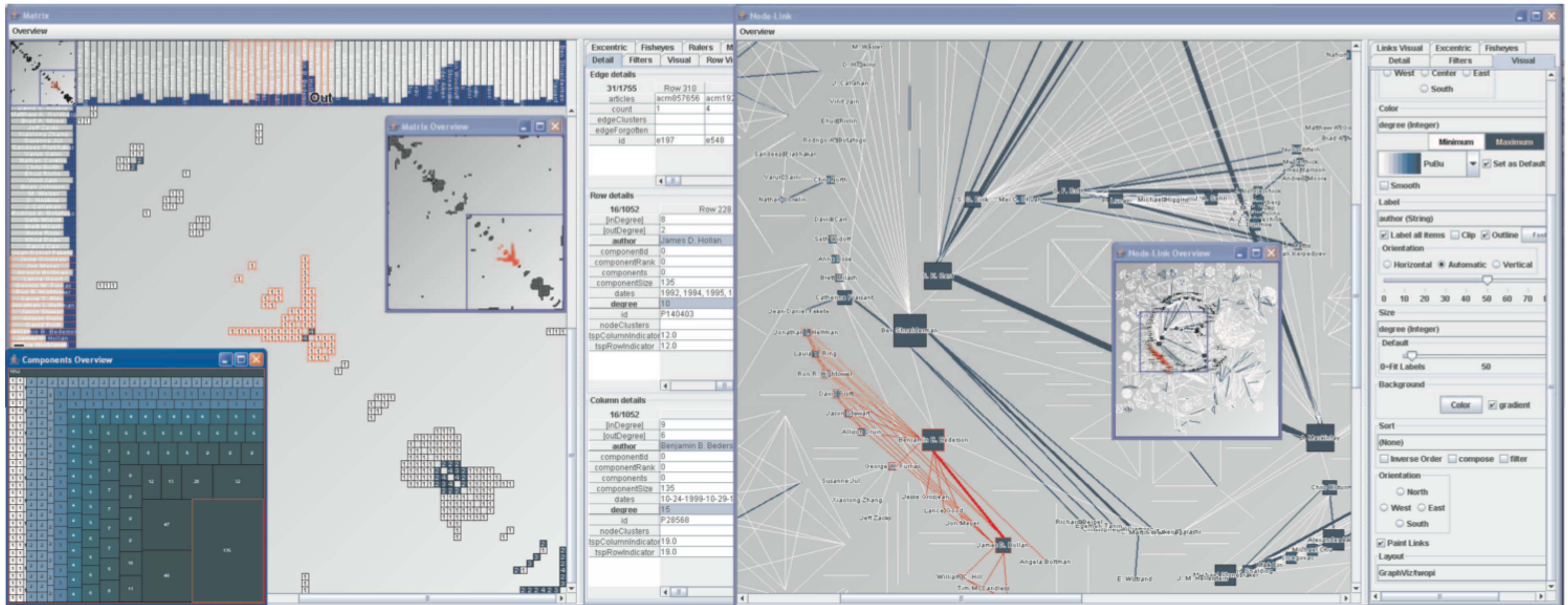
Brush selection is:

- North Carolina
- Georgia
- Arizona
- Missouri
- Indiana
- South Carolina
- Mississippi
- Montana
- Alaska

**Multiform**  
Different Views  
here also same data



# MatrixExplorer



Same Data - Different Idioms (Multiform)

Henry 2006



Start  End    Length Paths 

0 1 2 3 4

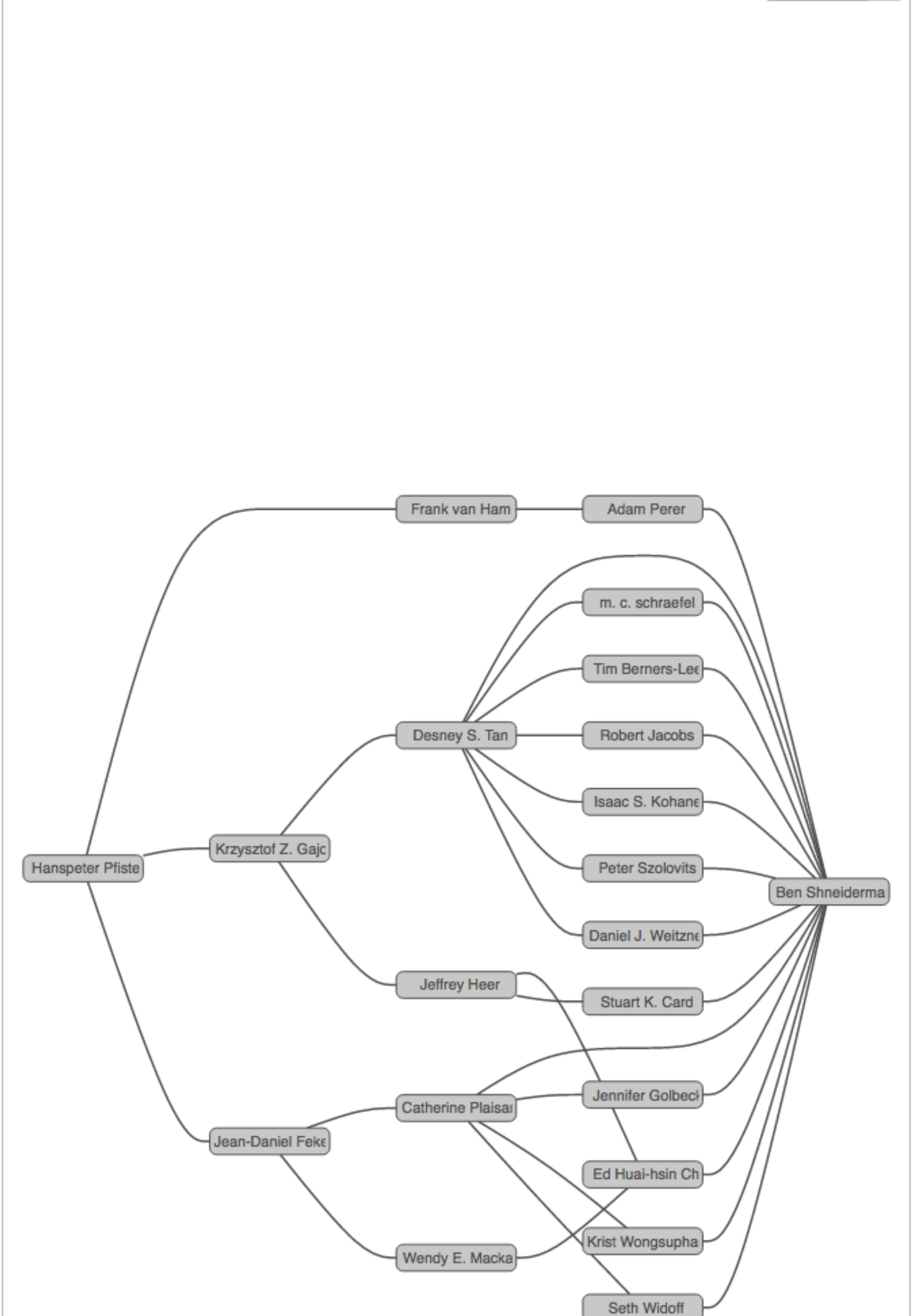
0 0 0 3 105

Path List

1.	Hanspeter Pfister	Frank van Ham	Adam Perer	Ben Shneiderma	3	
CHI						
TVCG						
chi_publications	1	0	8	38		
cited						
degree						
tvcg_publication						
1.	Hanspeter Pfister	Krzysztof Z. Gajc	Desney S. Tan	Ben Shneiderma	3	
CHI						
TVCG						
chi_publications						
cited						
degree						
tvcg_publication						
1.	Hanspeter Pfister	Jean-Daniel Fekete	Catherine Plaisant	Ben Shneiderma	3	
CHI						
TVCG						
chi_publications						
cited						
degree						
tvcg_publication						
4.	Hanspeter Pfister	Jean-Daniel Fekete	Catherine Plaisant	Jennifer Golbeck	Ben Shneiderma	4
CHI						
TVCG						
chi_publications						
cited						
degree						
tvcg_publication						
4.	Hanspeter Pfister	Jean-Daniel Fekete	Wendy E. Macka	Ed Huai-hsin Ch	Ben Shneiderma	4
CHI						
TVCG						
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tvcg_publication						
4.	Hanspeter Pfister	Krzysztof Z. Gajc	Jeffrey Heer	Ed Huai-hsin Ch	Ben Shneiderma	4
CHI						
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degree						
tvcg_publication						
4.	Hanspeter Pfister	Krzysztof Z. Gajc	Jeffrey Heer	Stuart K. Card	Ben Shneiderma	4
CHI						
TVCG						
chi_publications						
cited						
degree						
tvcg_publication						
4.	Hanspeter Pfister	Jean-Daniel Fekete	Catherine Plaisant	Krist Wongsupha	Ben Shneiderma	4
CHI						
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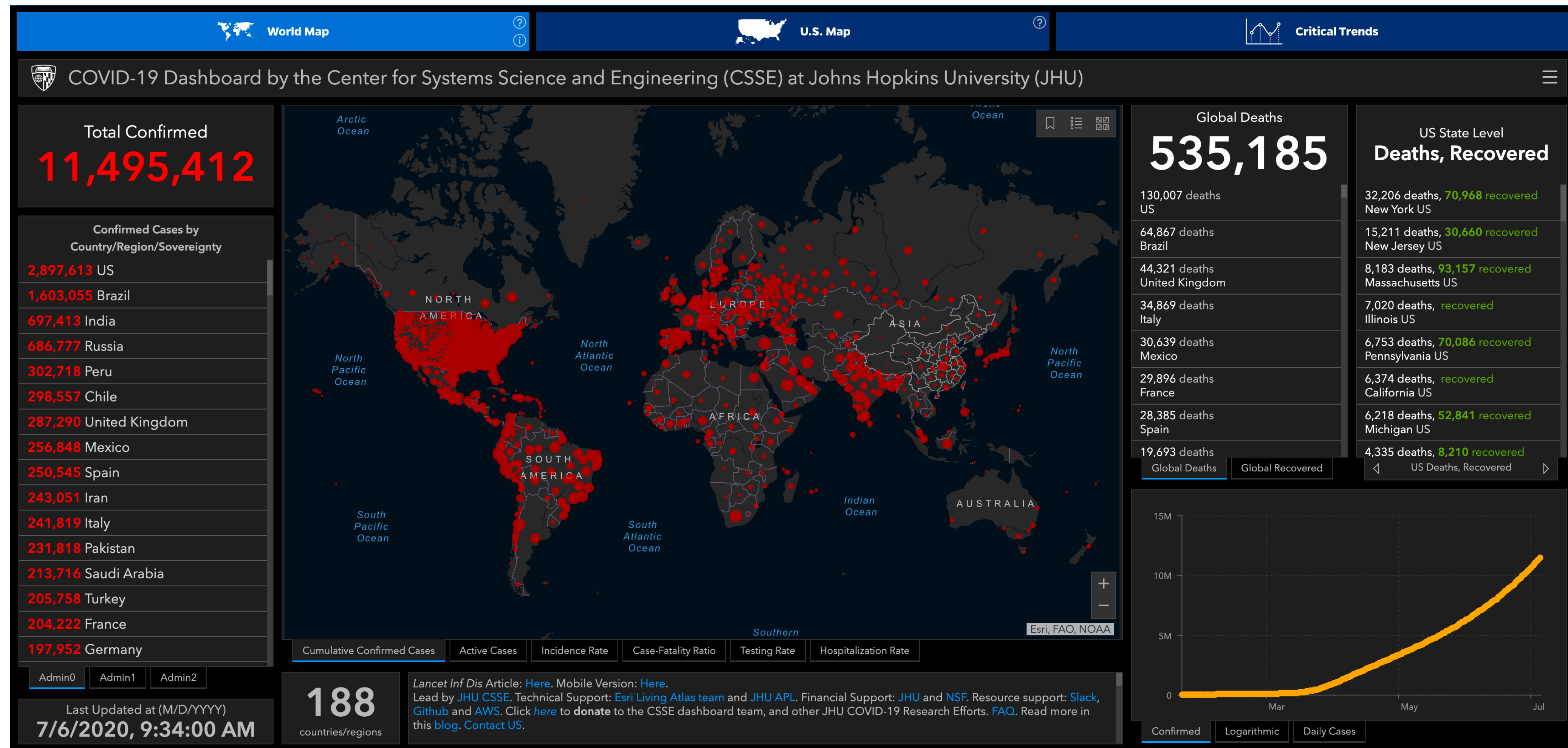
Path Topology

