# Tips for Effective Data Visualization

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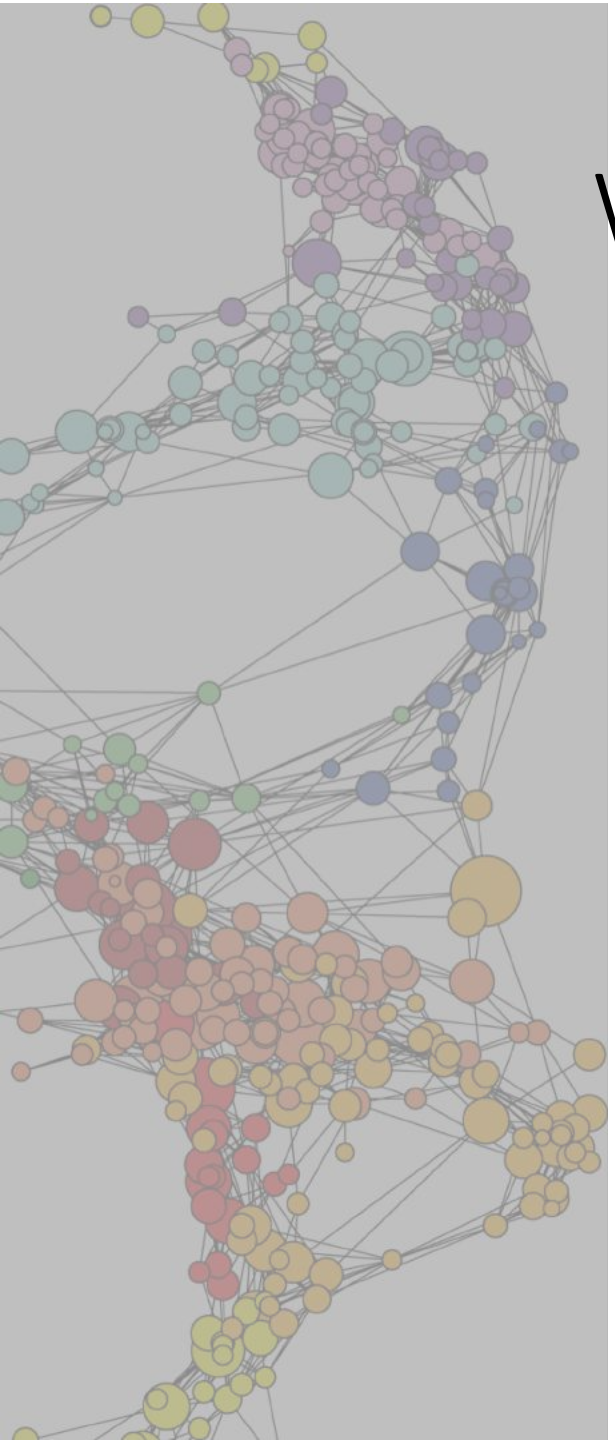
Duke Data and Visualization Services

STA199 · Spring 2019

Slides: https://bit.ly/STA199visSpring2019



# What is data visualization?

**Anything that converts data sources into a visual representation**

*charts, graphs, maps, even just tables*

http://guides.library.duke.edu/datavis

# Why do we visualize?

| | *1* | | *2* | | *3* | | *4* |
|---|---|---|---|---|---|---|---|
| x | y | x | y | x | y | x | y |
| 10.0 | 8.04 | 10.0 | 9.14 | 10.0 | 7.46 | 8.0 | 6.58 |
| 8.0 | 6.95 | 8.0 | 8.14 | 8.0 | 6.77 | 8.0 | 5.76 |
| 13.0 | 7.58 | 13.0 | 8.74 | 13.0 | 12.74 | 8.0 | 7.71 |
| 9.0 | 8.81 | 9.0 | 8.77 | 9.0 | 7.11 | 8.0 | 8.84 |
| 11.0 | 8.33 | 11.0 | 9.26 | 11.0 | 7.81 | 8.0 | 8.47 |
| 14.0 | 9.96 | 14.0 | 8.10 | 14.0 | 8.84 | 8.0 | 7.04 |
| 6.0 | 7.24 | 6.0 | 6.13 | 6.0 | 6.08 | 8.0 | 5.25 |
| 4.0 | 4.26 | 4.0 | 3.10 | 4.0 | 5.39 | 19.0 | 12.50 |
| 12.0 | 10.84 | 12.0 | 9.13 | 12.0 | 8.15 | 8.0 | 5.56 |
| 7.0 | 4.82 | 7.0 | 7.26 | 7.0 | 6.42 | 8.0 | 7.91 |
| 5.0 | 5.68 | 5.0 | 4.74 | 5.0 | 5.73 | 8.0 | 6.89 |