Active Page All



# Design Critique

# Johns Hopkins COVID-19 Dashboard





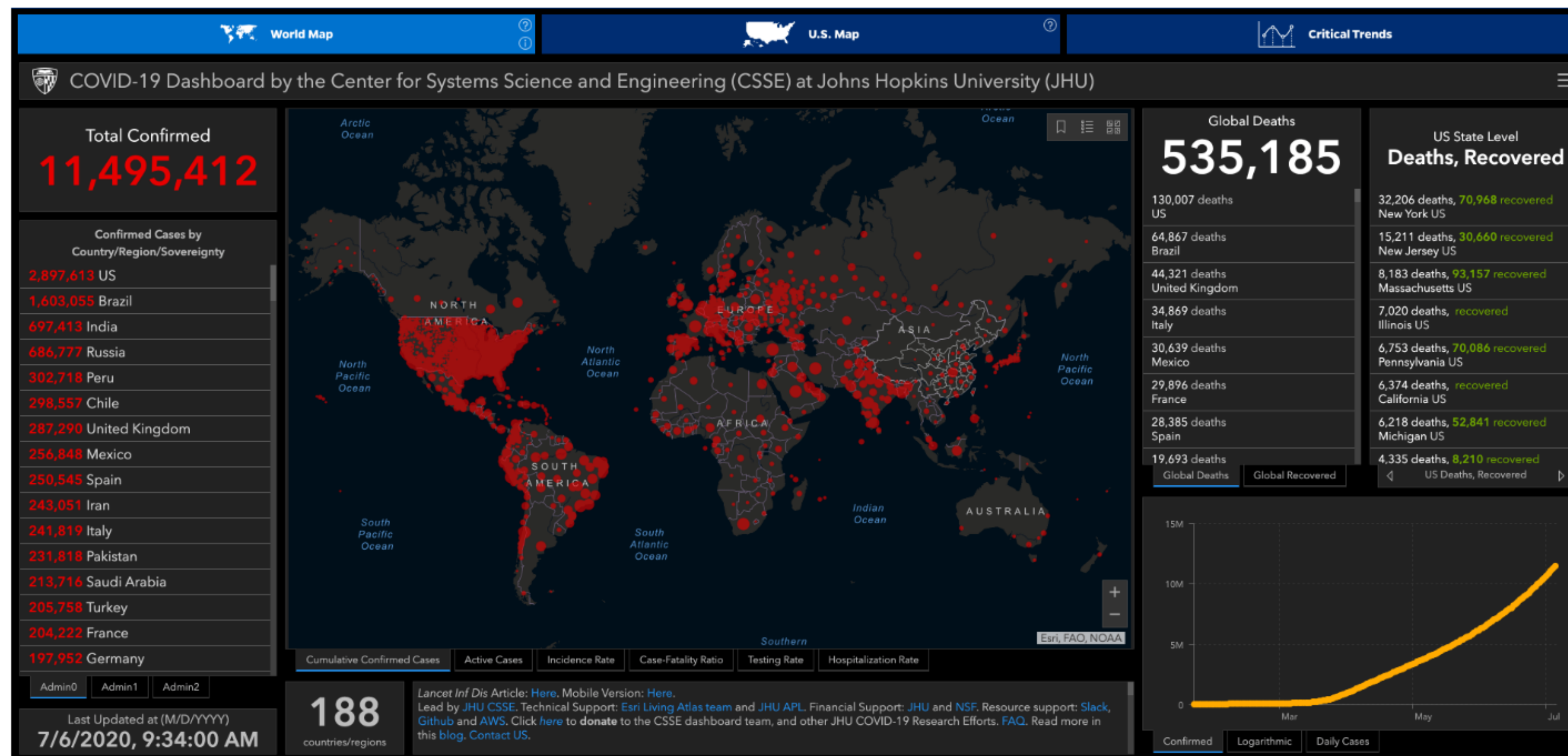
# The Case Against Dashboards (when Visualizing a Pandemic)



Alexander Lex

July 6, 2020

*tldr: Using dashboards comes with risks: they leave out critical context by over-simplifying and hence give false certainty. A more nuanced approach including interpretation by experts, and showing multiple perspectives is needed when visualizing data for something as complex as the COVID-19 pandemic.*



Source: Screenshot of <https://coronavirus.jhu.edu/map.html>, taken on July 6, 2020.

# OVERVIEW + DETAIL

one view shows (often summarized) information about entire dataset, while additional view(s) shows more detailed information about a subset of the data

## **rational**

for large or complex data, a single view of the entire dataset cannot capture fine details



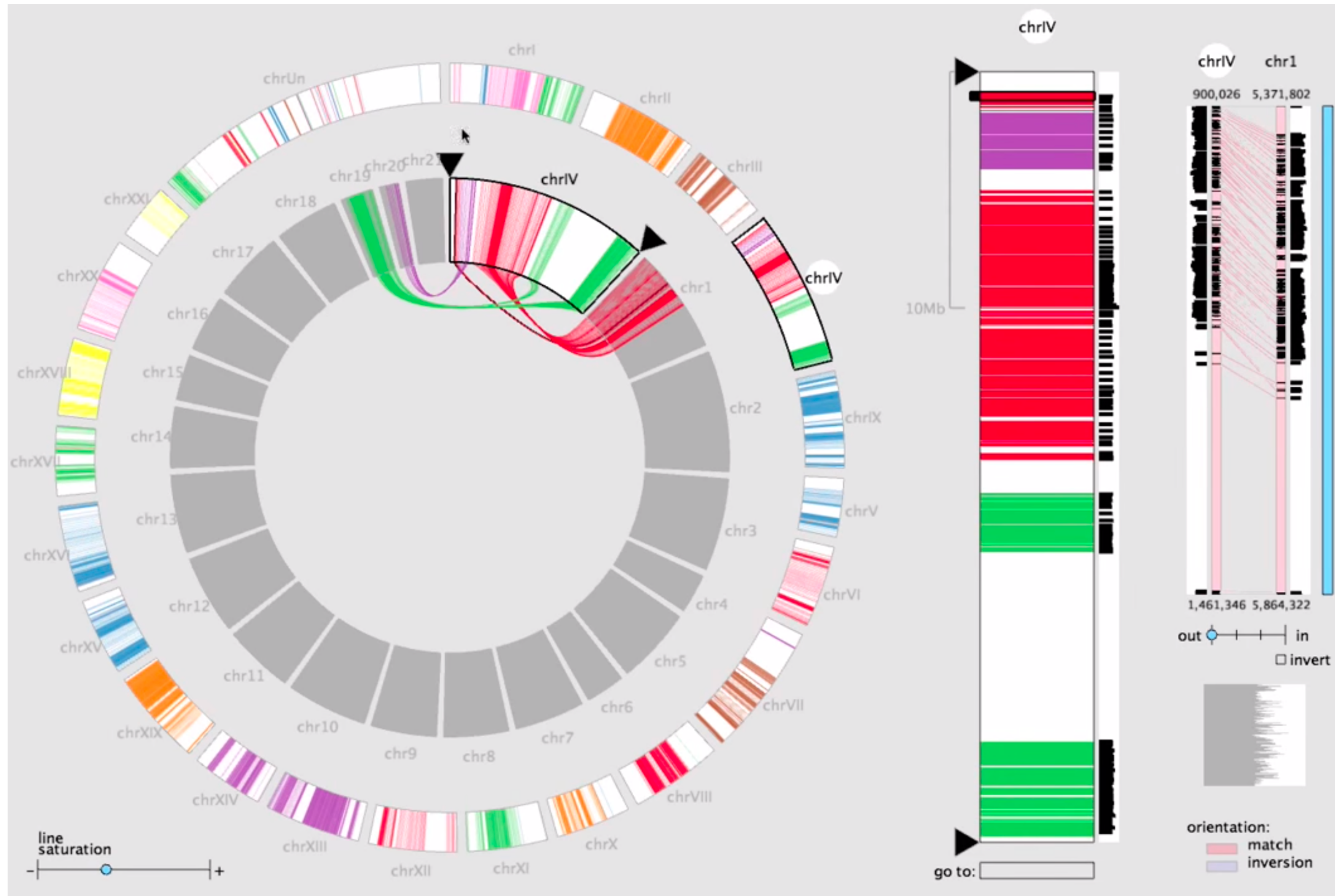
# Stack Zooming



Same Data - Same Encoding, Different Resolution



# MizBee

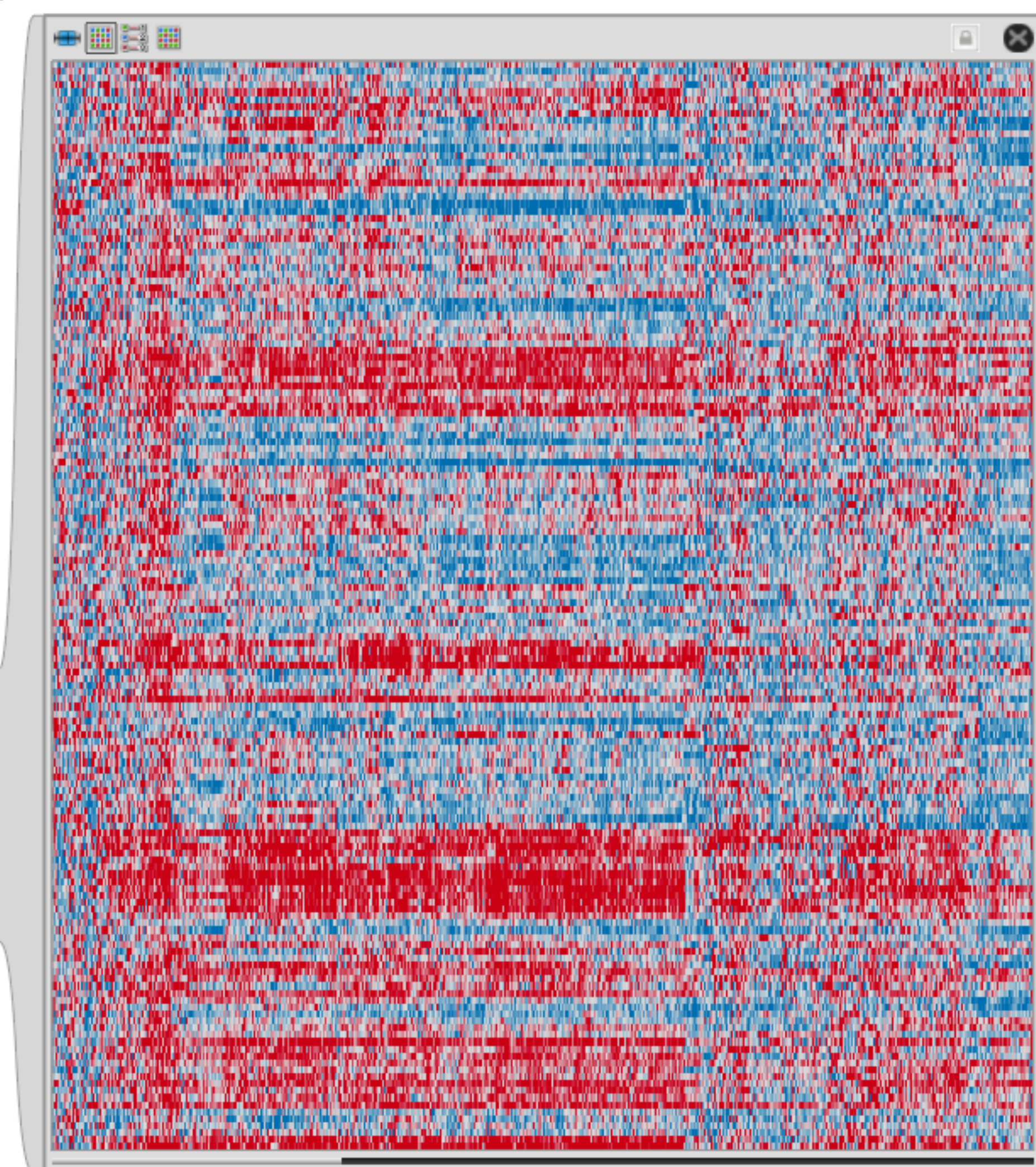


# Multiform Overview & Detail

[Meyer 2009]



# StratomeX





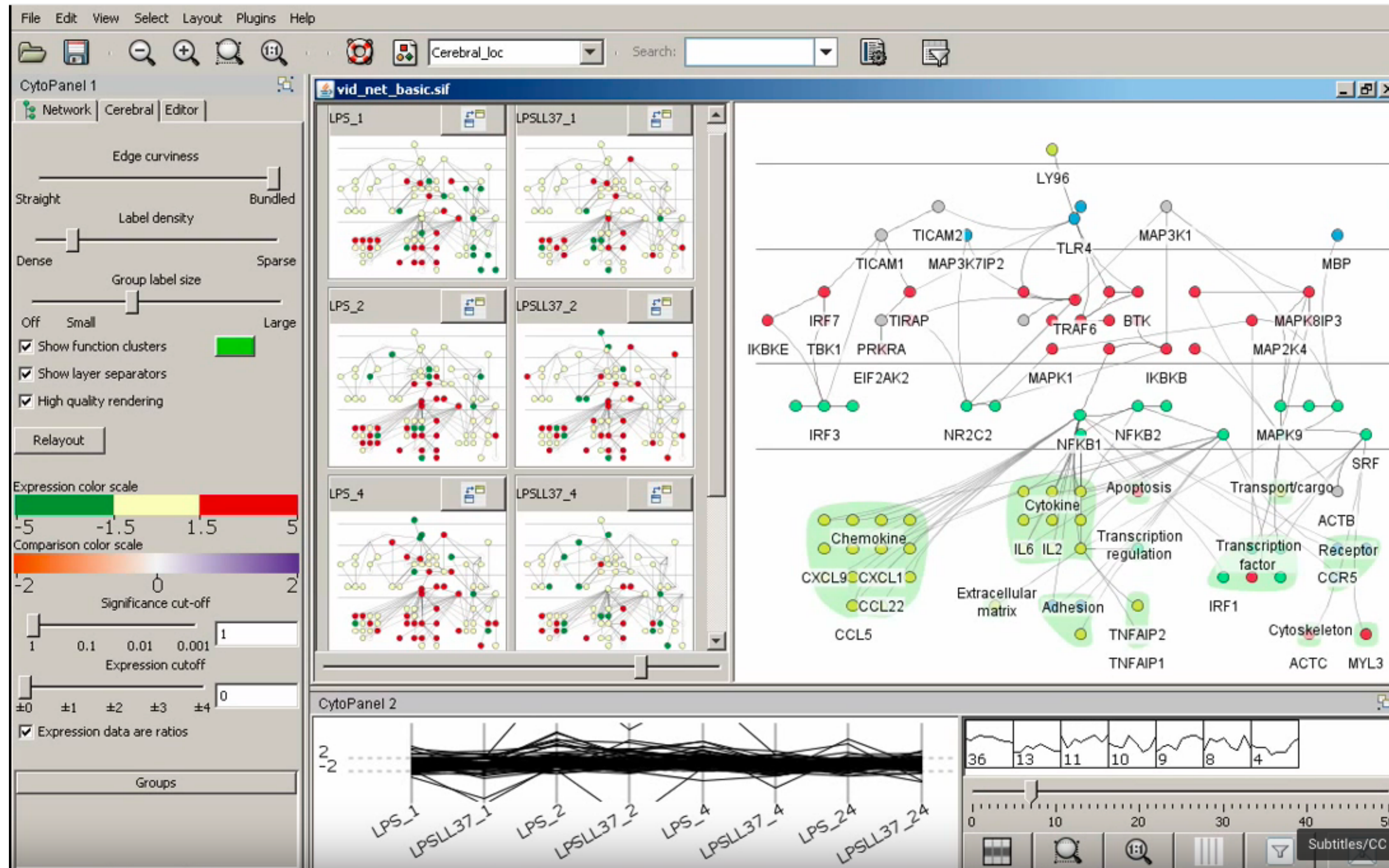
# SMALL MULTIPLES

each view uses the same visual encoding, but shows a different subset of the data

## **rational**

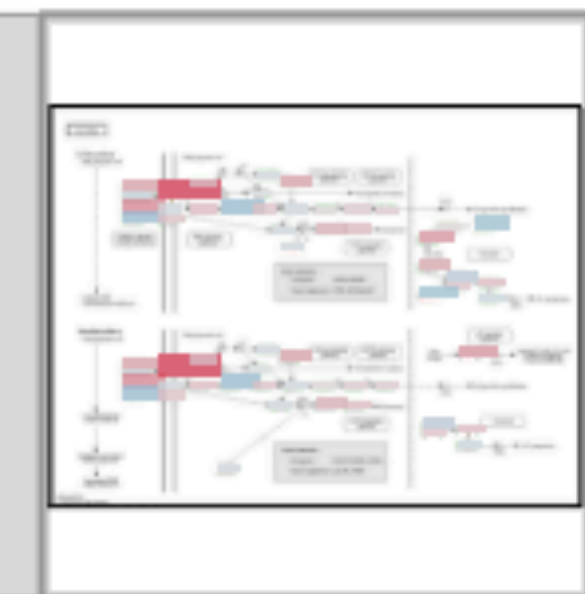
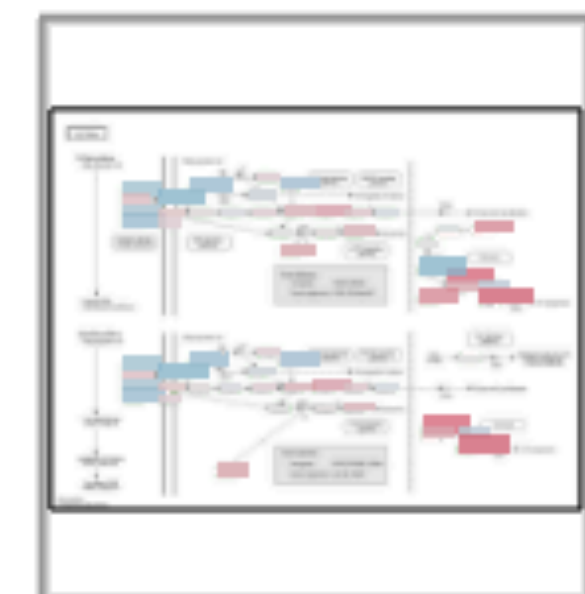
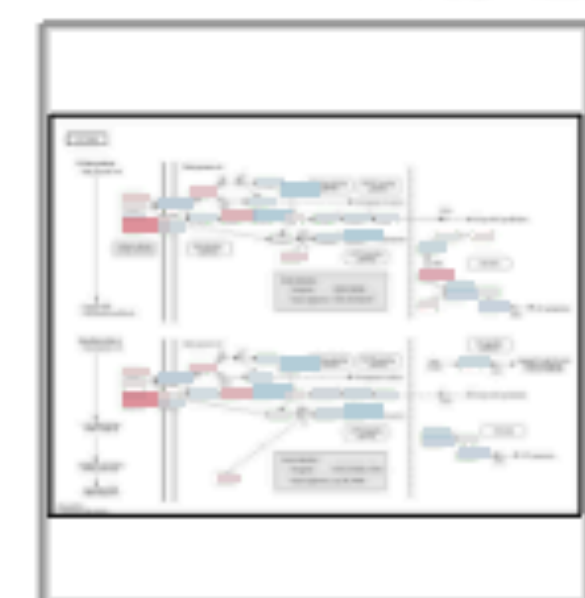
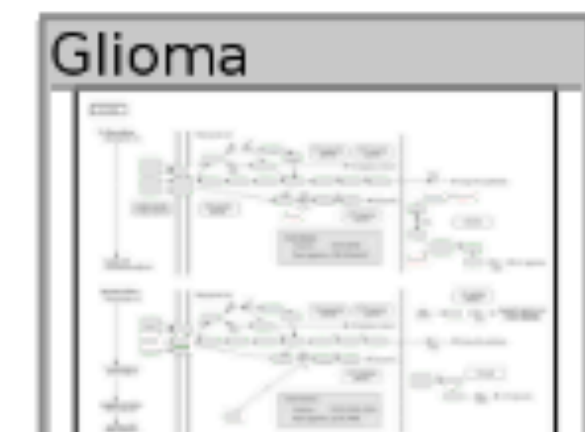
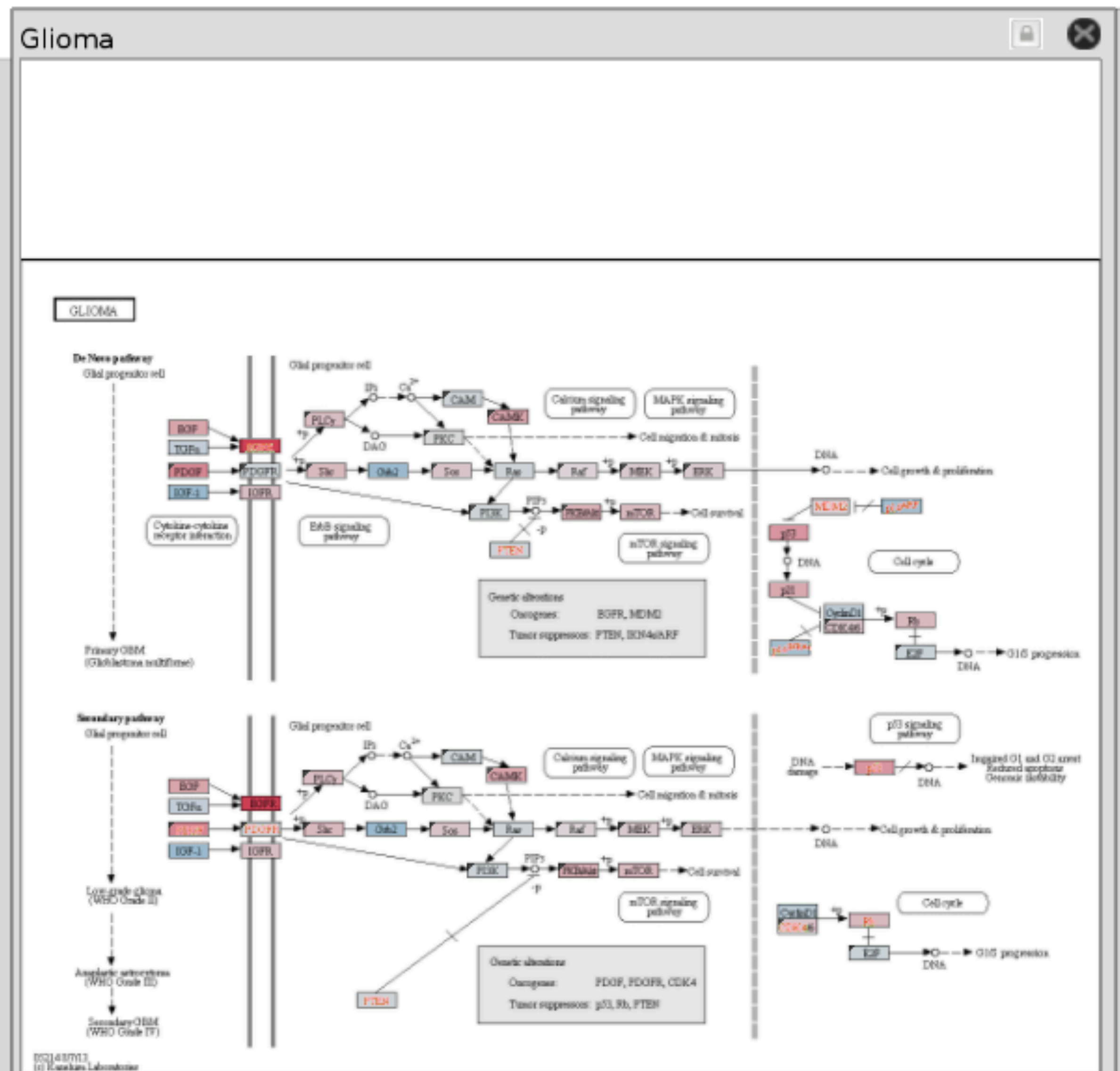
quickly compare different parts of a data set, relying on eyes instead of memory