***Almost identical summary statistics:***

x & y mean

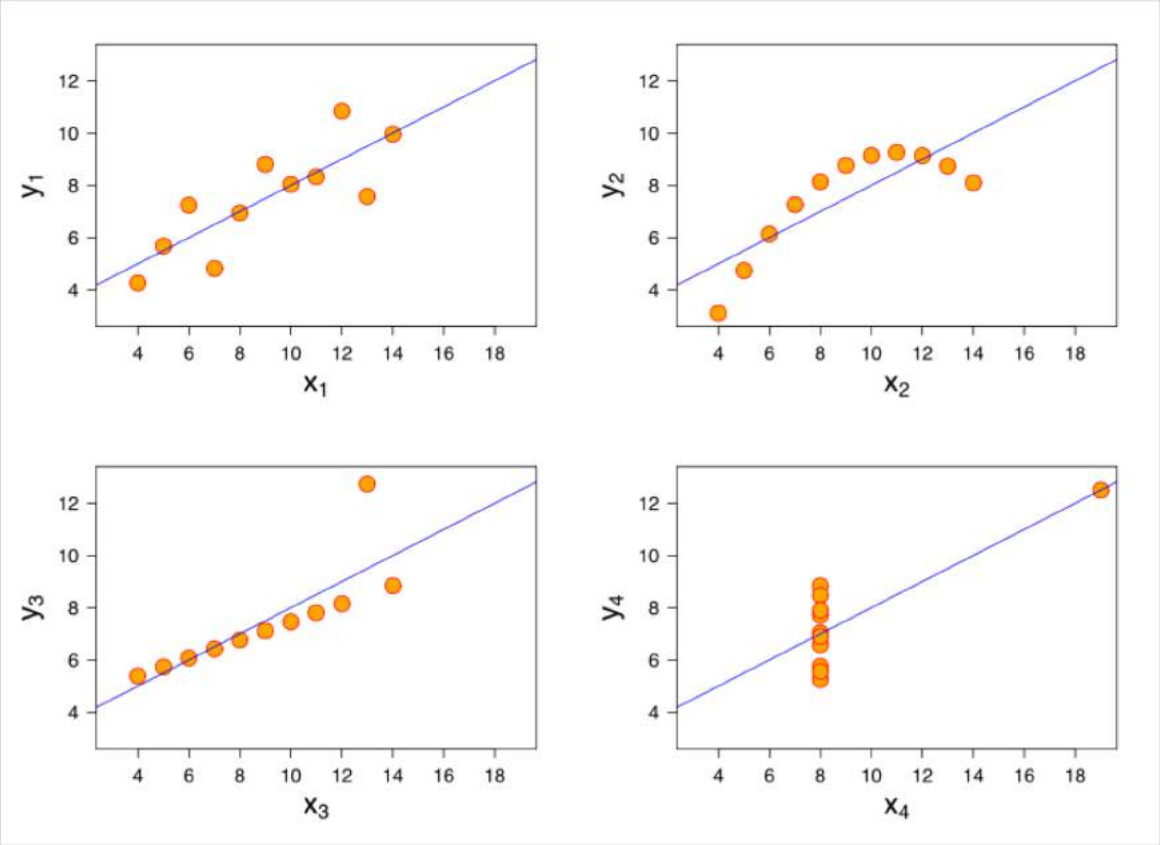
x & y variance

x-y correlation

x-y linear regression

https://en.wikipedia.org/wiki/Anscombe%27s_quartet

# We visualize to see patterns

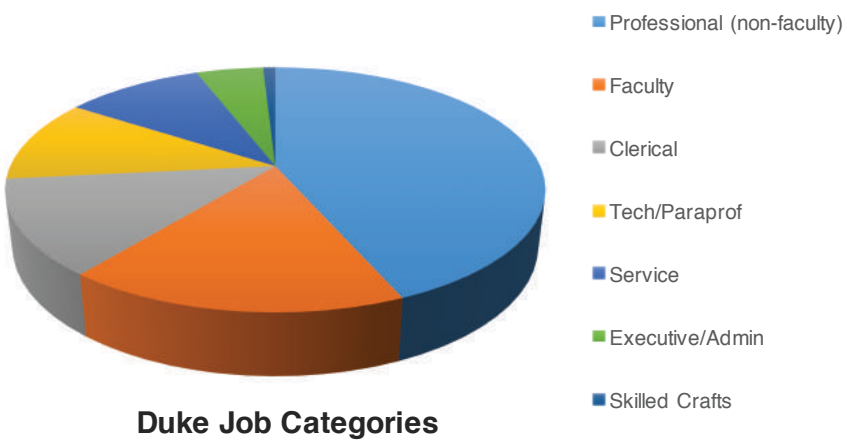


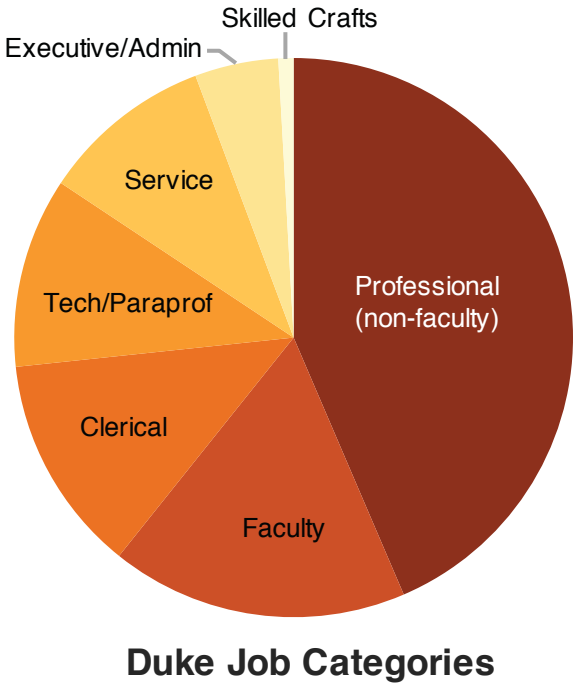

**Anscombe's Quartet**

*http://en.wikipedia.org/wiki/Anscombe%27s_quartet*

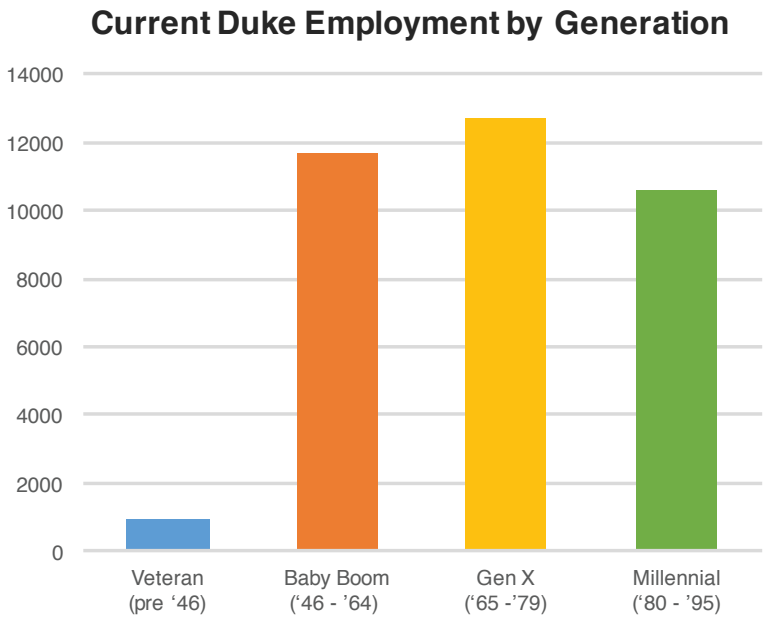
# Designing effective visualizations

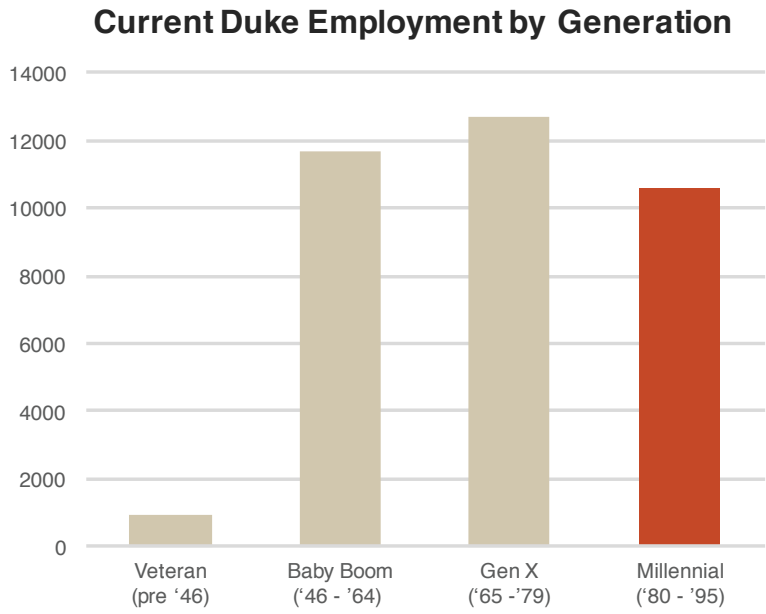
# Keep it simple



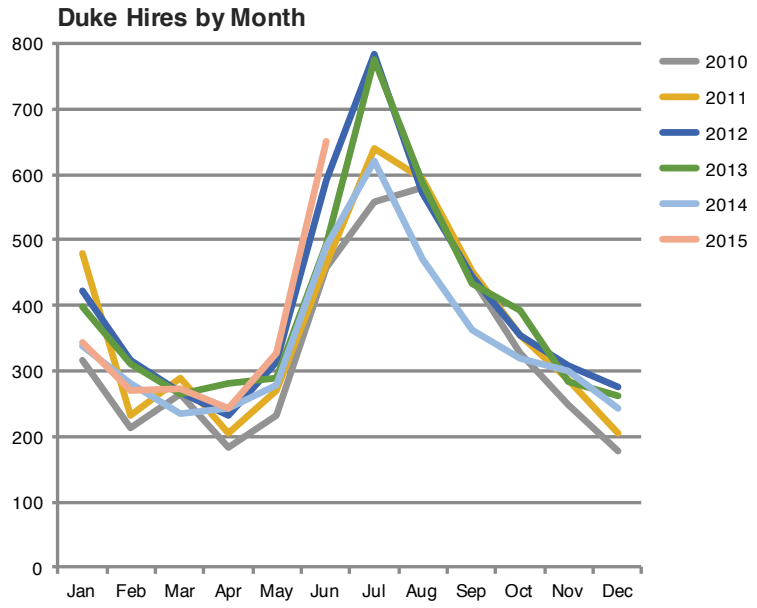



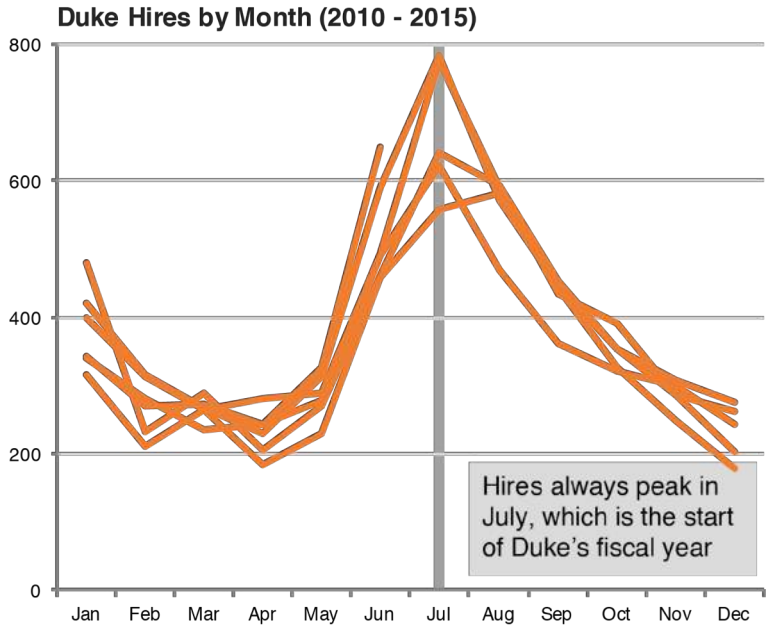
# Use color to draw attention



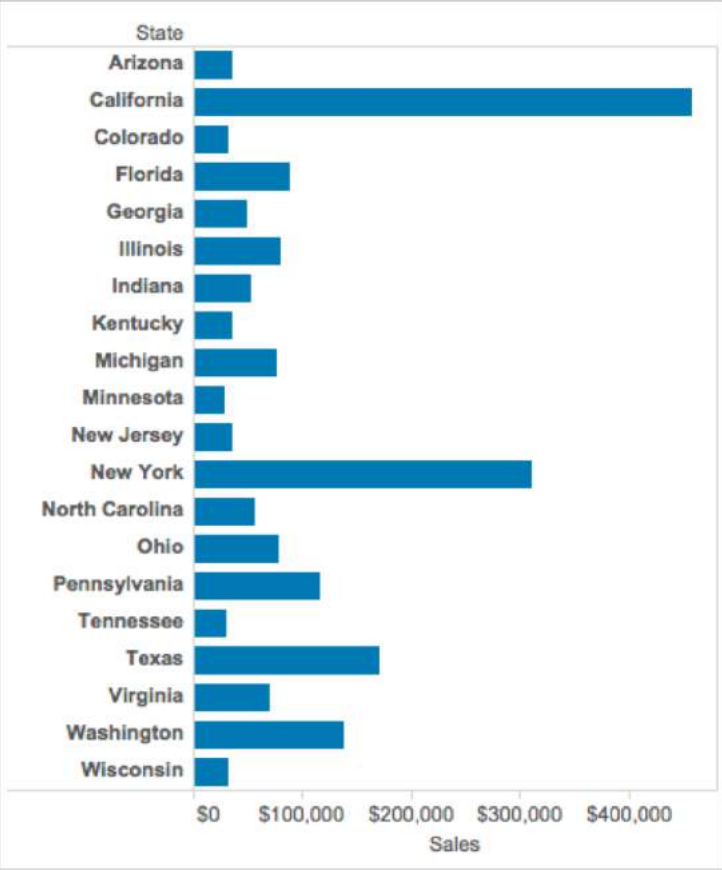
# Every figure should have a purpose: tell a story or make an argument



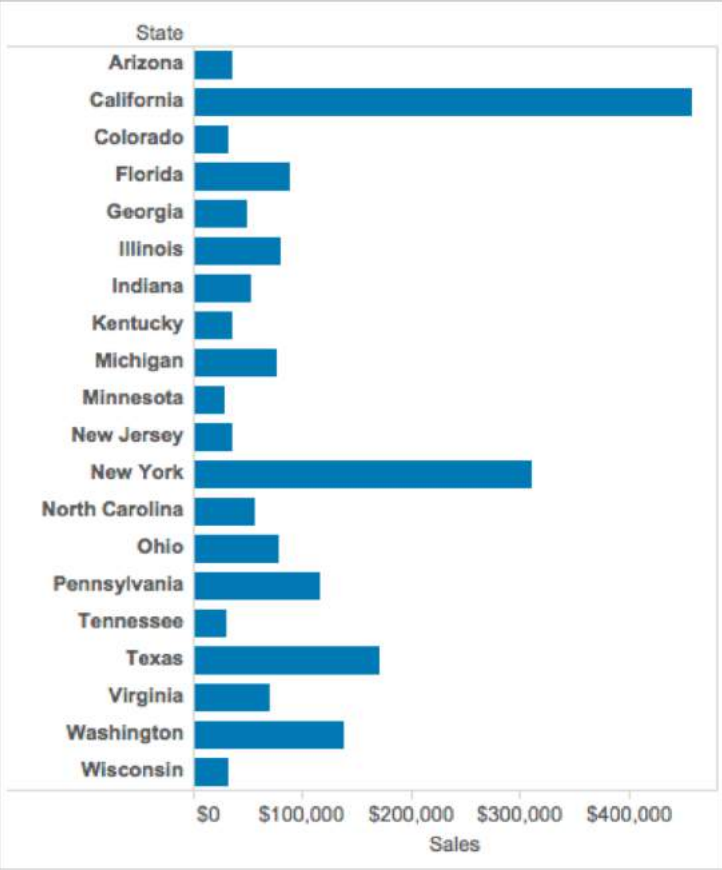



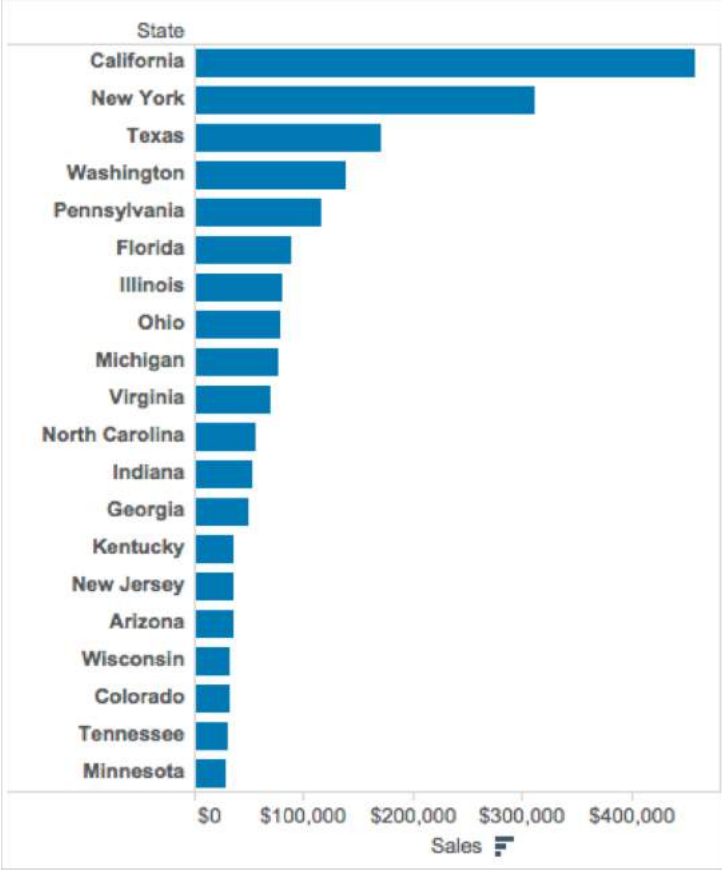
# Common missteps

# Default ordering hides patterns



# Sorting reveals patterns

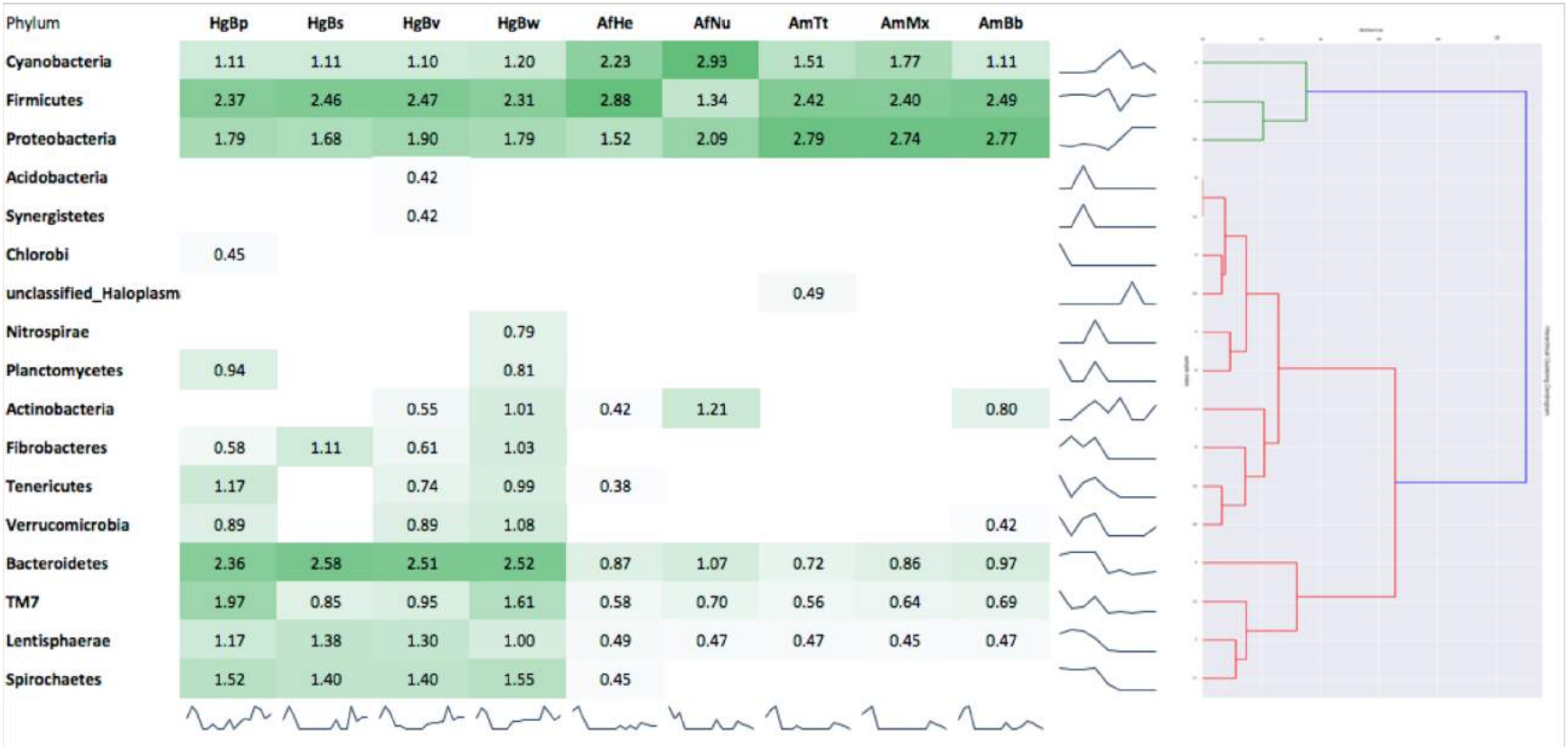


# Alphabetical again hides patterns

| Phylum | HgBp | HgBs | HgBv | HgBw | AfHe | AfNu | AmTt | AmMx | AmBb | |
|---|---|---|---|---|---|---|---|---|---|---|
| Acidobacteria | | | 0.42 | | | | | | | |
| Actinobacteria | | | 0.55 | 1.01 | 0.42 | 1.21 | | | 0.80 | |
| Bacteroidetes | 2.36 | 2.58 | 2.51 | 2.52 | 0.87 | 1.07 | 0.72 | 0.86 | 0.97 | |
| Chlorobi | 0.45 | | | | | | | | | |
| Cyanobacteria | 1.11 | 1.11 | 1.10 | 1.20 | 2.23 | 2.93 | 1.51 | 1.77 | 1.11 | |
| Fibrobacteres | 0.58 | 1.11 | 0.61 | 1.03 | | | | | | |
| Firmicutes | 2.37 | 2.46 | 2.47 | 2.31 | 2.88 | 1.34 | 2.42 | 2.40 | 2.49 | |
| Lentisphaerae | 1.17 | 1.38 | 1.30 | 1.00 | 0.49 | 0.47 | 0.47 | 0.45 | 0.47 | |
| Nitrospirae | | | | 0.79 | | | | | | |
| Planctomycetes | 0.94 | | | 0.81 | | | | | | |
| Proteobacteria | 1.79 | 1.68 | 1.90 | 1.79 | 1.52 | 2.09 | 2.79 | 2.74 | 2.77 | |
| Spirochaetes | 1.52 | 1.40 | 1.40 | 1.55 | 0.45 | | | | | |
| Synergistetes | | | 0.42 | | | | | | | |
| TM7 | 1.97 | 0.85 | 0.95 | 1.61 | 0.58 | 0.70 | 0.56 | 0.64 | 0.69 | |
| Tenericutes | 1.17 | | 0.74 | 0.99 | 0.38 | | | | | |
| Verrucomicrobia | 0.89 | | 0.89 | 1.08 | | | | | 0.42 | |
| unclassified_Haloplasm | | | | | | | 0.49 | | | |
| | | | | | | | | | | |

# Clustering to see response groups



| Phylum | HgBp | HgBs | HgBv | HgBw | AfHe | AfNu | AmTt | AmMx | AmBb |
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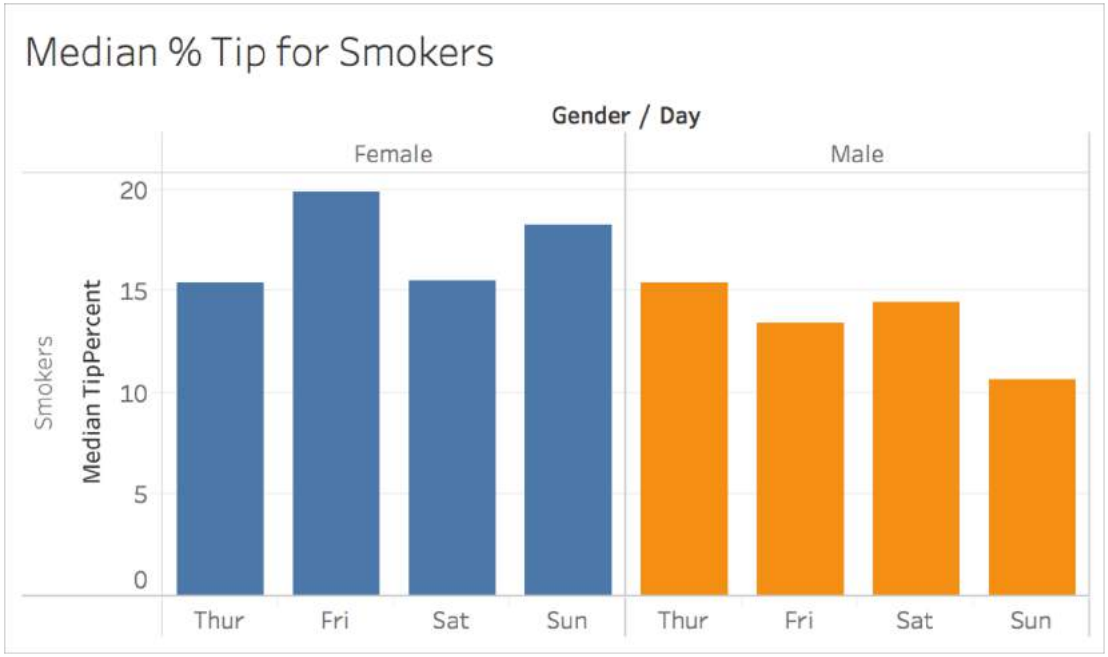
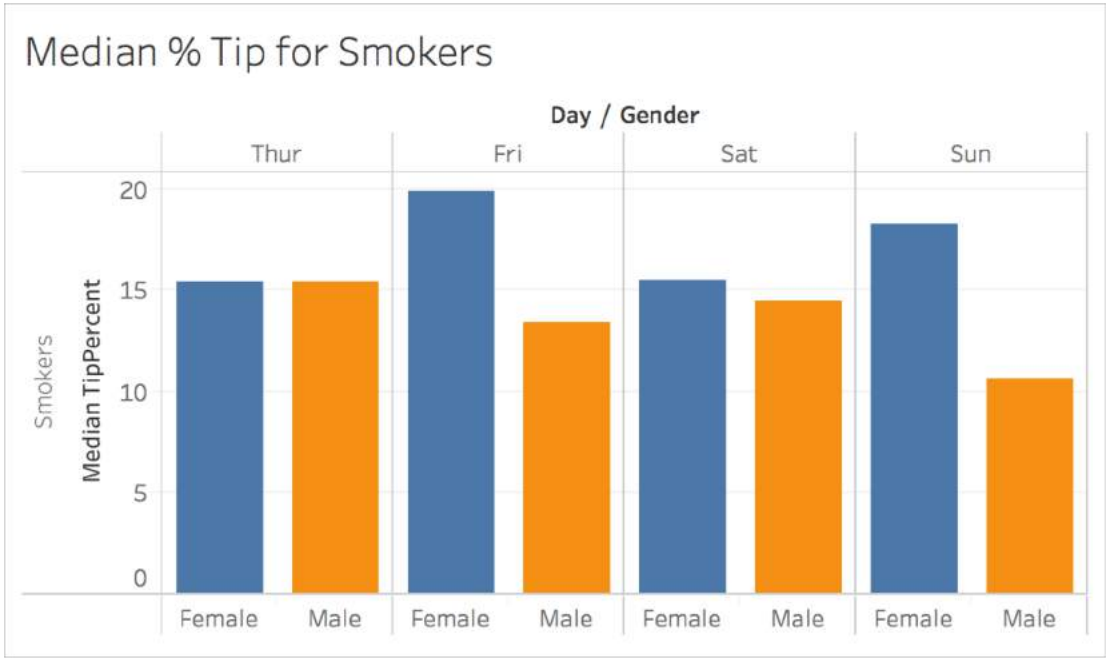
| Nitrospirae | | | | 0.79 | | | | | |
| Planctomycetes | 0.94 | | | 0.81 | | | | | |
| Actinobacteria | | | 0.55 | 1.01 | 0.42 | 1.21 | | | 0.80 |
| Fibrobacteres | 0.58 | 1.11 | 0.61 | 1.03 | | | | | |
| Tenericutes | 1.17 | | 0.74 | 0.99 | 0.38 | | | | |
| Verrucomicrobia | 0.89 | | 0.89 | 1.08 | | | | | 0.42 |
| Bacteroidetes | 2.36 | 2.58 | 2.51 | 2.52 | 0.87 | 1.07 | 0.72 | 0.86 | 0.97 |
| TM7 | 1.97 | 0.85 | 0.95 | 1.61 | 0.58 | 0.70 | 0.56 | 0.64 | 0.69 |
| Lentisphaerae | 1.17 | 1.38 | 1.30 | 1.00 | 0.49 | 0.47 | 0.47 | 0.45 | 0.47 |
| Spirochaetes | 1.52 | 1.40 | 1.40 | 1.55 | 0.45 | | | | |

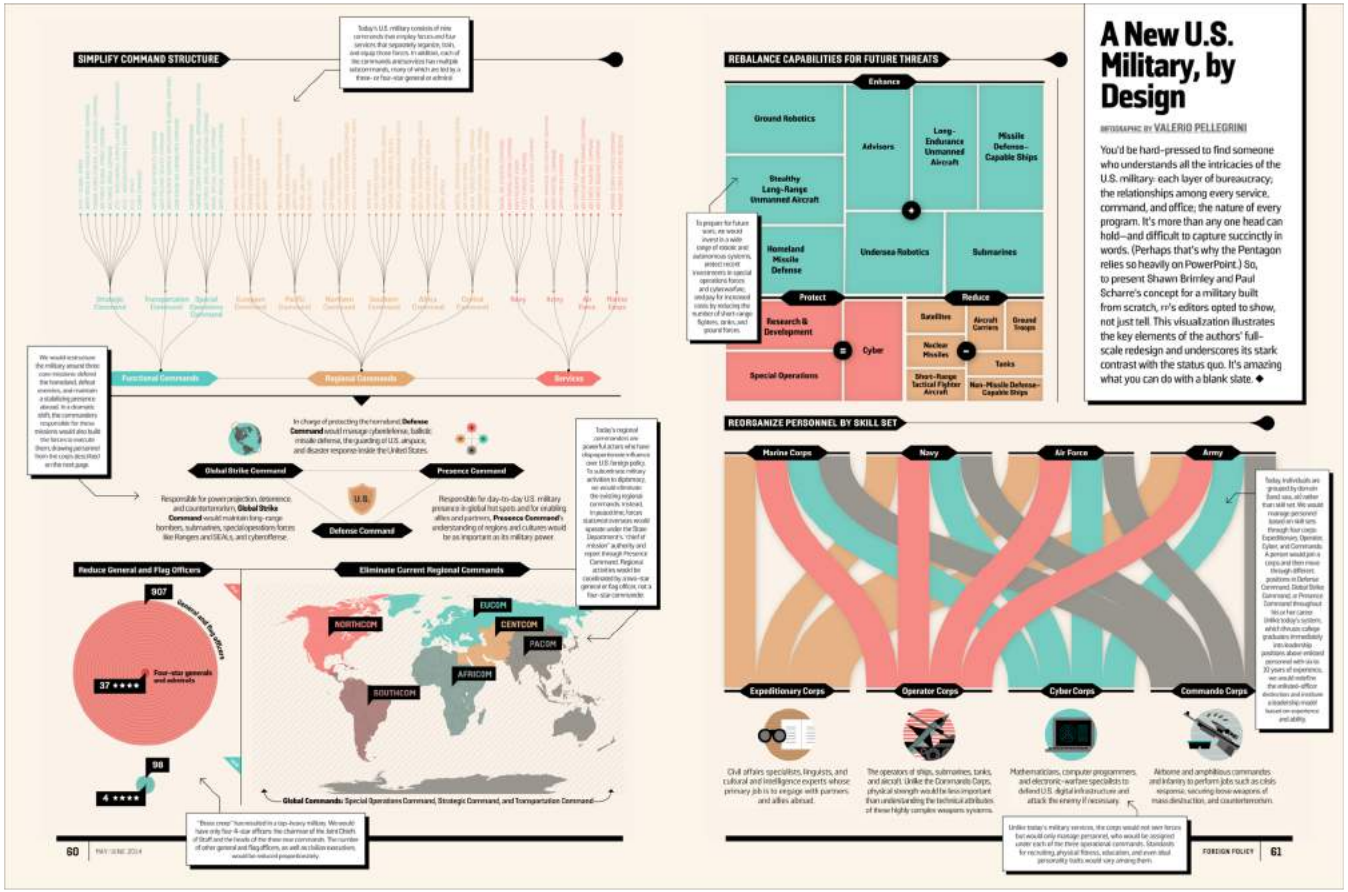
# Distant comparisons are harder



# Put important comparisons nearby



# Colors shouldn’t switch meanings




https://www.informationisbeautifulawards.com/showcase/556

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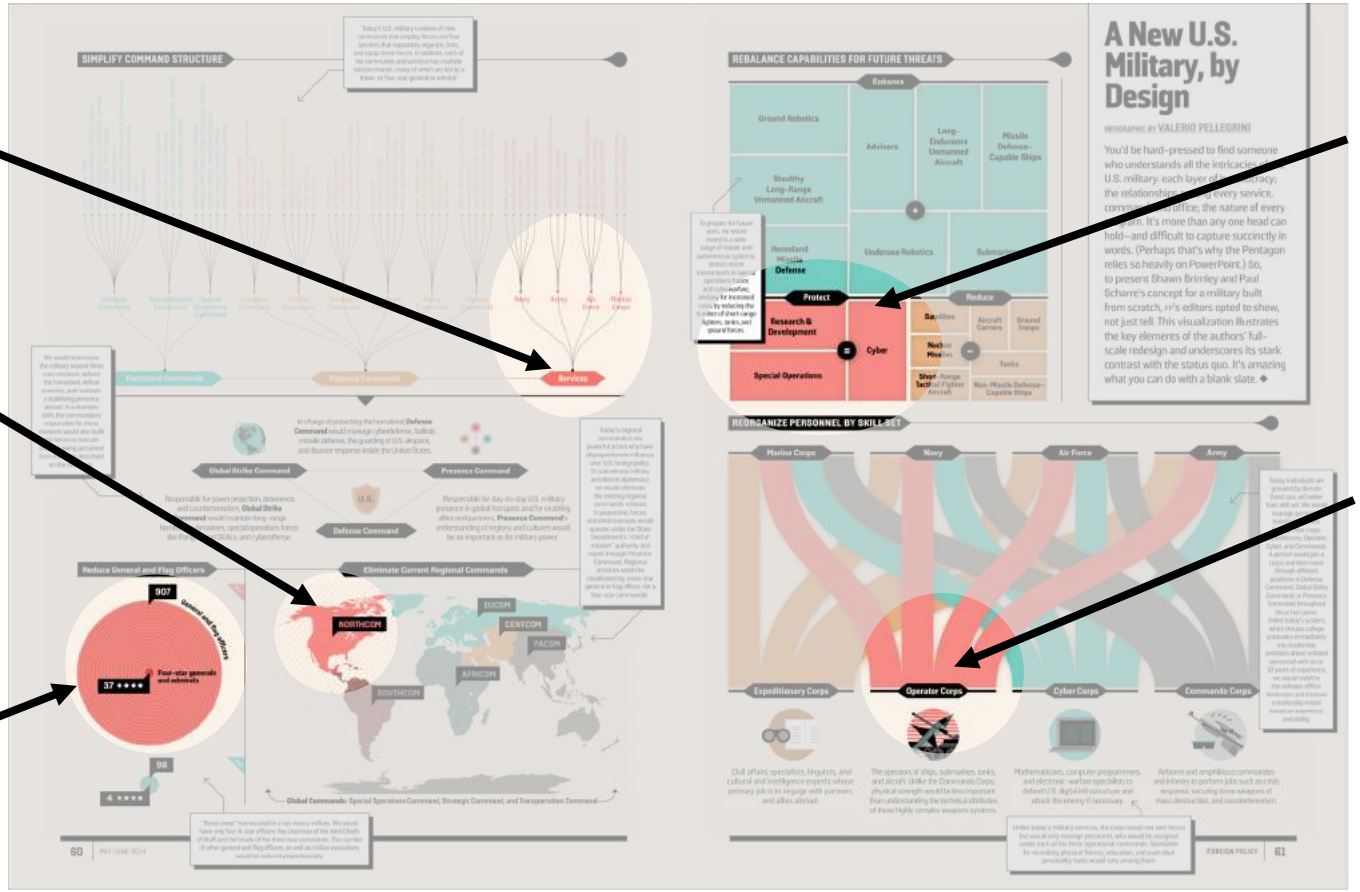


https://www.informationisbeautifulawards.com/showcase/556

# Tables easily hide patterns

| The study group (to compare with the control group) | Cancer and age group | Type of analysis | White females | AA females |
|---|---|---|---|---|
| Females living in communities located in zip codes with kind of bad contions | Uterine cancer, all ages | Univariate | 1.09, p=0.1027 | |
| | | Multivariate | 1.24, p=0.0002 | |
| | Uterine cancer, age 65+ | Univariate | 1.05, p=0.5702 | 1.05, p=0.6438 |
| | | Multivariate | 1.18, p=0.0723 | 1.18, p=0.1789 |
| | Cancer of corpus uteri, age 65+ | Univariate | 1.13, p=0.2861 | 1.07, p=0.6547 |
| | | Multivariate | 1.27, p=0.0513 | 1.07, p=0.6763 |
| Females living in communities with lots of really bad stuff | Uterine cancer, all ages | Univariate | 1.29, p=0.0665 | 1.14, p=0.3630 |
| | | Multivariate | 1.57, p=0.0019 | 1.28, p=0.1440 |
| | Uterine cancer, age 65+ | Univariate | 1.55, p=0.0061 | 1.16, p=0.3800 |
| | | Multivariate | 1.94, p=7.3x10$^{-5}$ | 1.27, p=0.2300 |
| | Cancer of corpus uteri, all ages | Univariate | 1.68, p=0.0022 | 1.19, p=0.3820 |
| | | Multivariate | 1.98, p=0.0001 | 1.09, p=0.7170 |
| | Cancer of corpus uteri, age 65+ | Univariate | 1.91, p=0.0011 | 1.20, p=0.4330 |
| | | Multivariate | 2.41, p=3.01x10$^{-5}$ | 1.07, p=0.8120 |