# Small Multiples for Graph Attributes





# StratomeX





# Partitioning

# PARTITIONING

action on the dataset that **separates the data into groups**

## **design choices**

- how to divide data up between views, given a hierarchy of attributes

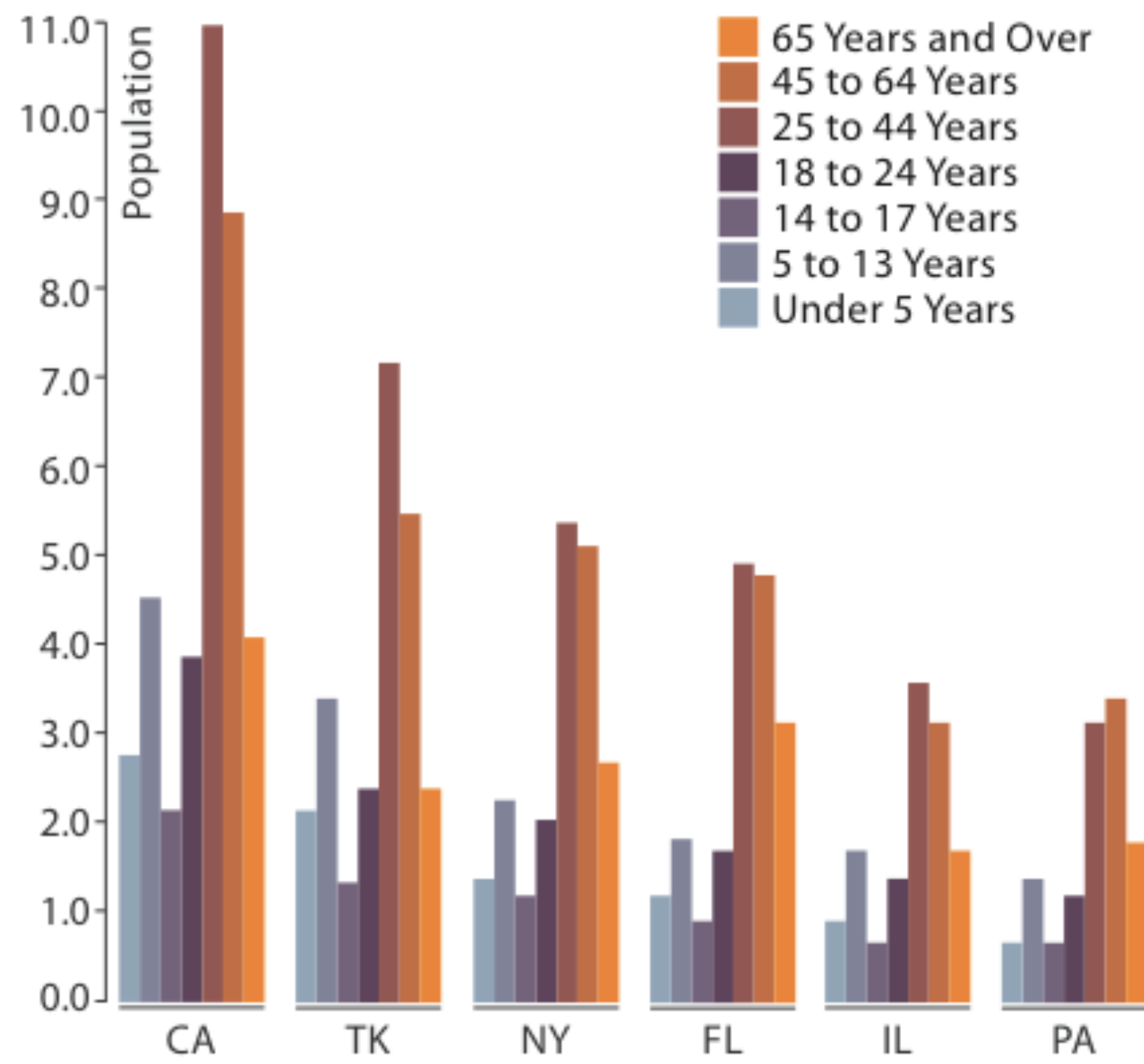
- how many splits, and order of splits

- how many views (usually data driven)

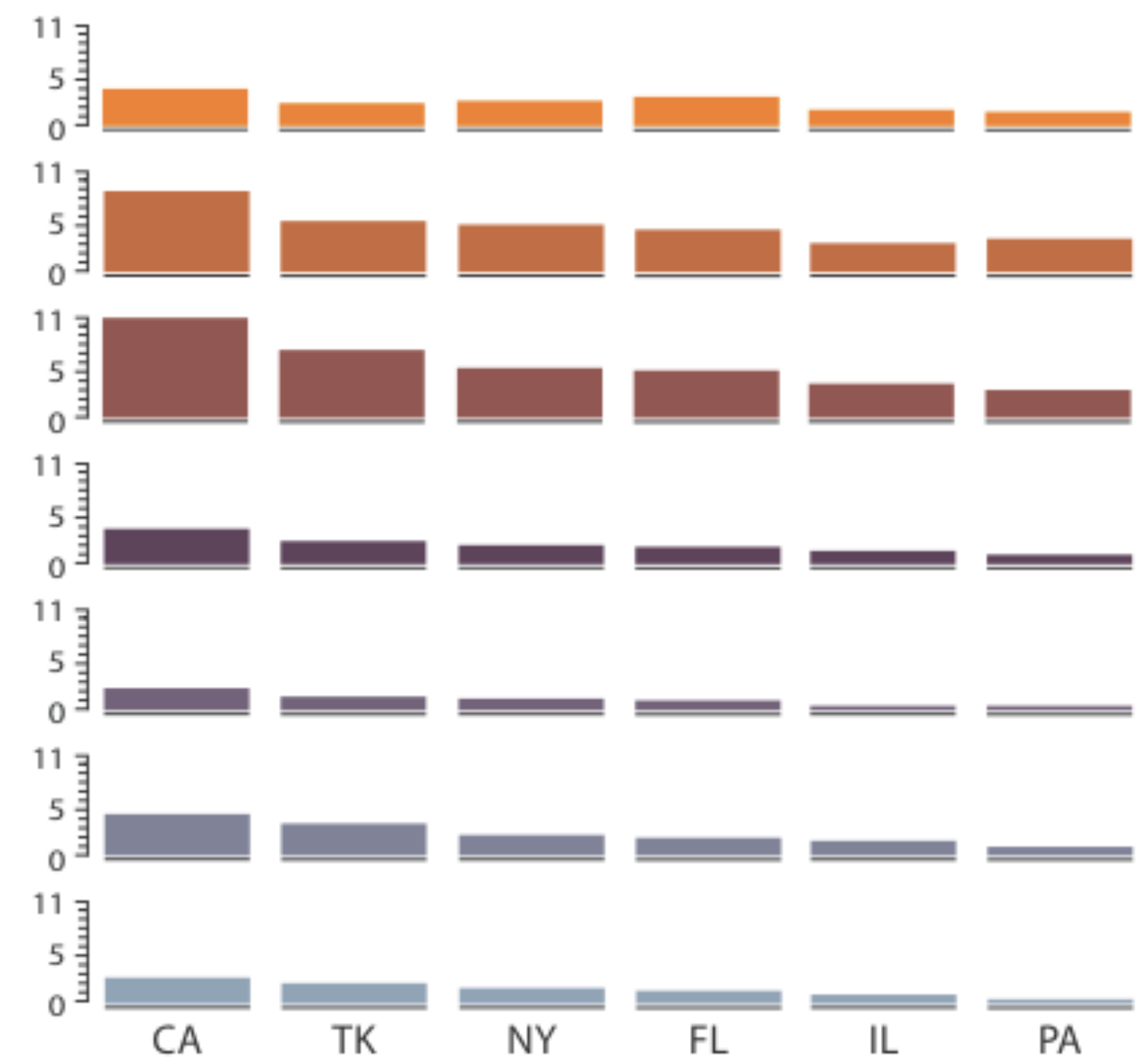
## **partition attribute(s)**

- typically categorical

# Partitioning - Age Distribution by State



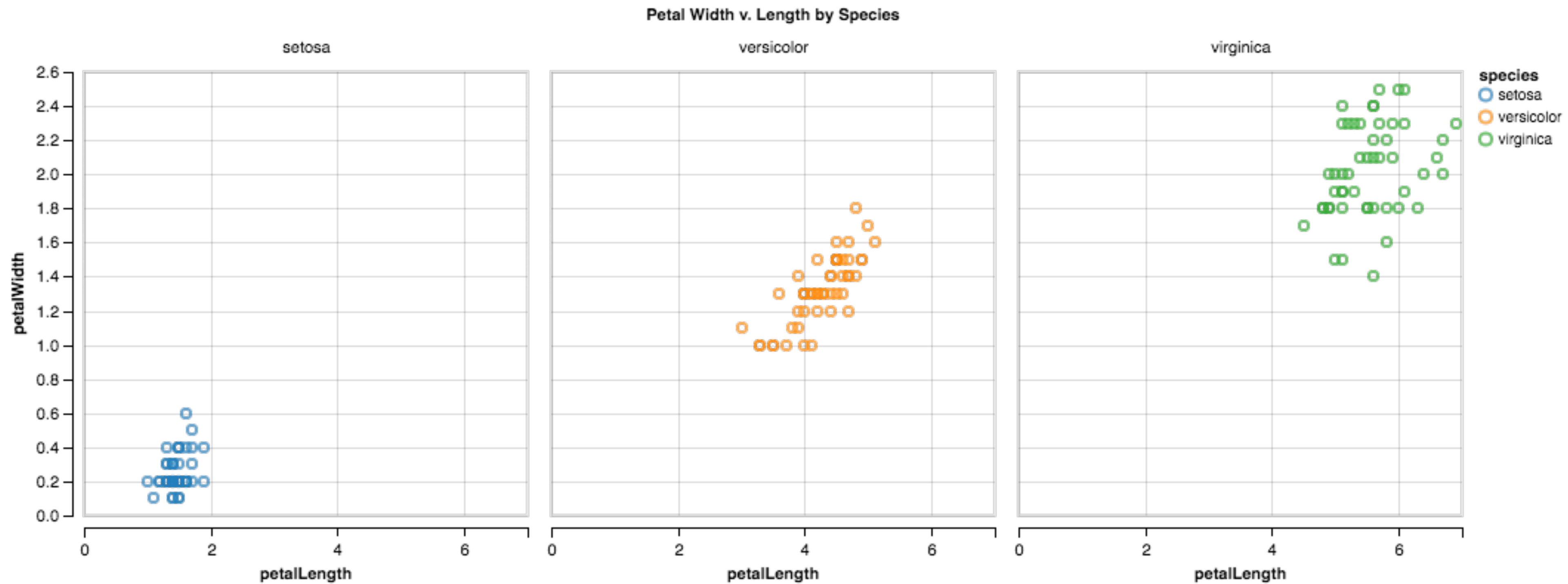
Partitioned by State



Partitioned by Age Group and State



# Partition by Category



# Trellis Plots

panel variables

attributes encoded in individual views

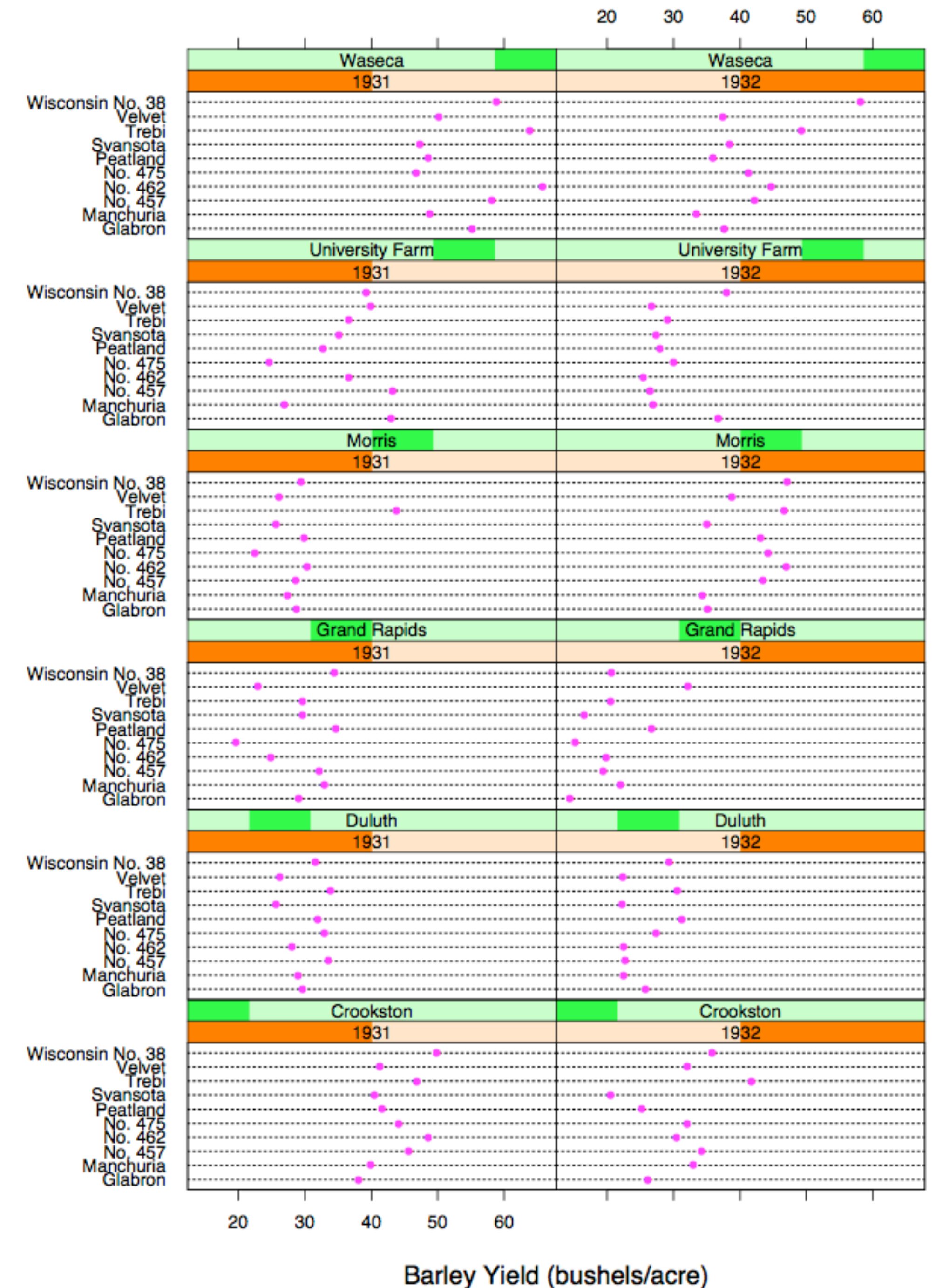
partitioning variables

partitioning attributes assigned to columns  
and rows

main-effects ordering

order partitioning variable based on derived  
data

support perception of trends and structure in  
data





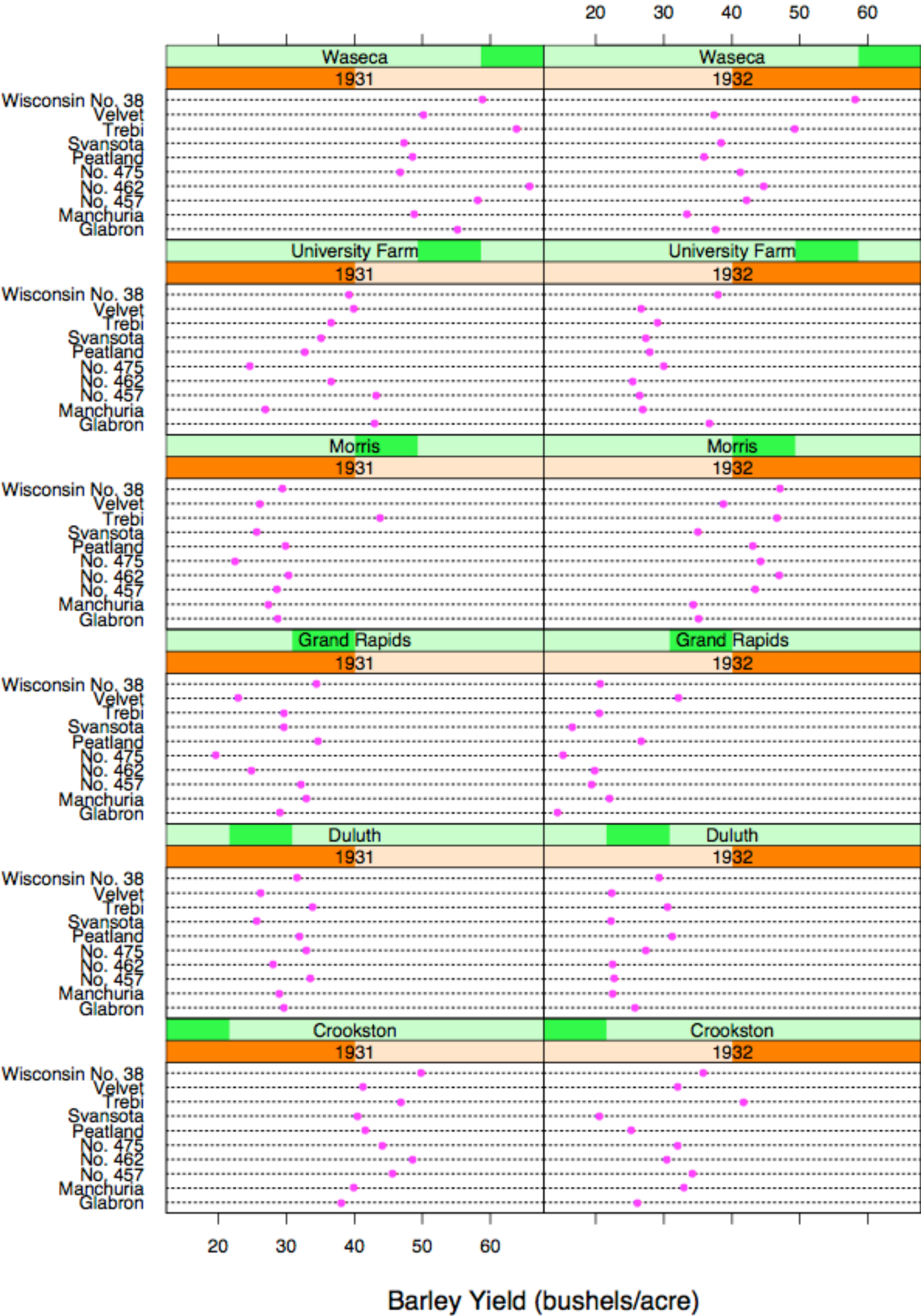
# Data

Barley Yields in two years across multiple farms for multiples barley strains

partitioning variables

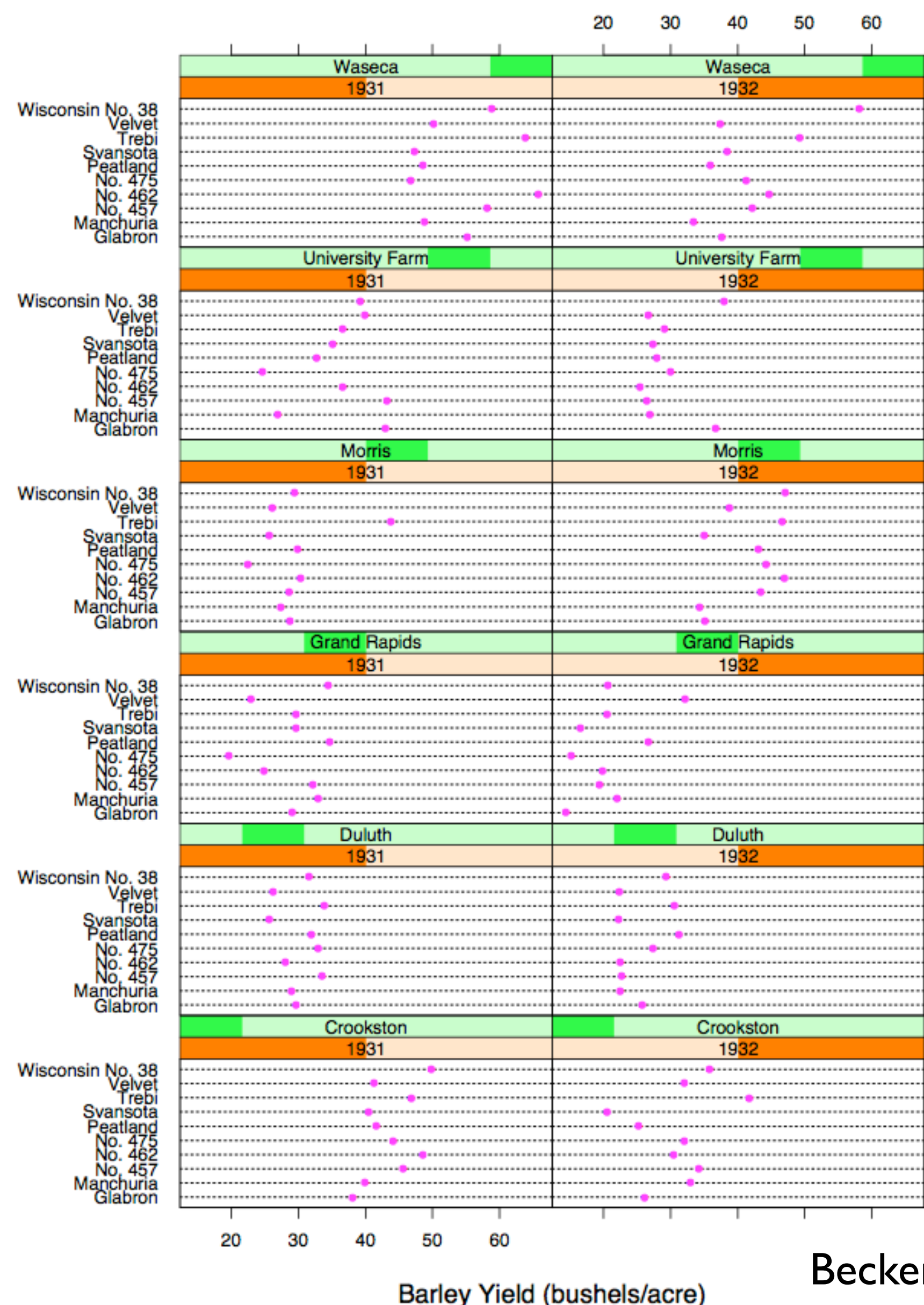
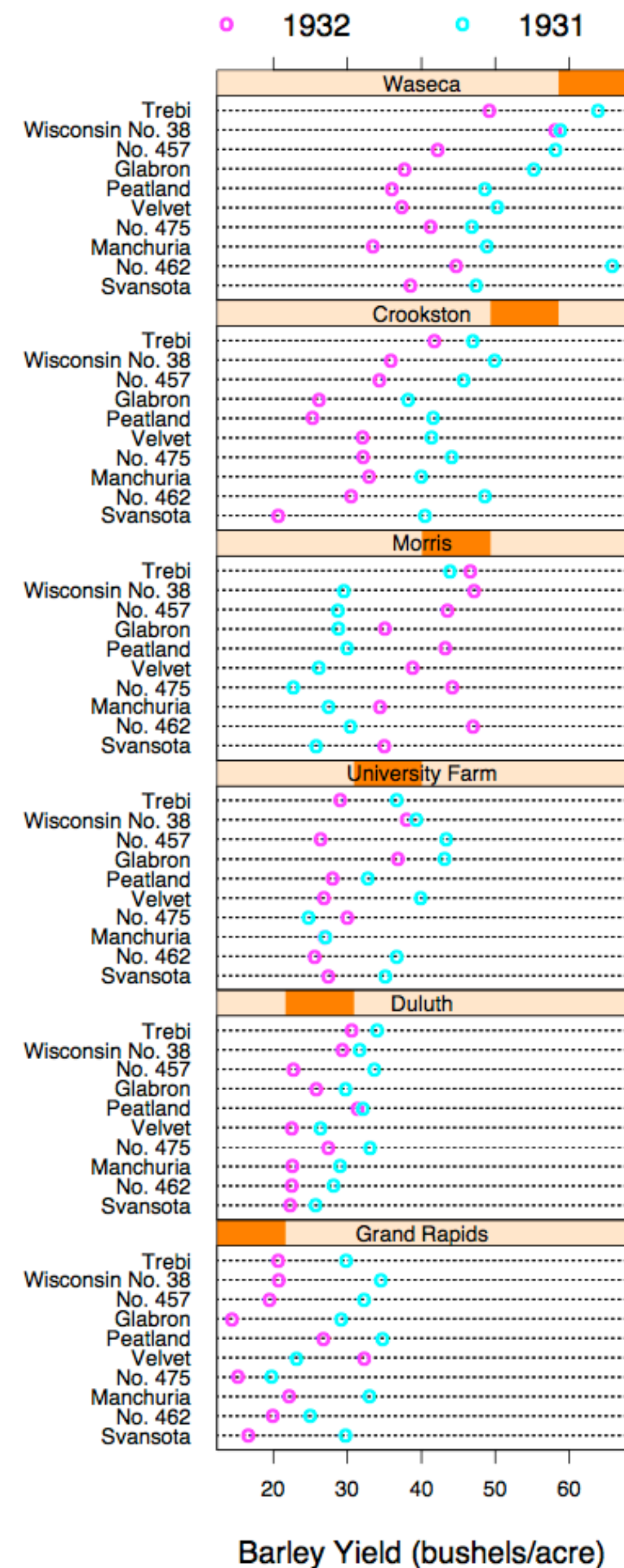
Columns partitioned by year