# Highlight patterns for the reader

| **The study group (to compare with the control group)** | **Cancer** | **Age group** | **Analysis type** | **White females** | p-value | **AA females** | p-value |
|---|---|---|---|---|---|---|---|
| Females living in communities located in zip codes **with kind of bad conditions** | Uterine | all ages | Univariate | 1.09 | 0.1027 | 1.09 | 0.1027 |
| | | | Multivariate | **1.24** | **0.0002** | **1.24** | **0.0002** |
| | Uterine | 65+ | Univariate | 1.05 | 0.5702 | 1.05 | 0.6438 |
| | | | Multivariate | 1.18 | 0.0723 | 1.18 | 0.1789 |
| | Corpus uteri | 65+ | Univariate | 1.13 | 0.2861 | 1.07 | 0.6547 |
| | | | Multivariate | 1.27 | 0.0513 | 1.07 | 0.6763 |
| Females living in communities with **lots of really bad stuff** | Uterine | all ages | Univariate | 1.29 | 0.0665 | 1.14 | 0.3630 |
| | | | Multivariate | **1.57** | **0.0019** | 1.28 | 0.1440 |
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| | | | Multivariate | **1.98** | **0.0001** | 1.09 | 0.7170 |
| | Corpus uteri | 65+ | Univariate | **1.91** | **0.0011** | 1.2 | 0.4330 |
| | | | Multivariate | **2.41** | **3.01E-05** | 1.07 | 0.8120 |

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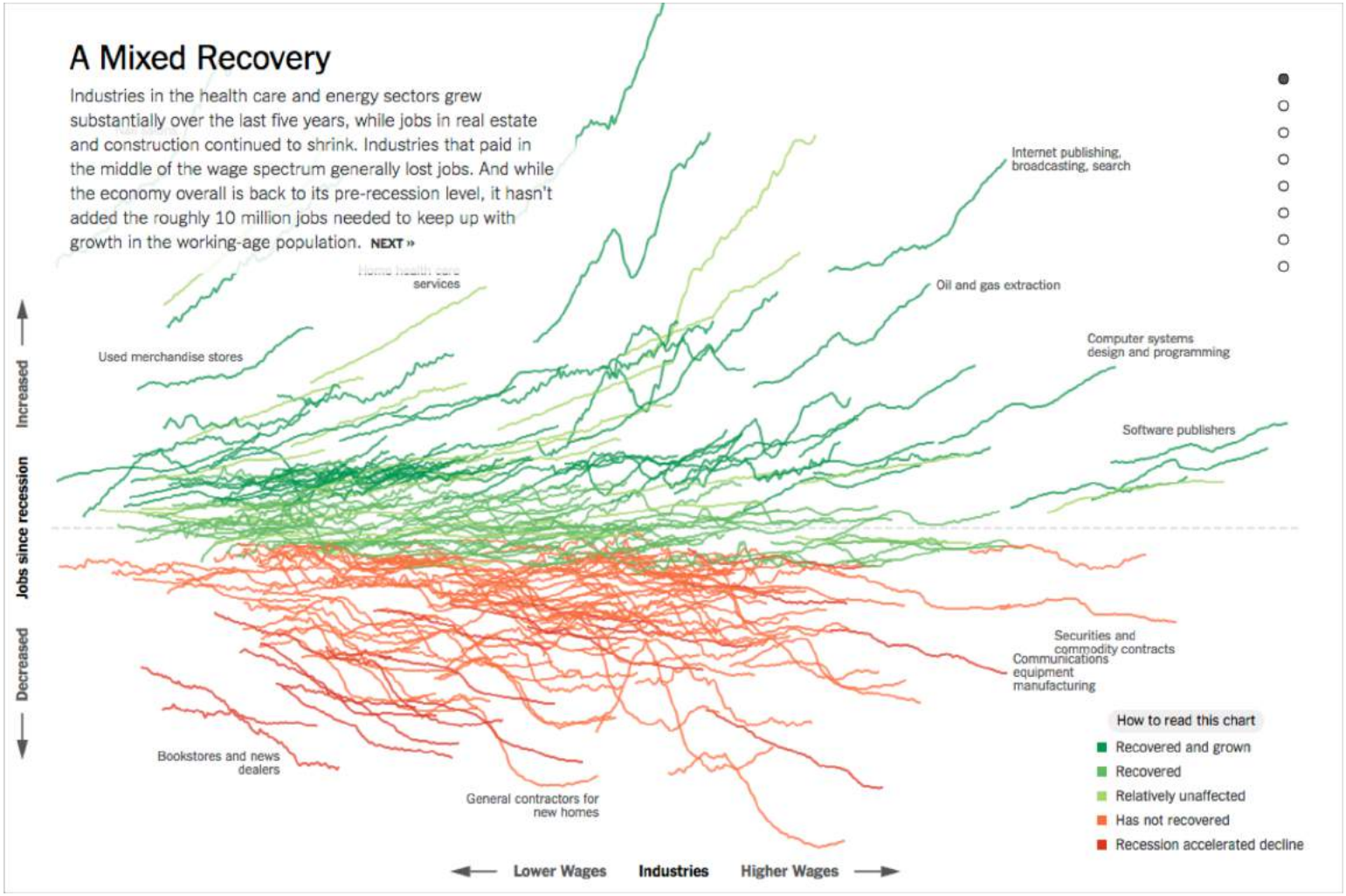
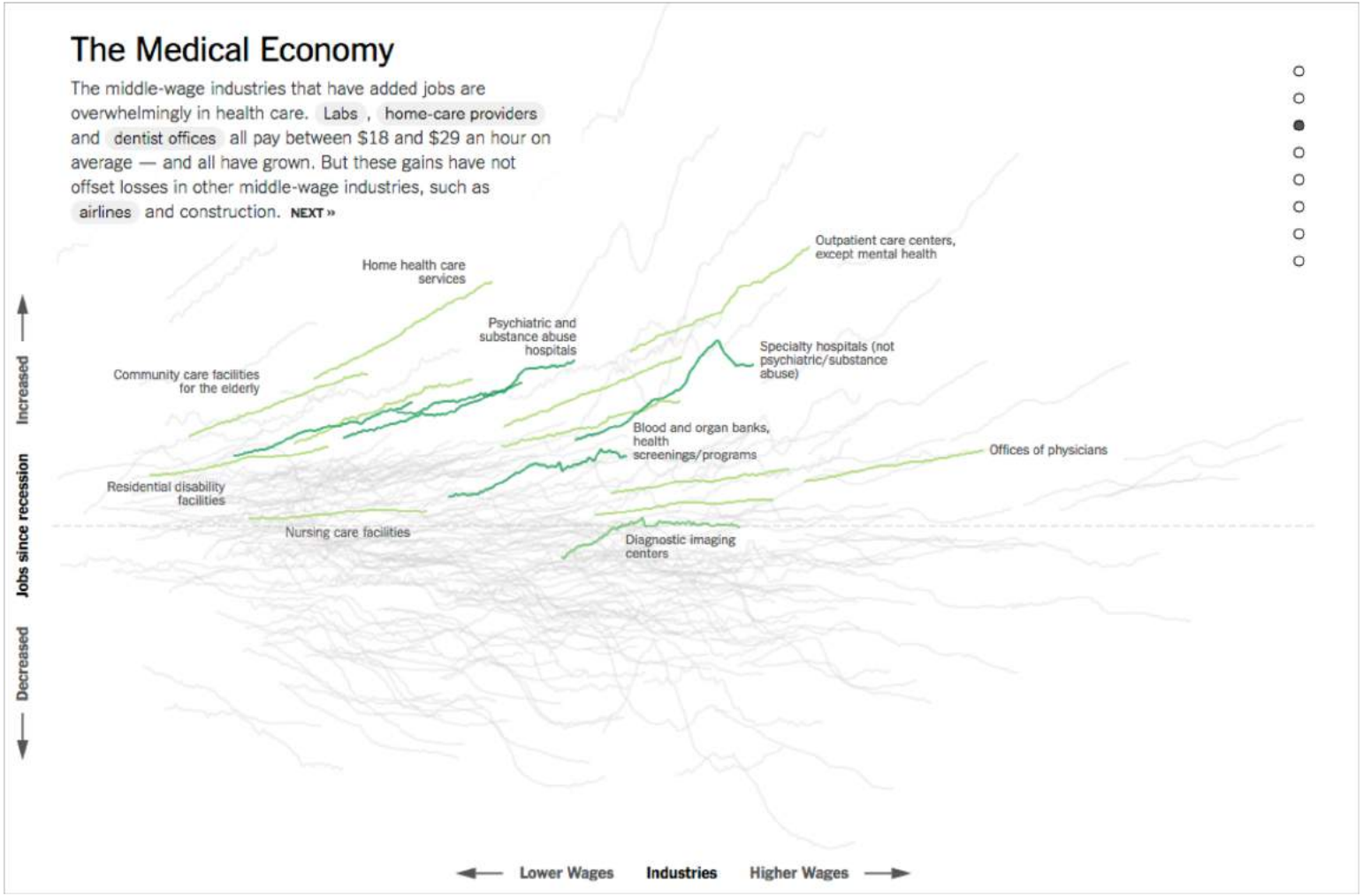
**Significantly impacted residents**

# All the data doesn't tell a story




http://www.nytimes.com/interactive/2014/06/05/upshot/how-the-recession-reshaped-the-economy-in-255-charts.html

# All the data doesn't tell a story

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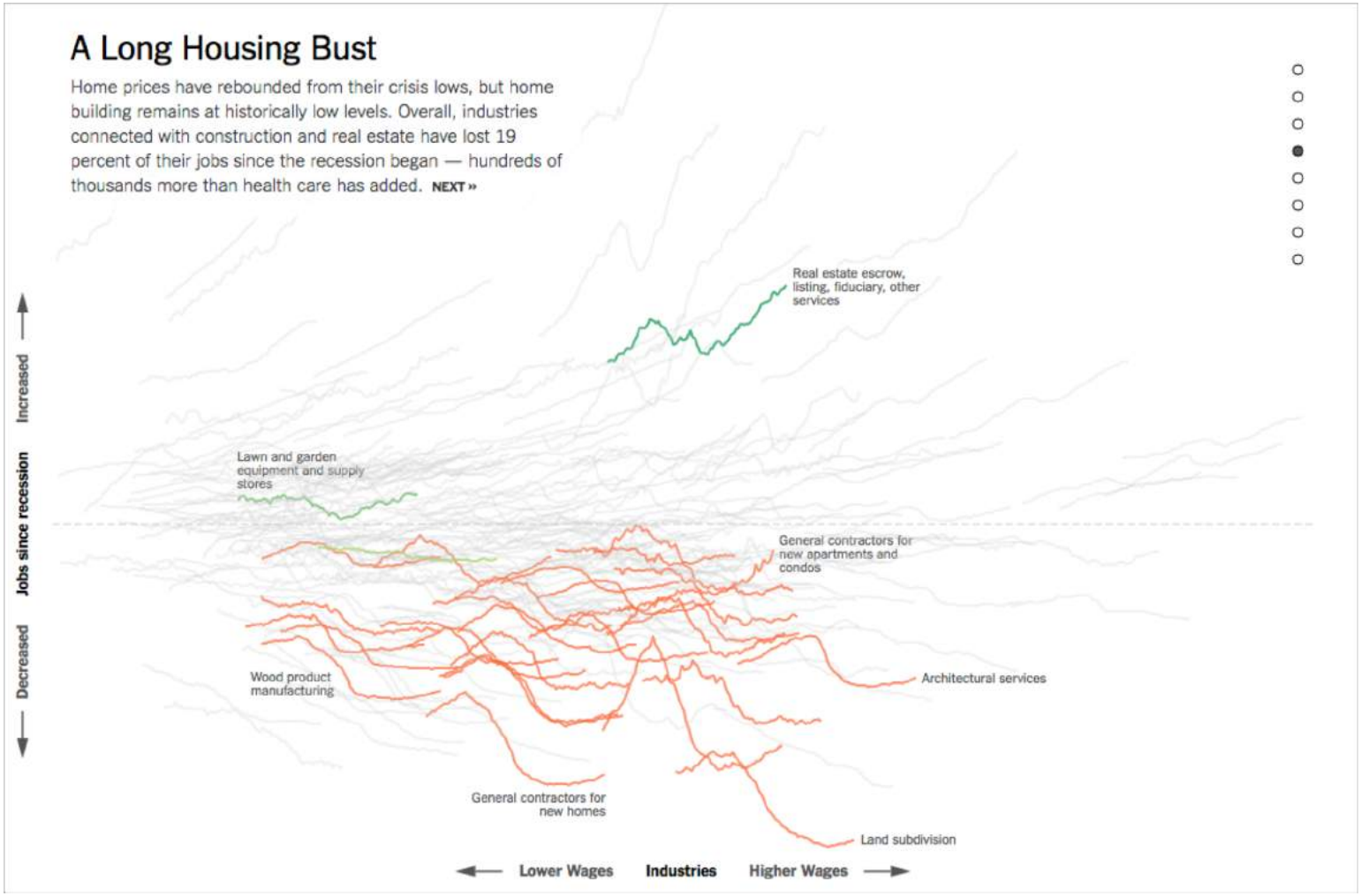
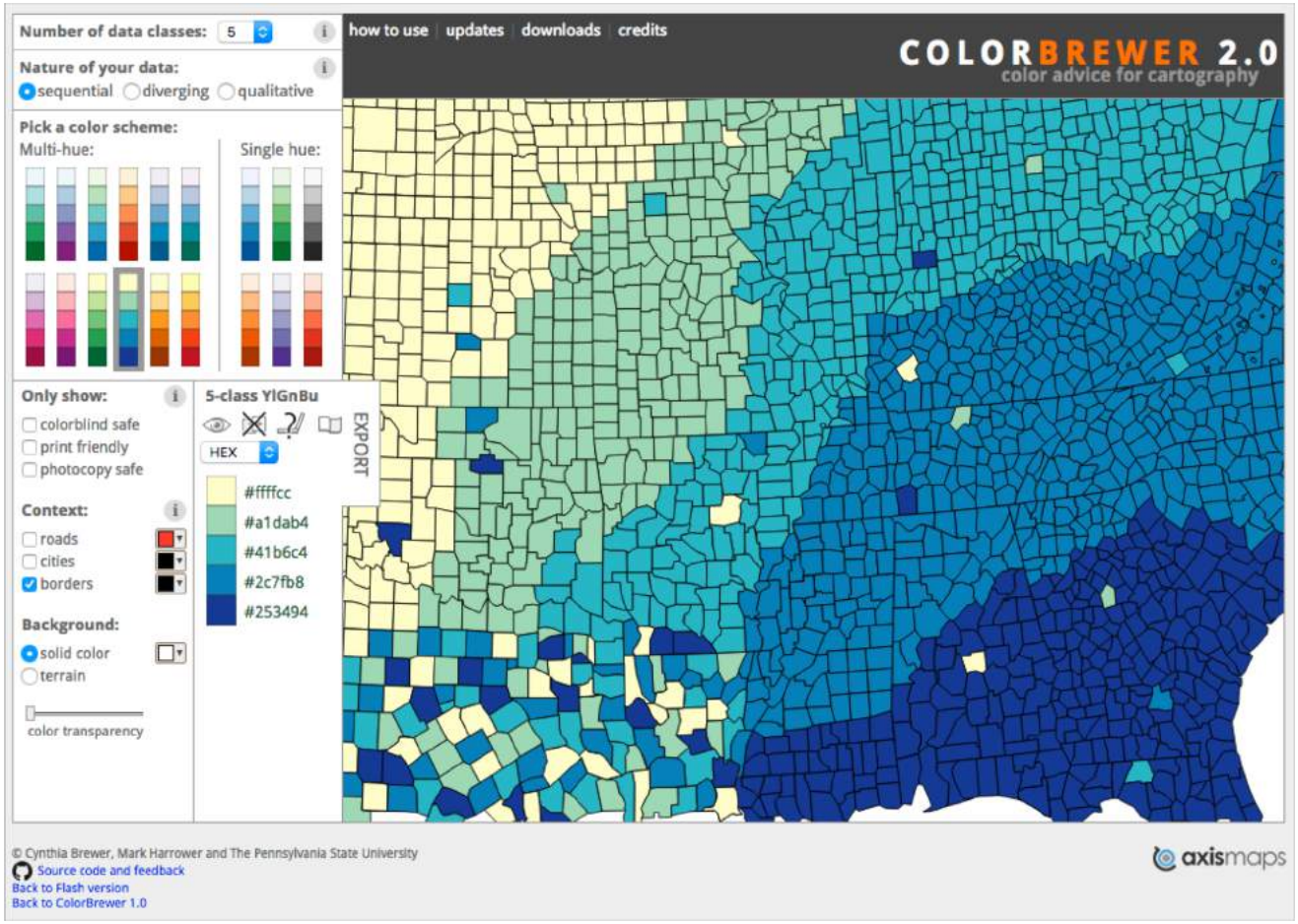



http://www.nytimes.com/interactive/2014/06/05/upshot/how-the-recession-reshaped-the-economy-in-255-charts.html

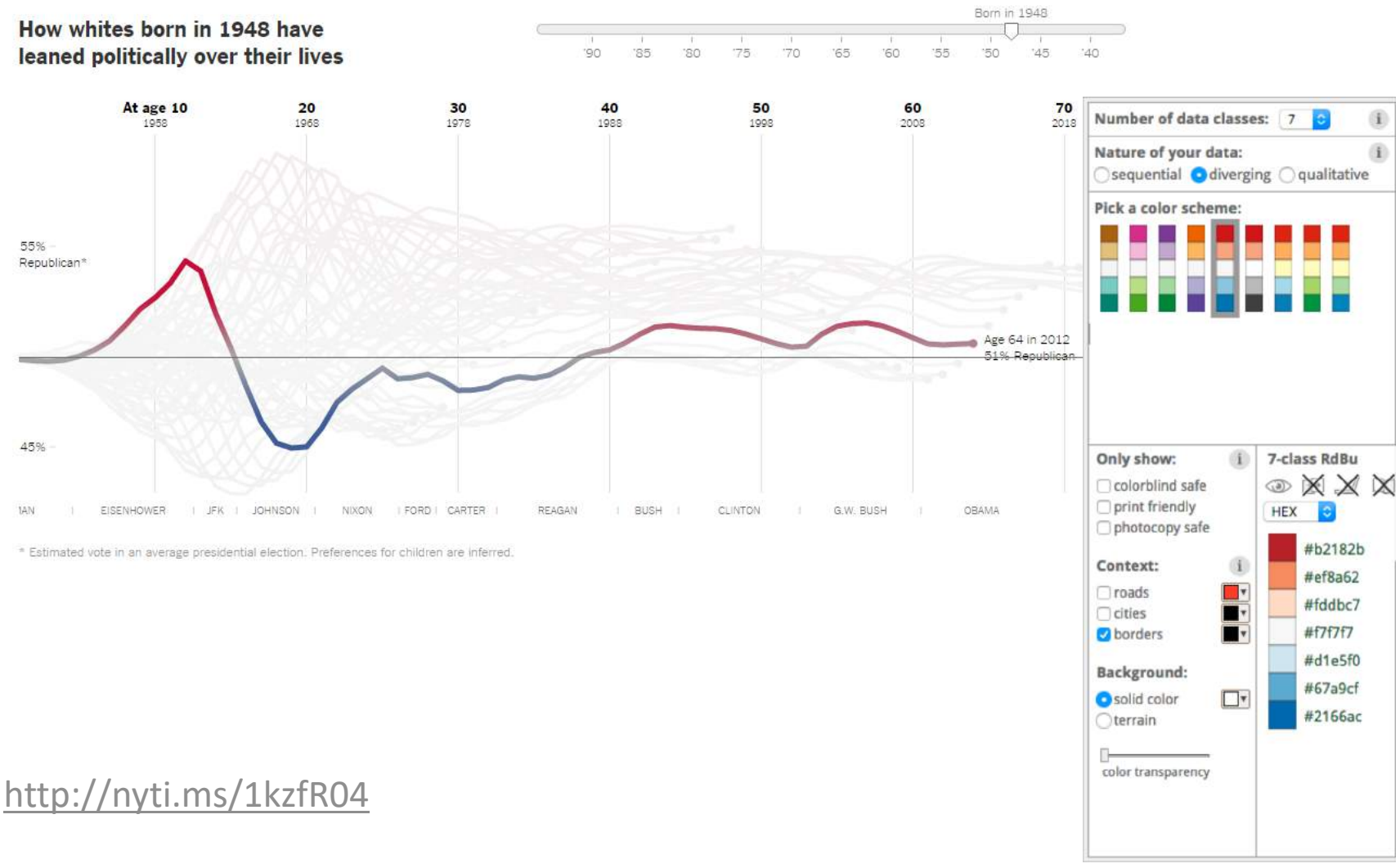
# Color

# Luminance ramp for good colormap

http://colorbrewer2.org/

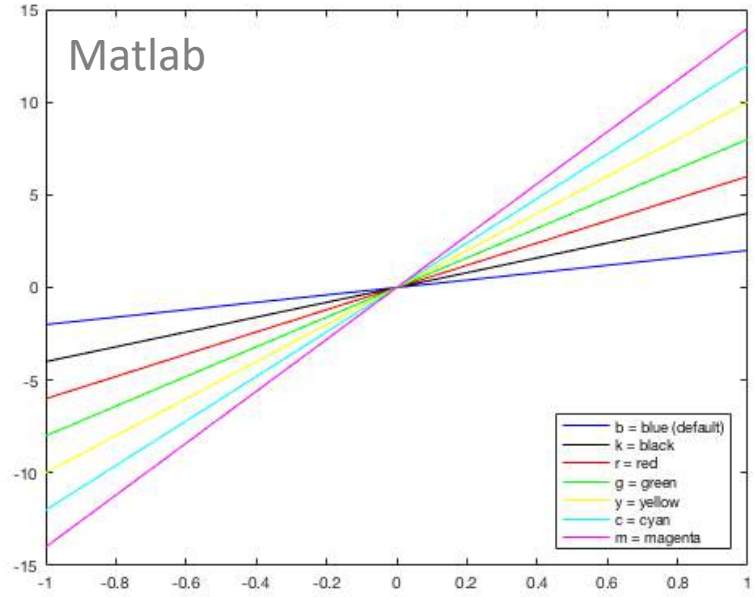


# Diverging if there's a natural center



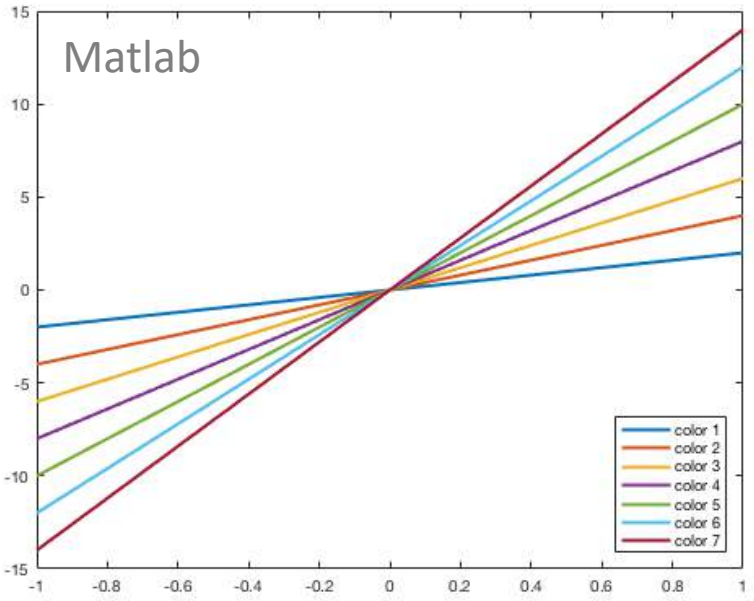

http://nyti.ms/1kzfR04

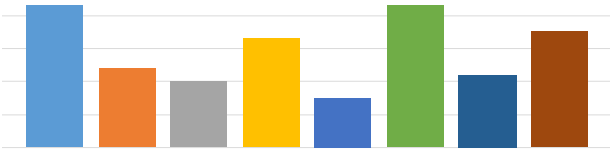
# Keep colors perceptually similar





Excel



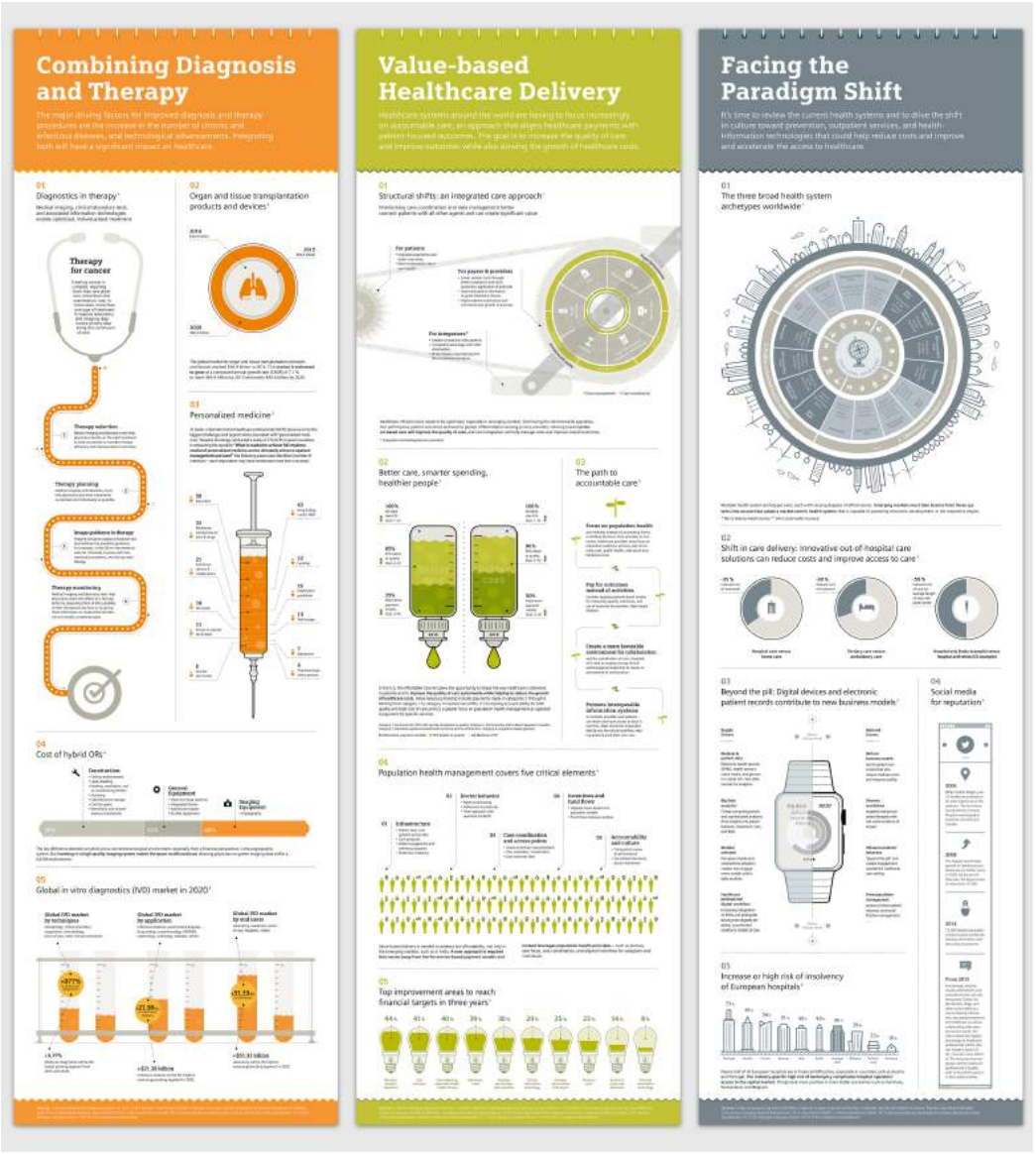
Excel

Tableau

# Color

*Professional designs often have more limited, muted colors*

***Use to create hierarchy and unity***




https://www.informationisbeautifulawards.com/showcase/2370-global-trends-in-healthcare-5-part-infographic-for-siemens-healthcare

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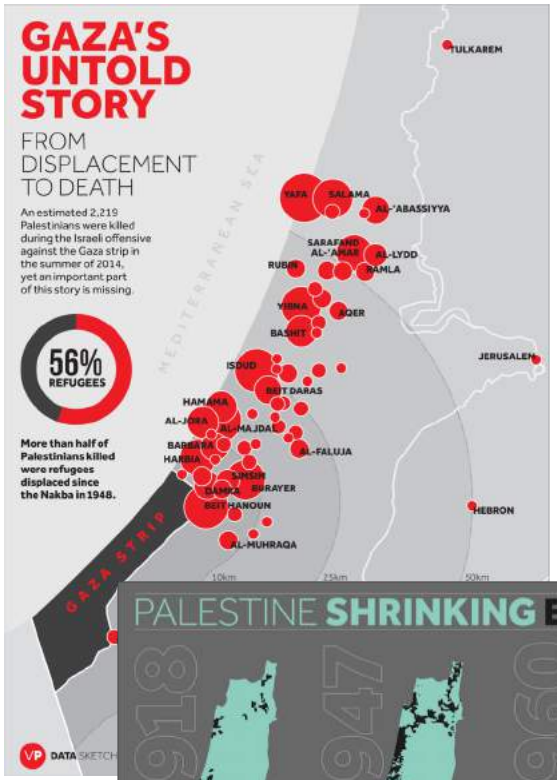
*Professional designs often have more limited, muted colors*