Rows partitioned by farm





# Superimposition vs Juxtaposition

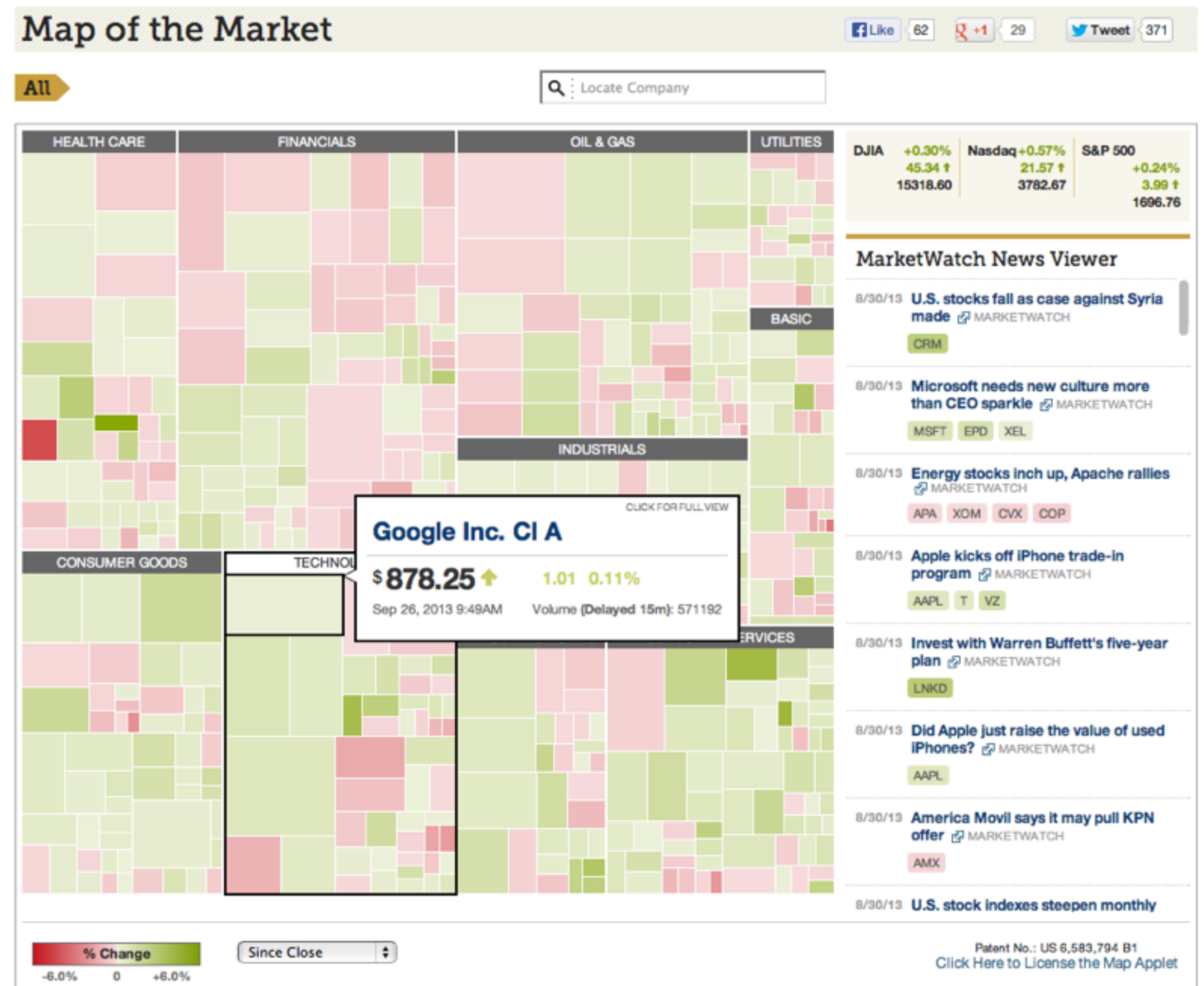




# Recursive Subdivision

partitioning: flexibly  
transform data  
attributes into a  
hierarchy

use treemaps as  
spacefilling  
rectangular layouts



Treemap

# HiVE example: London property

## partitioning attributes

house type  
neighborhood  
sale time

## encoding attributes

average price (color)  
number of sales (size)

## results

between neighborhoods,  
different housing distributions  
within neighborhoods,  
similar prices





# HiVE example: London property

## partitioning attributes

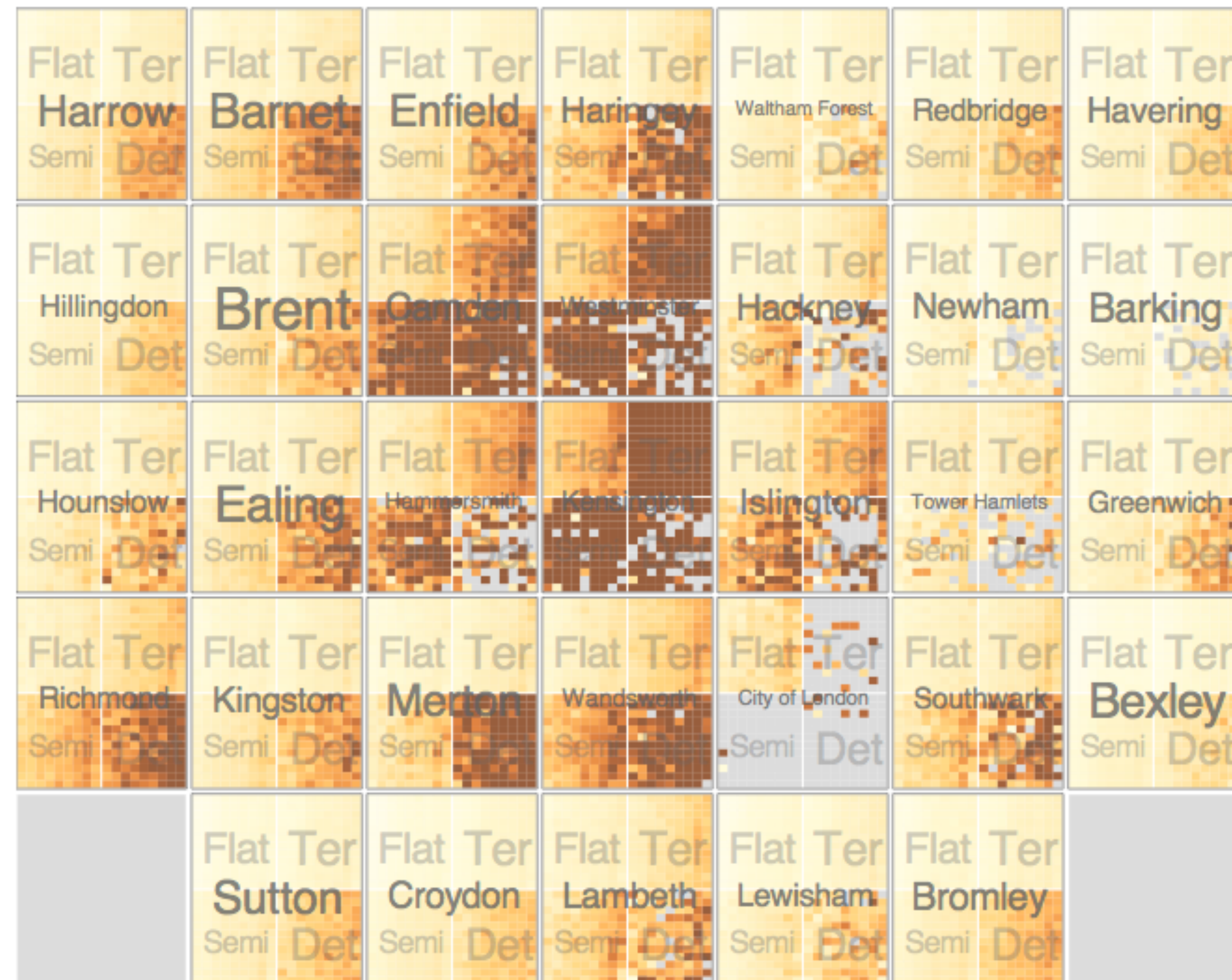
neighborhood  
house type  
sale time (year)  
sale time (month)

## encoding attributes

neighborhood location  
(approximate)  
average price (color)  
*n/a* (size)

## results

expensive neighborhoods near  
center of city



# Configuring Hierarchical Layouts to Address Research Questions



Aidan Slingsby, Jason Dykes and Jo Wood

giCentre, Department of Information Science, City University London

[http://www.gicentre.org/hierarchical\\_layouts/](http://www.gicentre.org/hierarchical_layouts/)



<https://vimeo.com/9870257>



# LAYERING

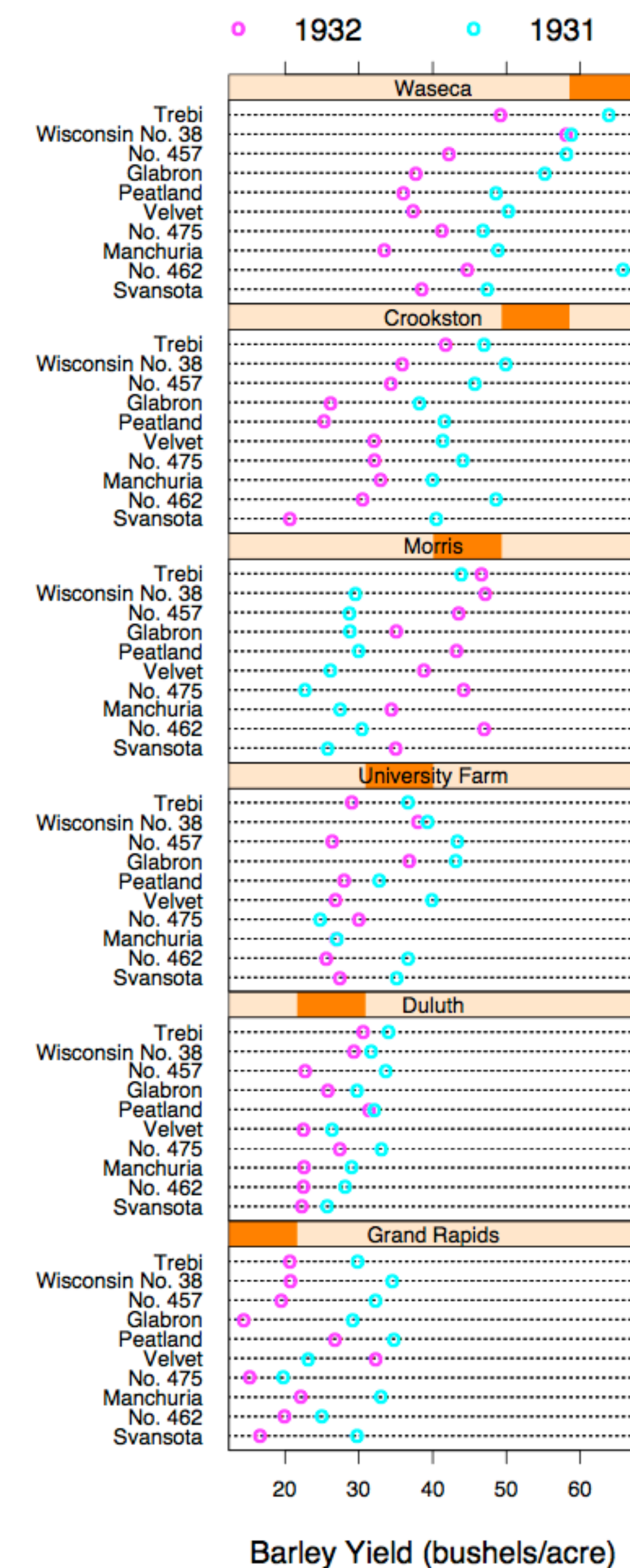
combining multiple views on top of one another  
to form a composite view

## rational

supports a larger, more detailed view than using  
multiple views

## trade-off

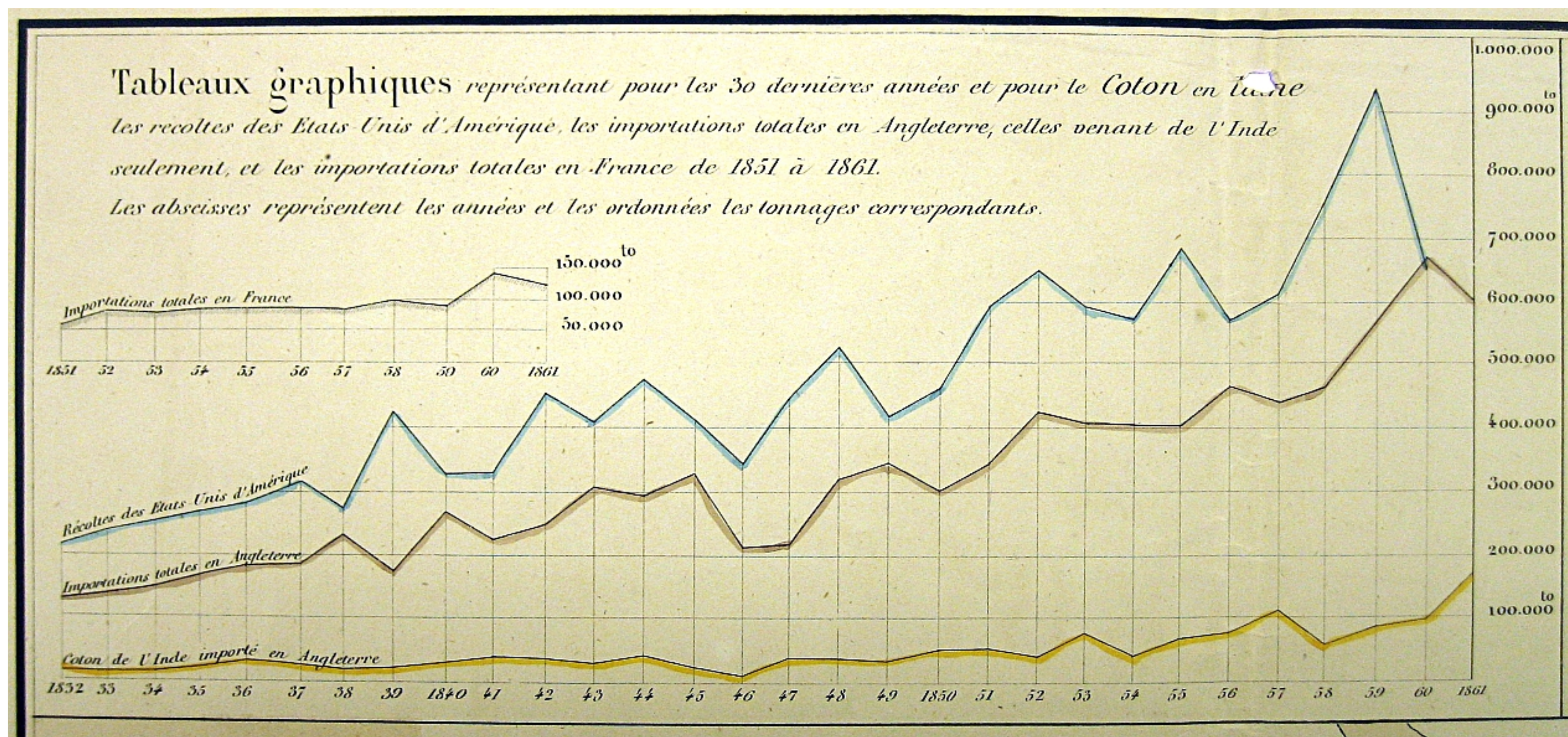
layering imposes constraints on visual encoding  
choice as well as number of layers that can be shown





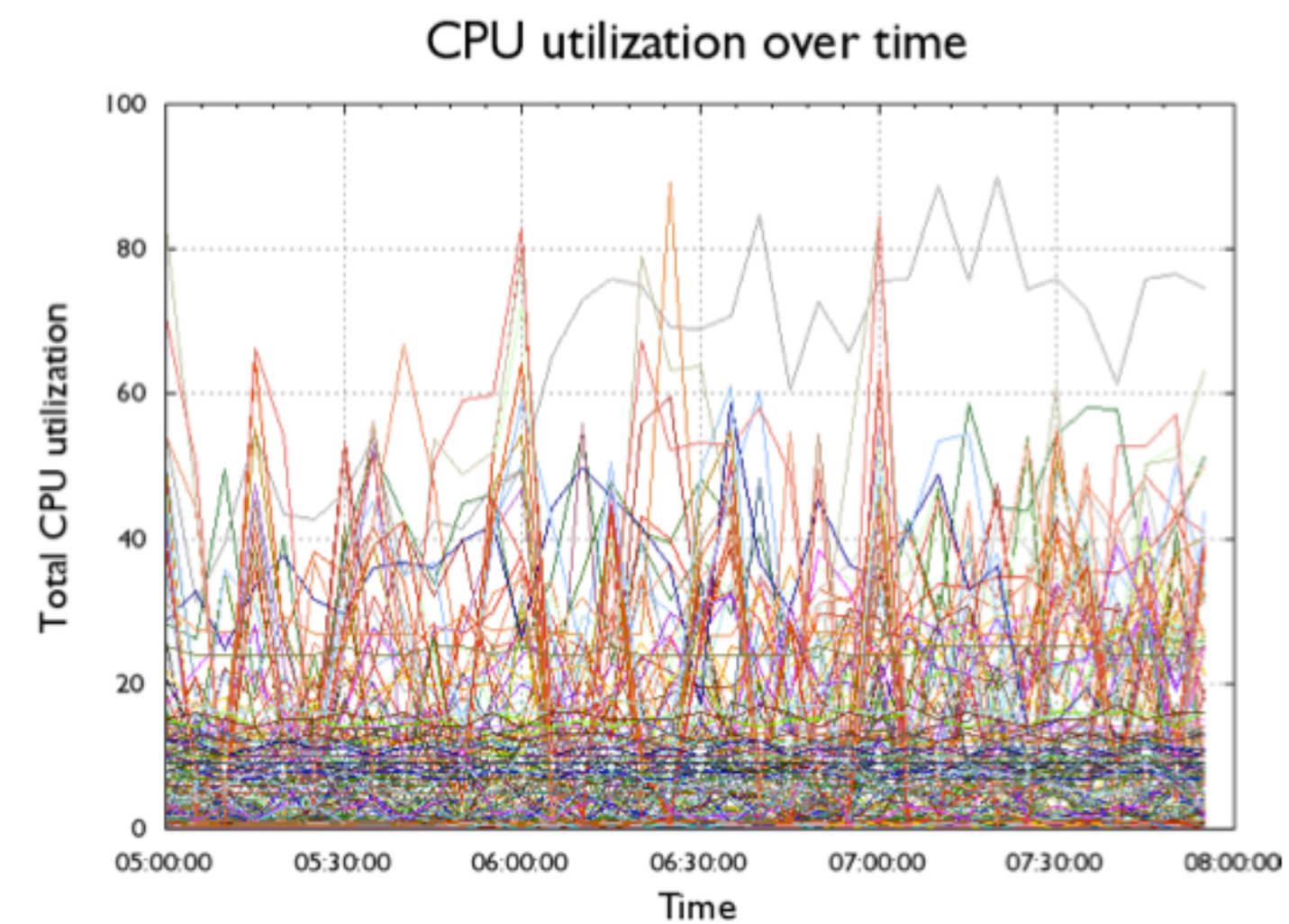
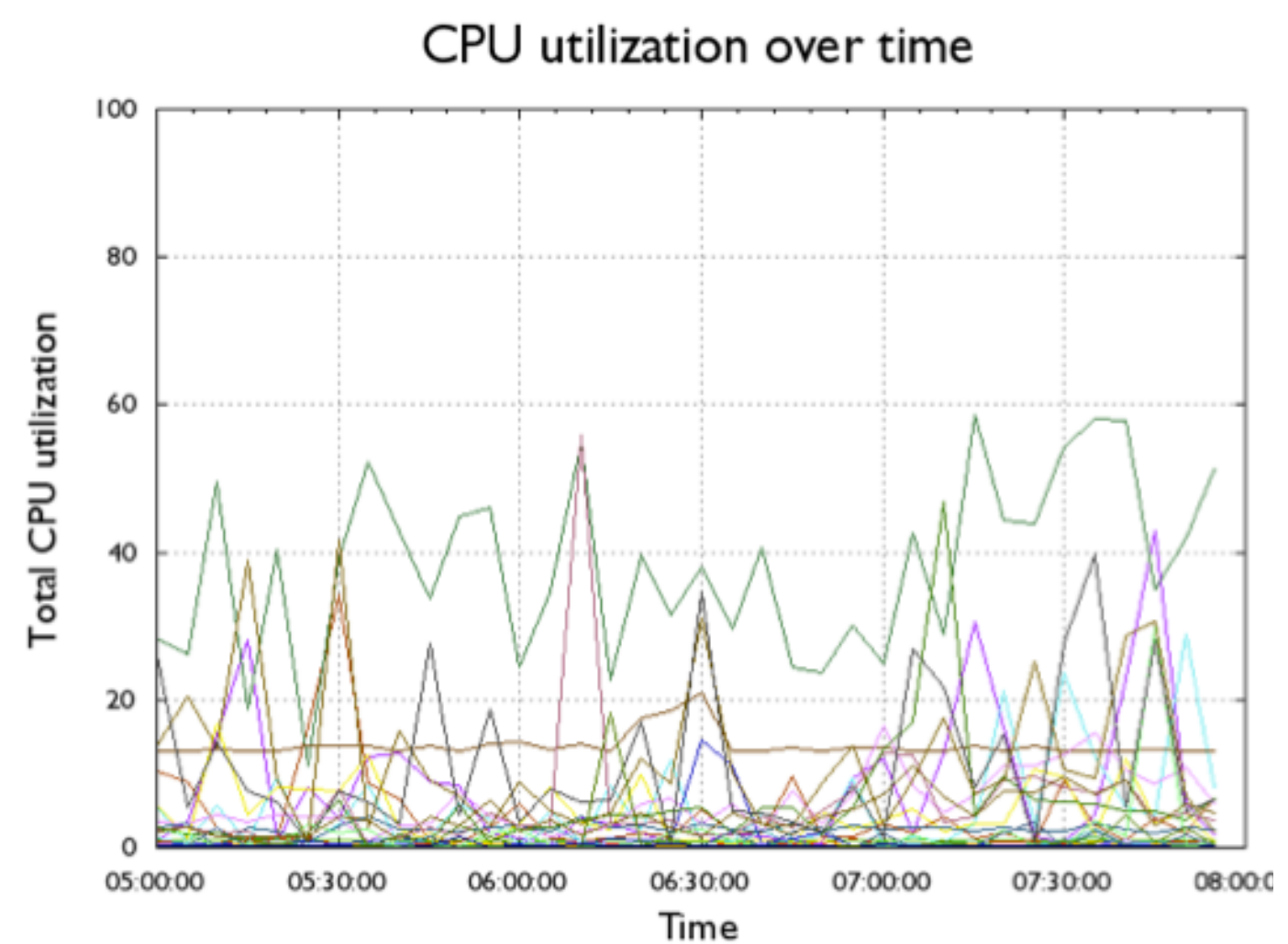
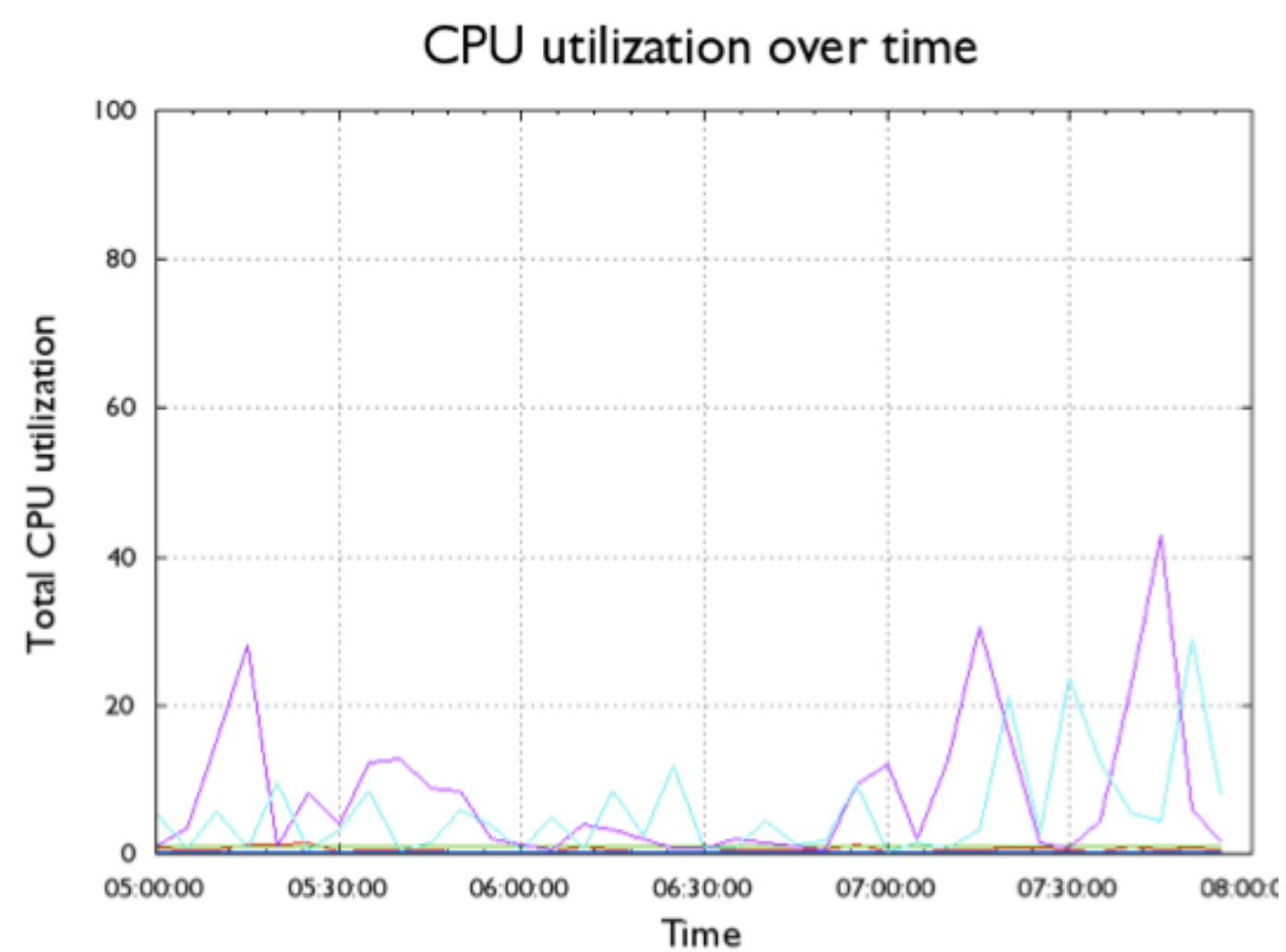
# JOSEPH MINARD