***Use to create hierarchy and unity***

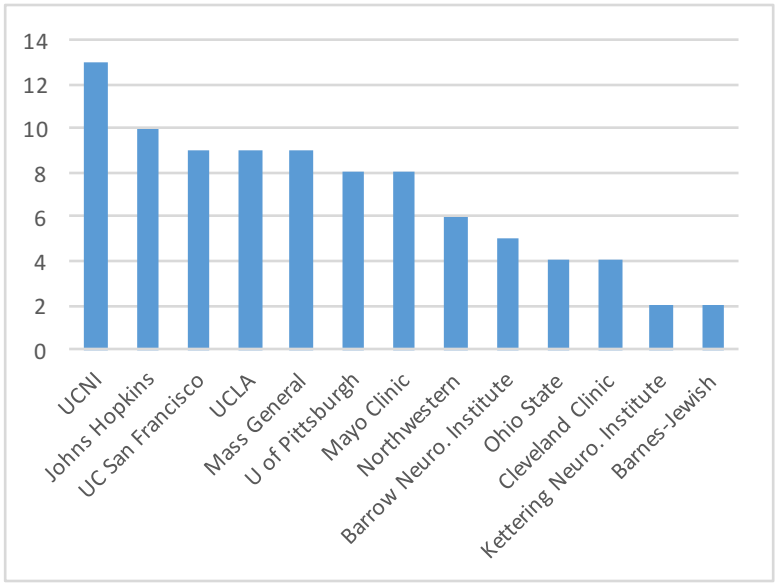


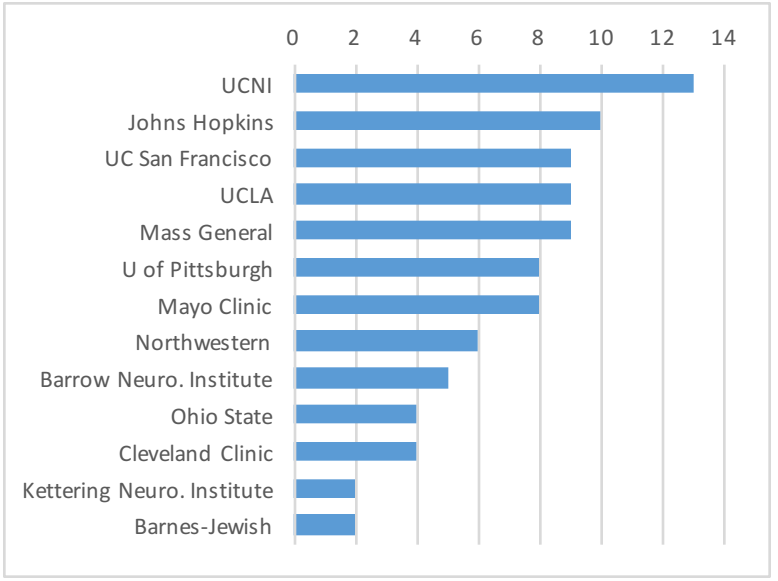



https://visualizingpalestine.org/visuals/gaza-refugee-deaths
https://visualizingpalestine.org/visuals/a-policy-of-displacement
https://visualizingpalestine.org/visuals/http-visualizingpalestine-org-visuals-shrinking-palestine-static

# Text to clarify

# Keep text horizontal



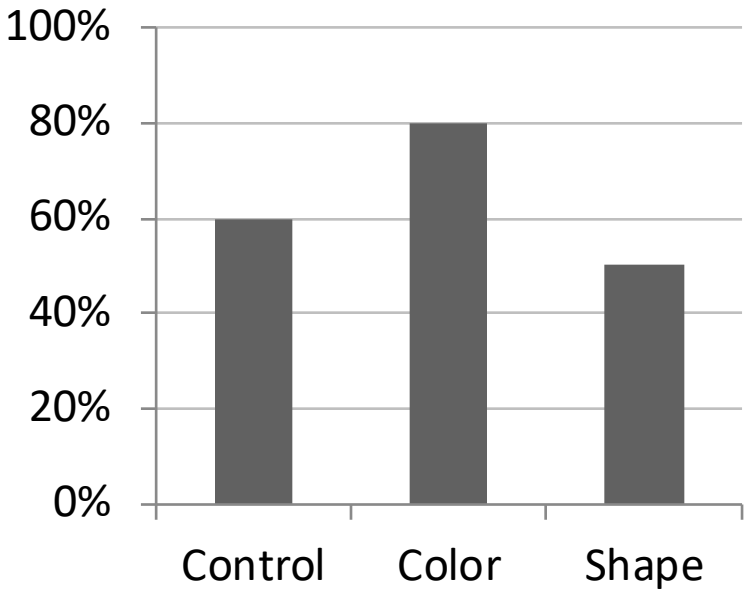




http://www.storytellingwithdata.com/2012/09/some-finer-points-of-data-visualization.html

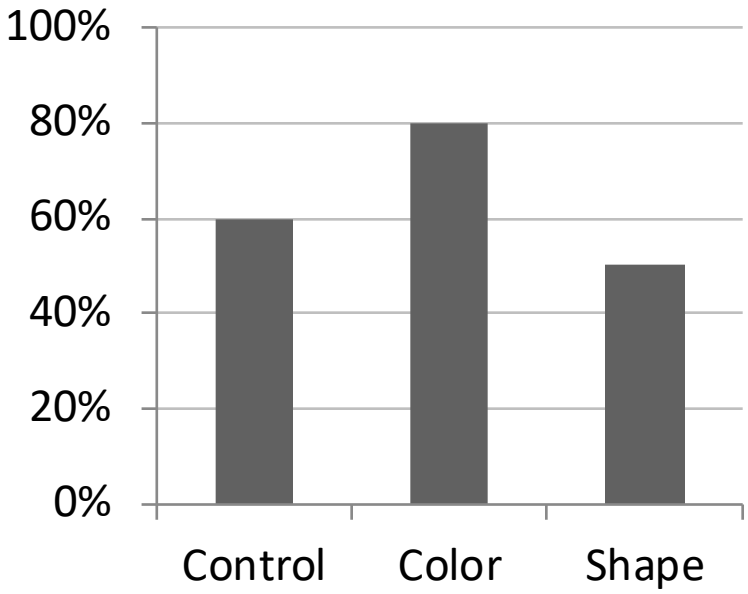
# Use descriptive titles

*Active titles summarize trends in the figure and reinforce your message.*

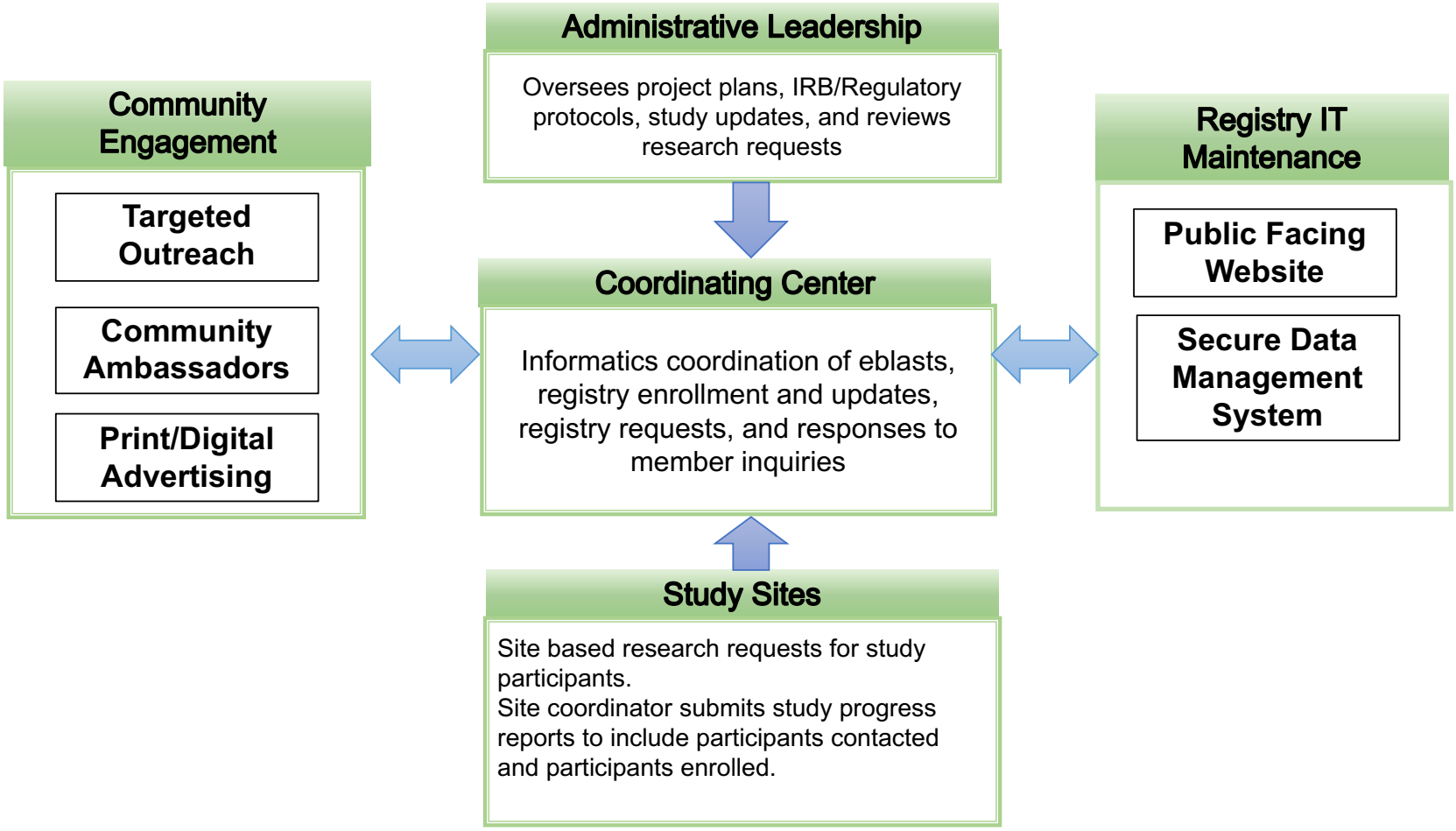
**Accuracy versus Color and Shape**



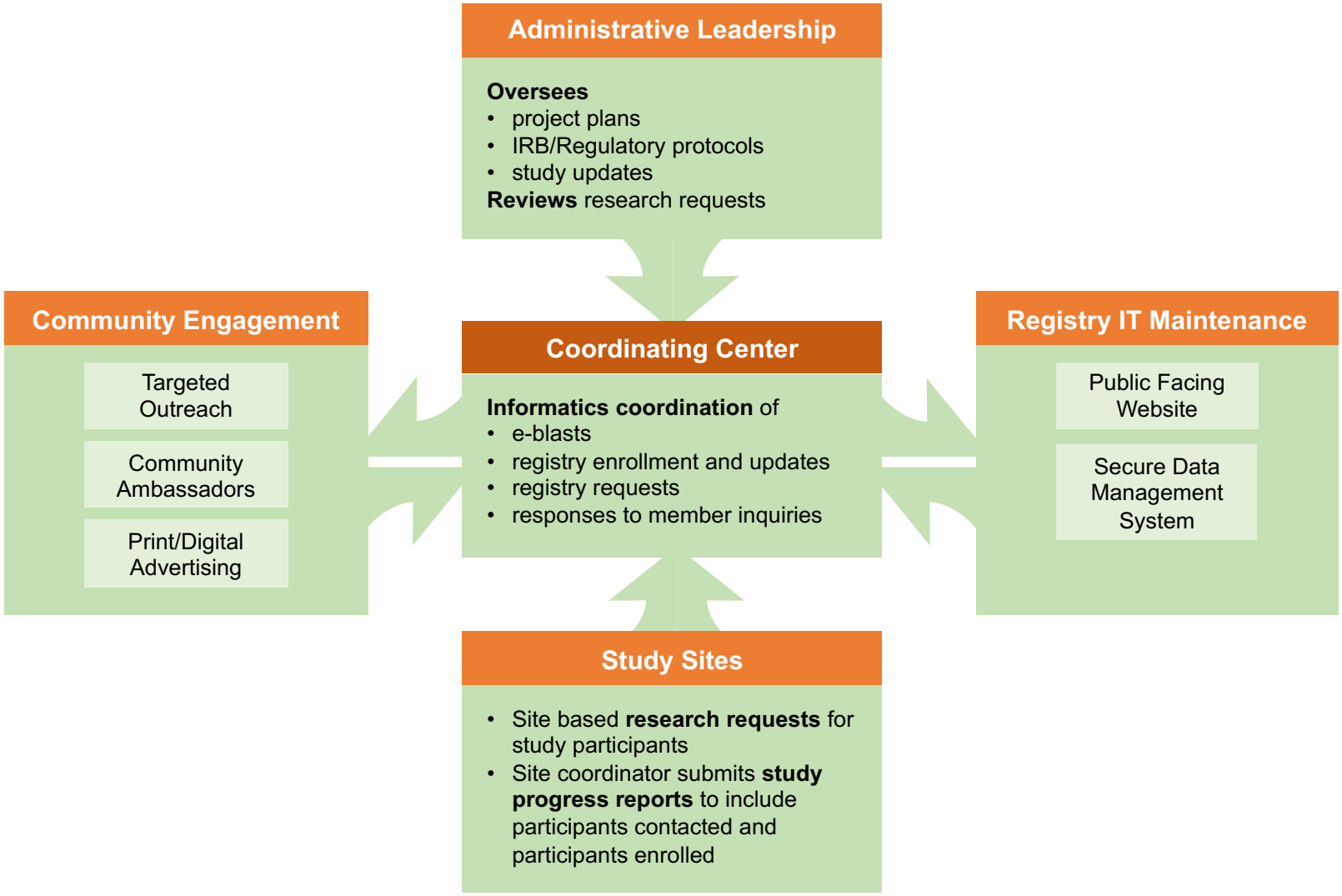

**Accuracy Improved by Color, not Shape**



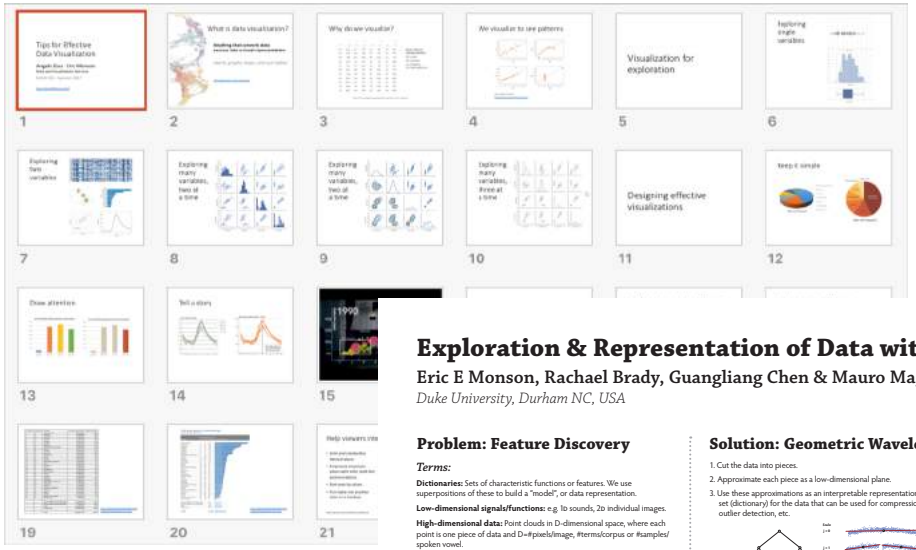
# Remove distractors & customize



# Remove distractors & customize



# With posters, presentations, and infographics, tell your story more like a comic book than an academic paper




## Exploration & Representation of Data with Geometric Wavelets

Eric E Monson, Rachael Brady, Guangliang Chen & Mauro Maggioni
*Duke University, Durham NC, USA*

### Problem: Feature Discovery

***Terms:***

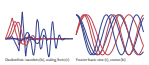
**Dictionaries:** Sets of characteristic functions or features. We use superpositions of these to build a "model", or data representation.