1781-1870



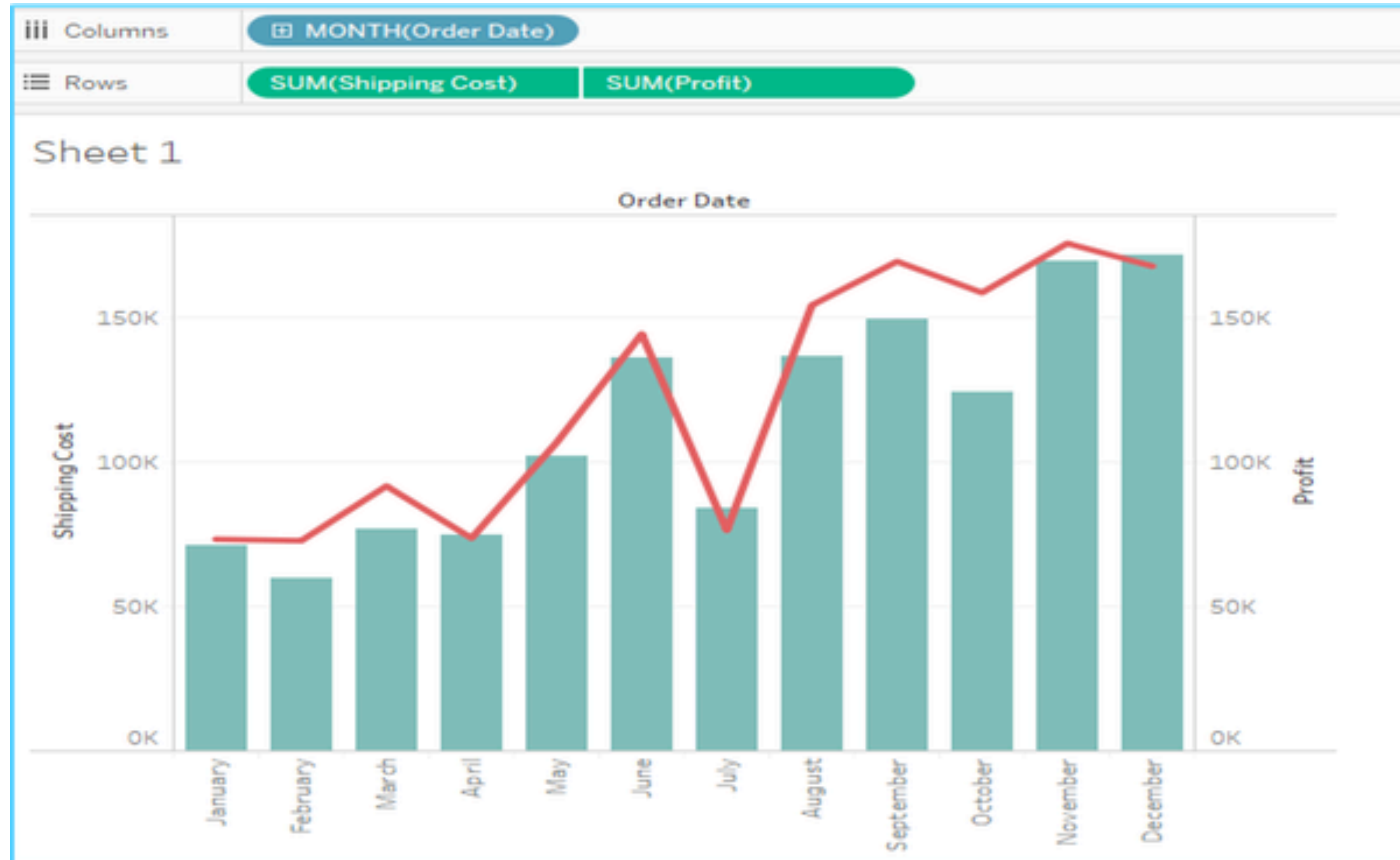


# overlays





# Dual Axis

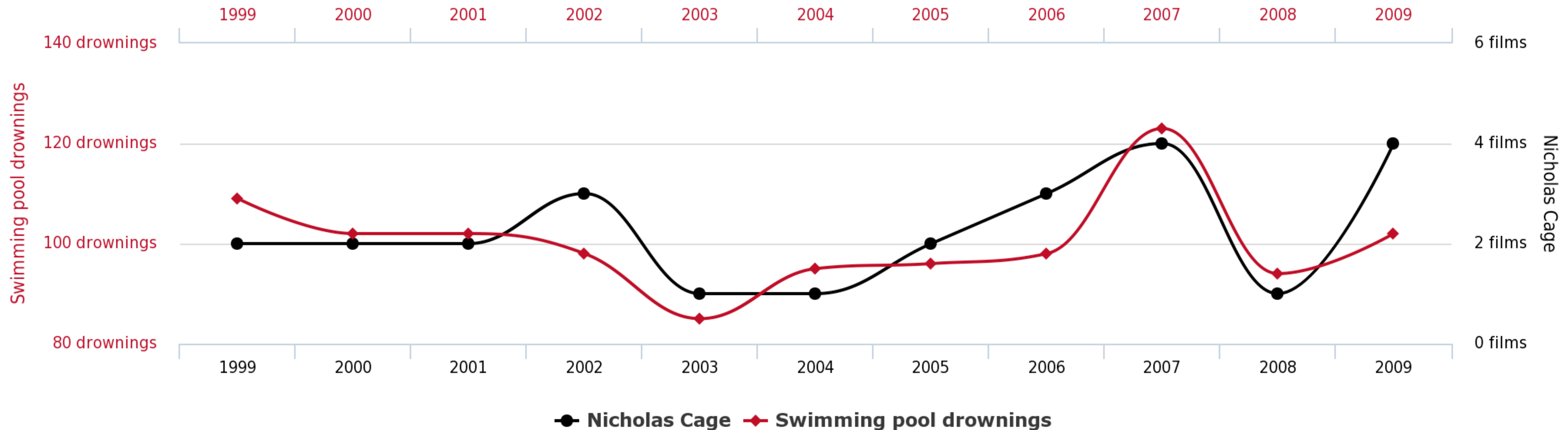


# Dual Axis (don't)

**Number of people who drowned by falling into a pool**

correlates with

**Films Nicolas Cage appeared in**

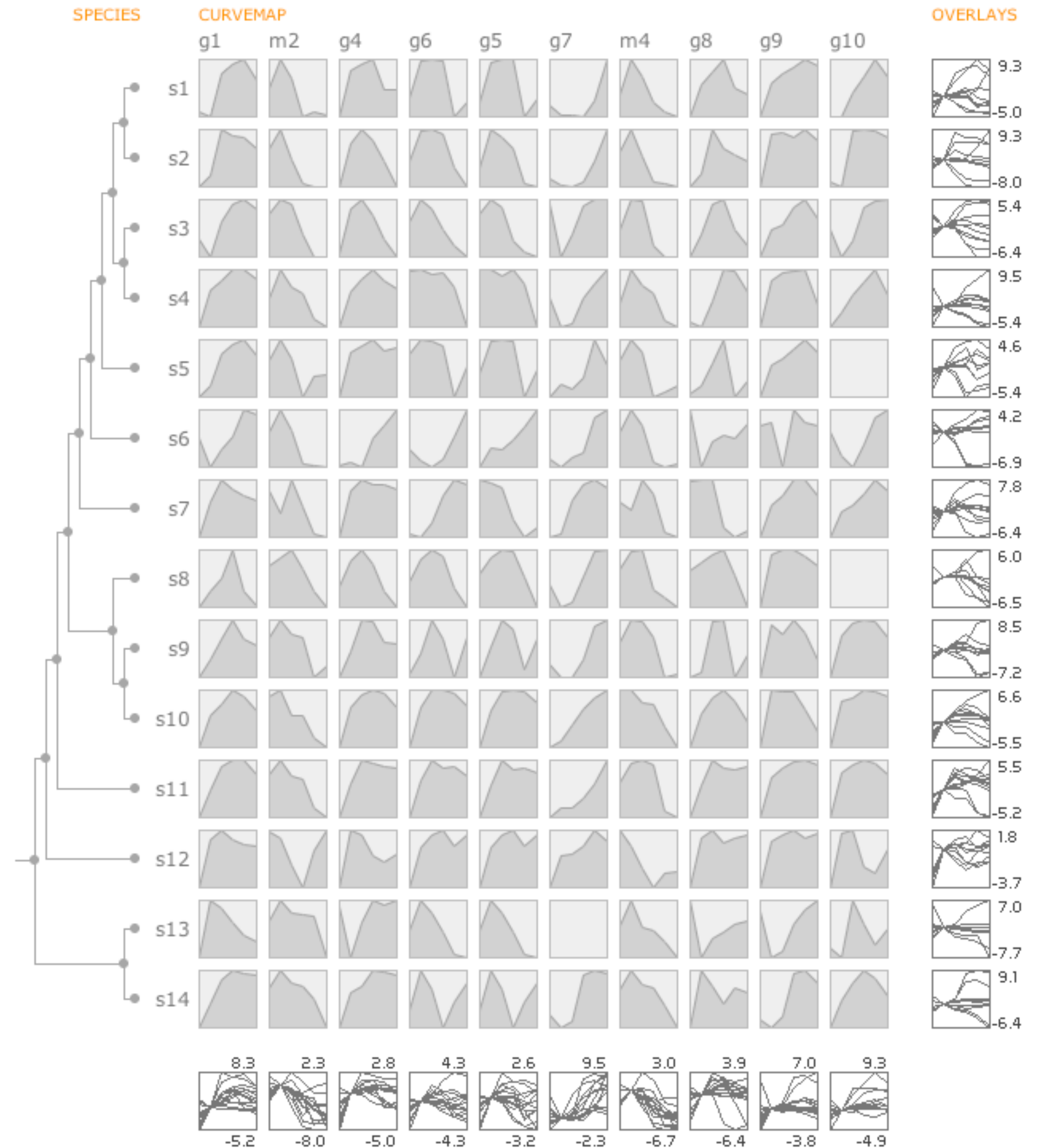




# Combined

Partitioned + layered graph

Synchronized through  
highlighting



# MCV to the Max