**Low-dimensional signals/functions:** e.g. 1D sounds, 2D individual images.

**High-dimensional data:** Point clouds in D-dimensional space, where each point is one piece of data and D=#pixels/image, #terms/corpus or #samples/spoken vowel.

***Challenge:***

**For low-dimensional signals** we have many different **"general-purpose" dictionaries** (Fourier basis, Wavelets, Curvelets) to model our data and do compression, de-noising, sharpening, etc.



**For high-dimensional data** we would like to do the same things, but **we do not have good, tractable models, so we must find features from the data itself**.

**Given the data (X) we want to learn a set of features (Φ) and coefficients (α)** to build a representation such that

$$X \approx \Phi \cdot \alpha$$

**Φ is "good" if α is sparse** (lots of zeros or very small values).

**Most methods are "black boxes" which have no guarantees, are costly to compute and don't yield interpretable data features.**

***Our Approach:***

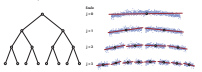
We do not try to solve this problem "in general", but exploit the fact that often **real data has lower-dimensional geometric structure**, such as lying near a **manifold ($\mathcal{M}$)** of dimensionality d<<D.

**Geometric Wavelets is a novel construction** which discovers features in high-dimensional data under these geometric assumptions.

It is **explicit**, which leads to **interpretable features**, and it comes with **guarantees** (as a function of an approximation error parameter) on **computational cost**, **number of elements in the dictionary** and **sparsity** of the representation. It is **globally non-linear, but piecewise linear**, so it is **fast**, but can **adapt to arbitrary non-linear manifolds**.

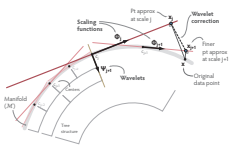
### Solution: Geometric Wavelets

1. Cut the data into pieces.
2. Approximate each piece as a low-dimensional plane.
3. Use these approximations as an interpretable representation or feature set (dictionary) for the data that can be used for compression, filtering, outlier detection, etc.



***More Details:***

1. Use a similarity measure to create a graph from the data points. Construct a set of multi-scale partitions of $\mathcal{M}$ by using recursive spectral cuts. (METIS uses Eigenfunctions of the Laplacian over the graph – we are also implementing Cover Trees. This step often involves task-specific method variations).
2. Compute the SVD of the data covariance for each piece. This gives Scaling Functions & $\mathcal{M}_{jk}$ – a manifold approximation at scale j for piece k – a projection onto that local approximate tangent space.
3. Higher-scale planes are small corrections to the previous parent. Efficiently encode the differences between $\mathcal{M}_{j+1} \to \mathcal{M}_j$ by constructing Wavelet spanning space & "detail" operators analogous to Wavelet theory.

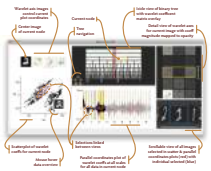



This results in a **multi-scale nonlinear transform** mapping data to a family of pieces of planes which **approximates the original data to any given precision**.

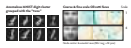
### Experience: Interactive GUI

- **Quickly see much more data** so mathematicians can evaluate methods during development.
- Begin **developing a platform** onto which we can build more specialized applications for **new tasks and data types**.
- Help **explain** Geometric Wavelets and **gain intuition** about the representation.

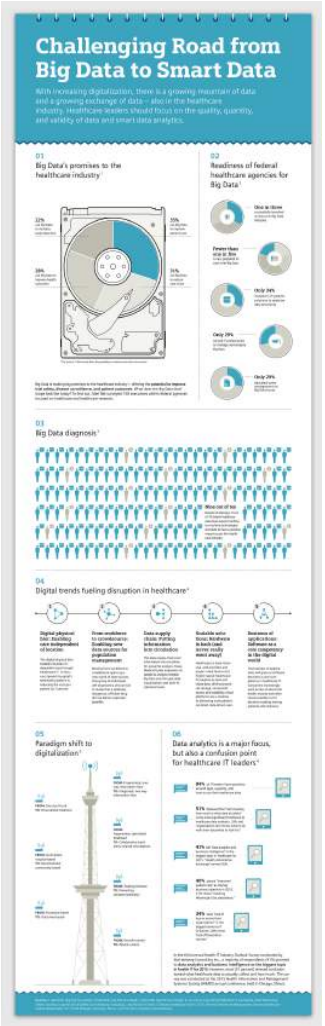
Implemented in Python, using PyQt4 to glue together custom VTK views. Currently the representation is not computed in the GUI – Matlab output is loaded from files.



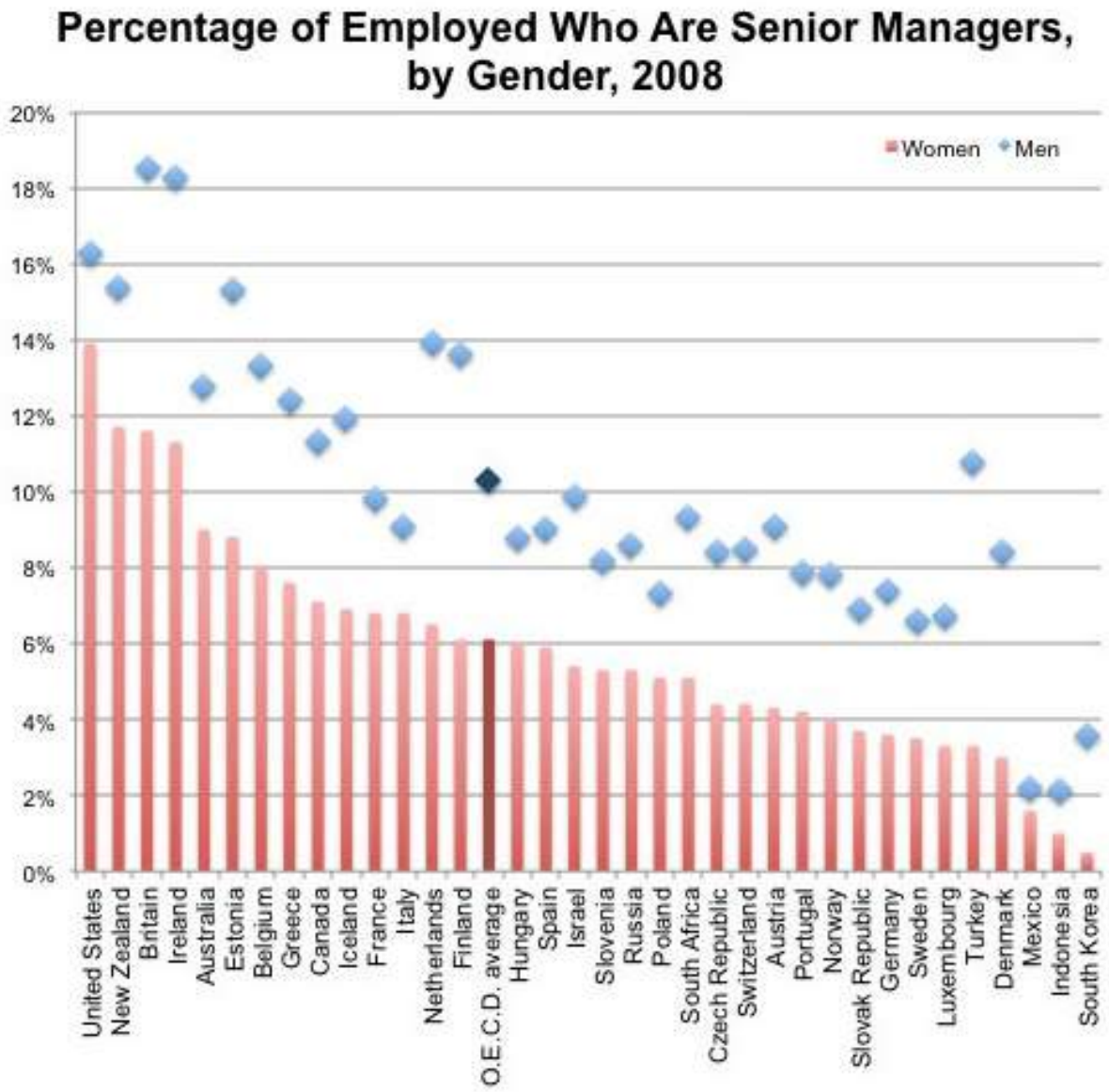
***Observations & Future Directions:***



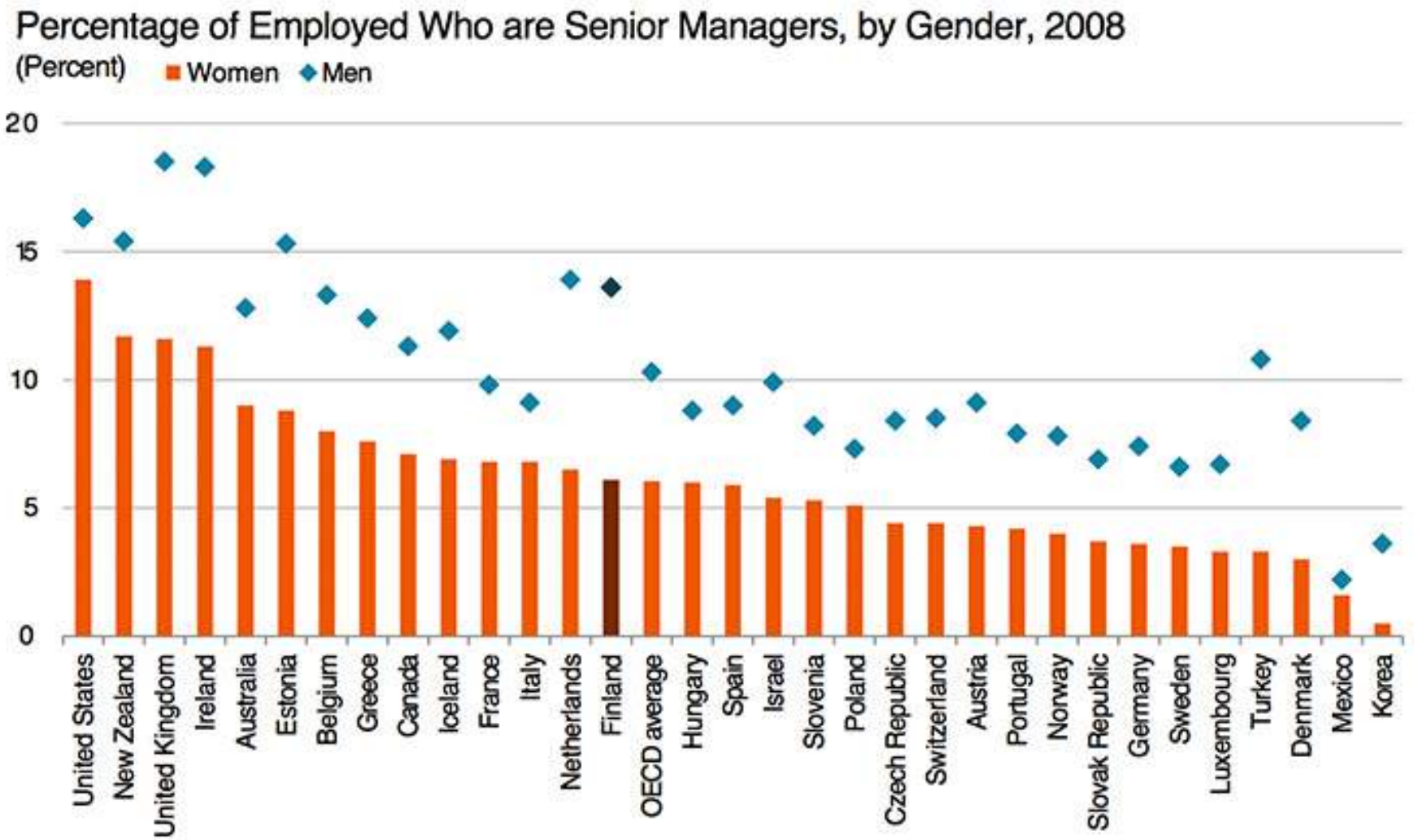
- **Coarser scales contain generalized approximations of the data**, with readily interpretable node centers and wavelet directions.
- **Finer scales reveal anomalous data** through extreme wavelet coefficients or "odd" wavelet axis images.
- Coarser-scale wavelets contain information which could be ignored for classification tasks, but **finer-scale wavelets** encode more specific features which **cluster and characterize individuals**.
- **Developers have changed their ideas** about data encoding after viewing their results in the GUI.
- We are already working on **variable dimensionality** group definition & labeling for **classification and outlier detection**, views for new data types.



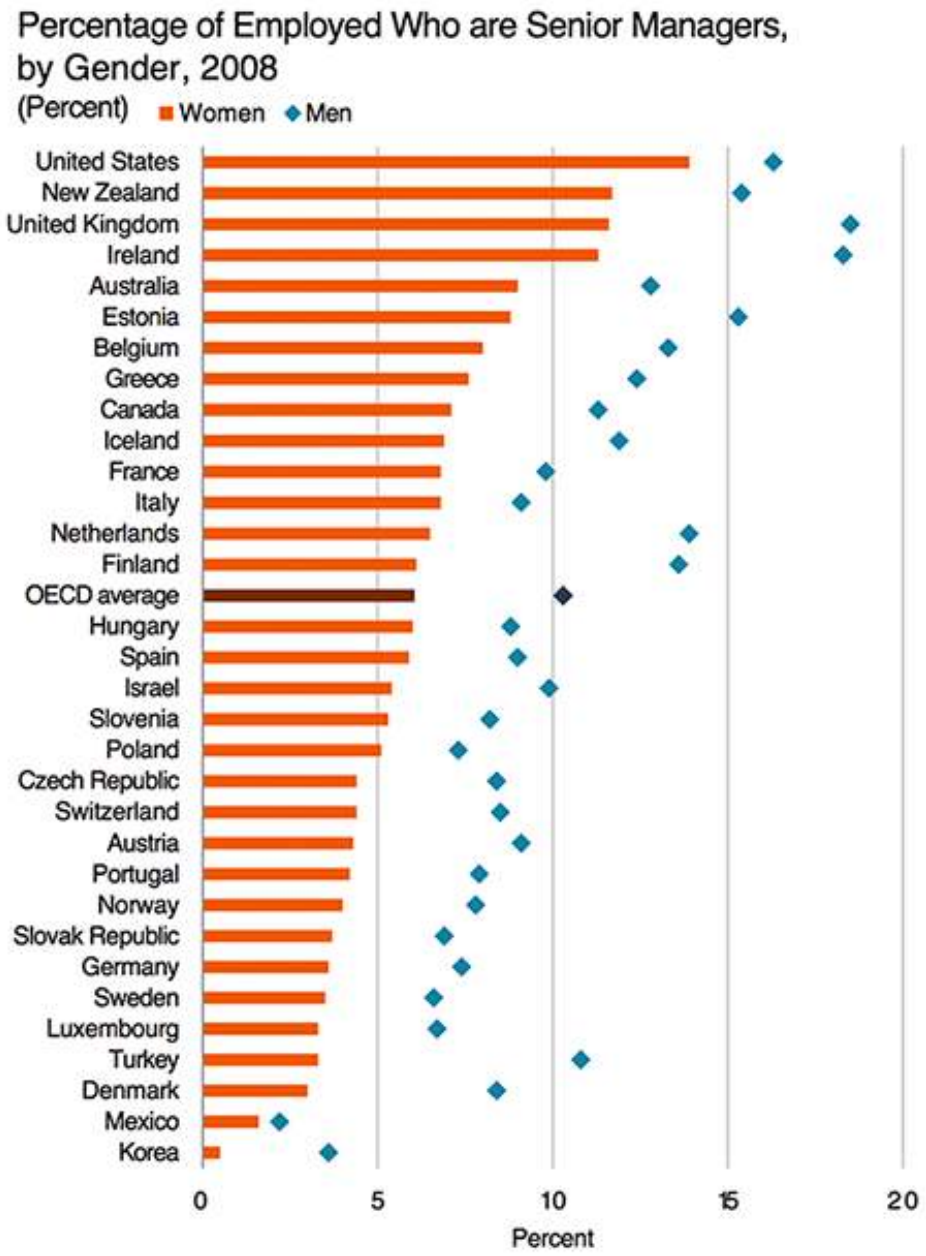
# Figure critique & reworks



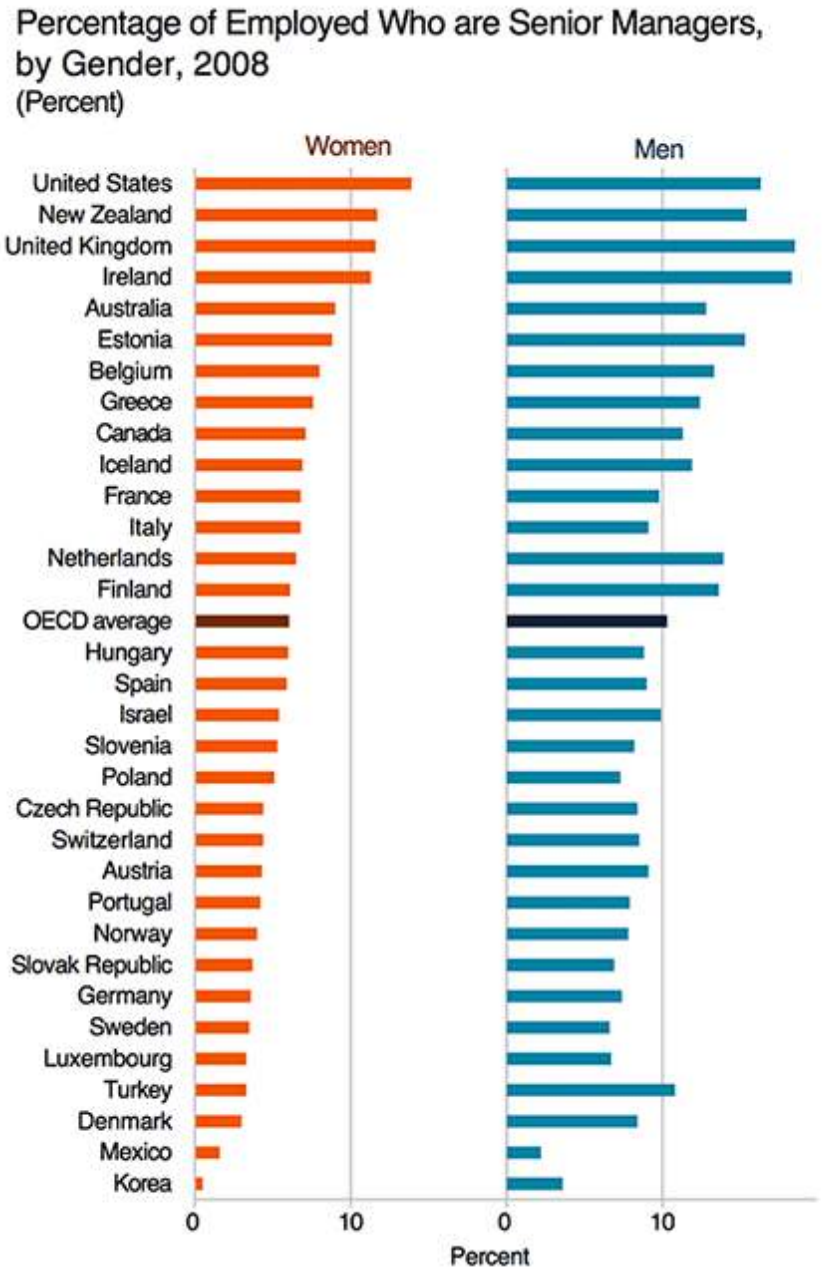

Jon Schwabish: http://thewhyaxis.info/gap-remake/



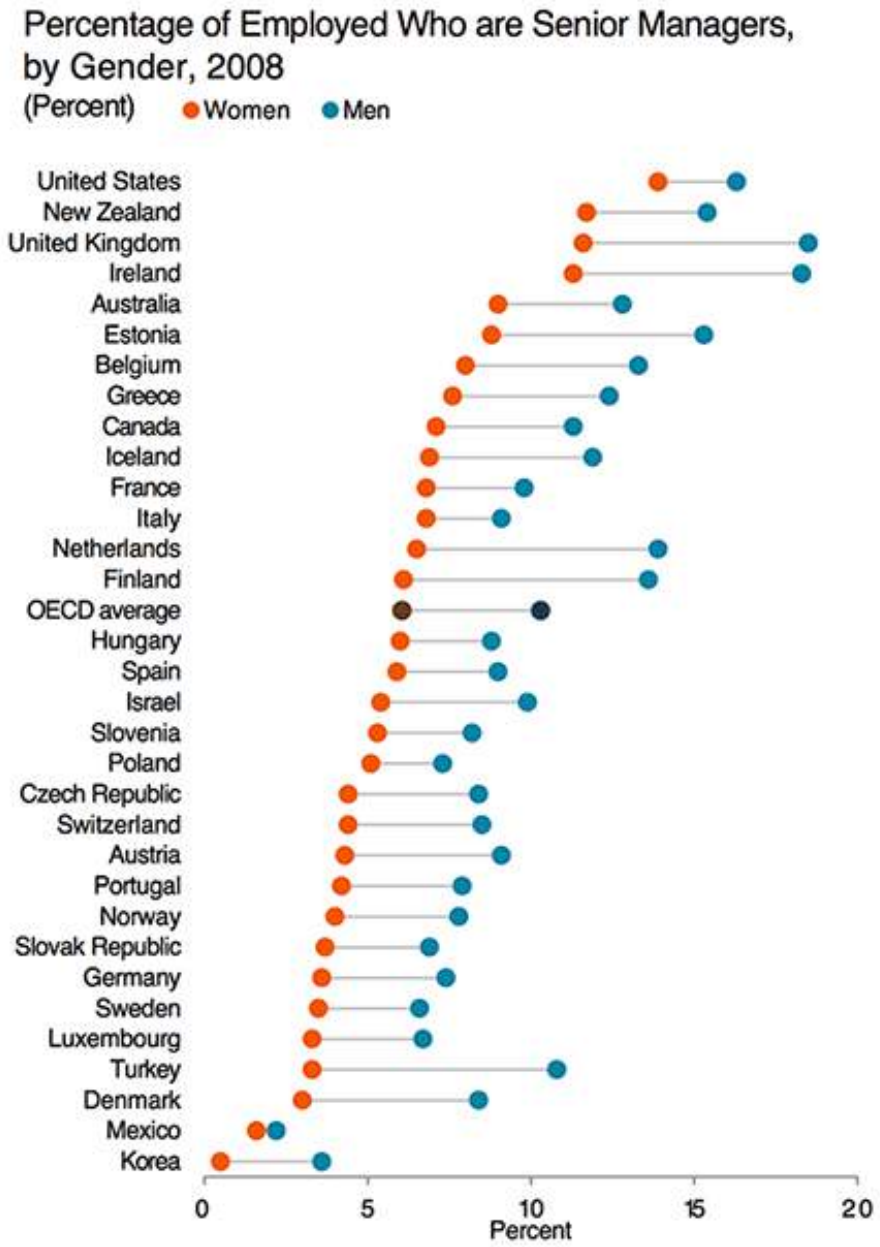

Jon Schwabish: http://thewhyaxis.info/gap-remake/



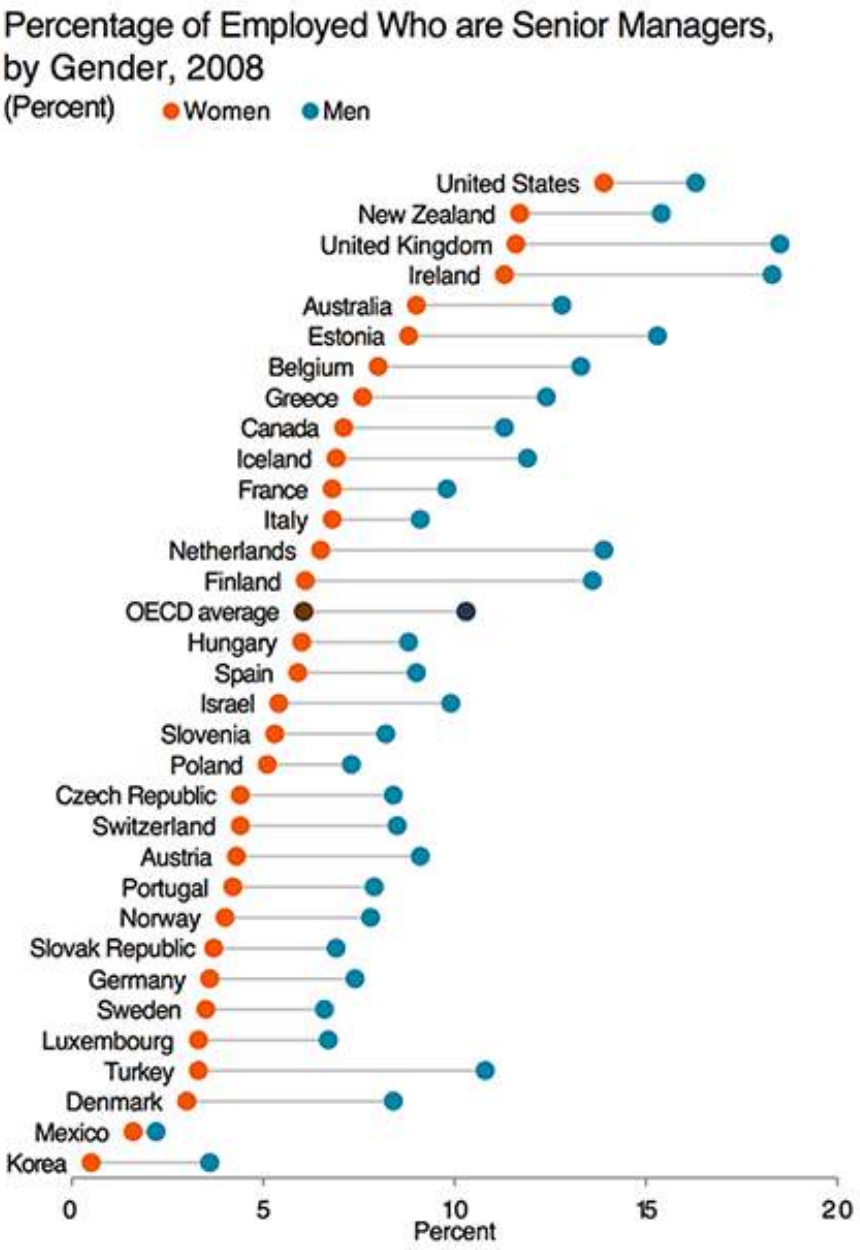

Jon Schwabish: http://thewhyaxis.info/gap-remake/




Jon Schwabish: http://thewhyaxis.info/gap-remake/




Jon Schwabish: http://thewhyaxis.info/gap-remake/




Jon Schwabish: http://thewhyaxis.info/gap-remake/

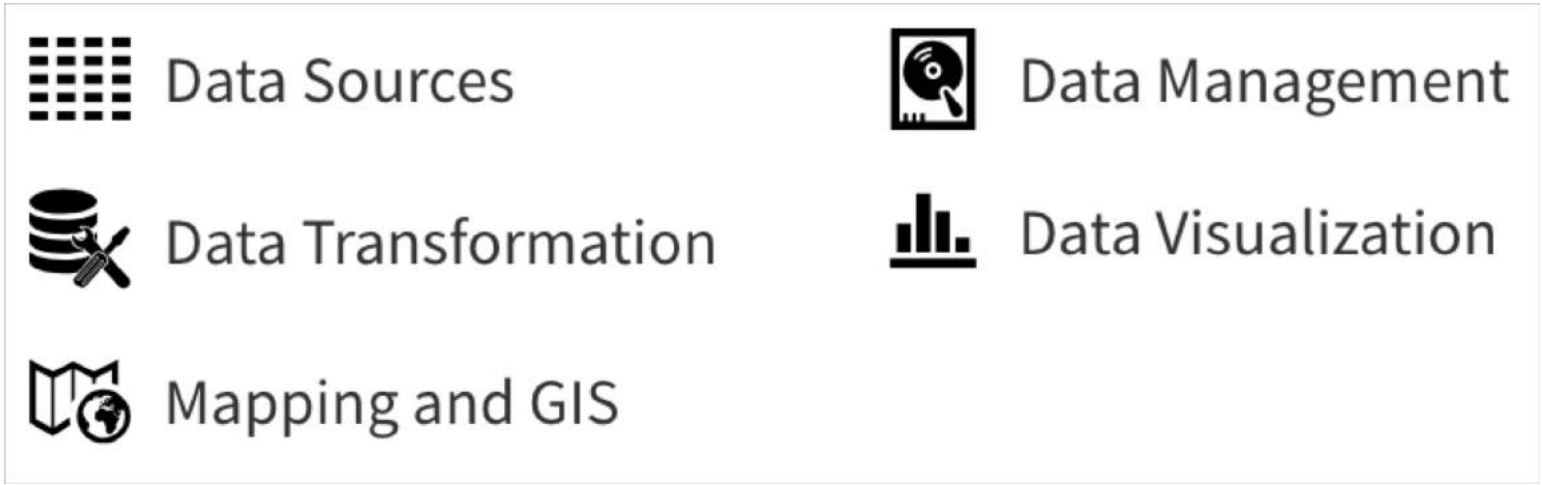
# Data and Visualization Services

Data and Visualization Services Department

http://library.duke.edu/data

askdata@duke.edu

# Support Areas

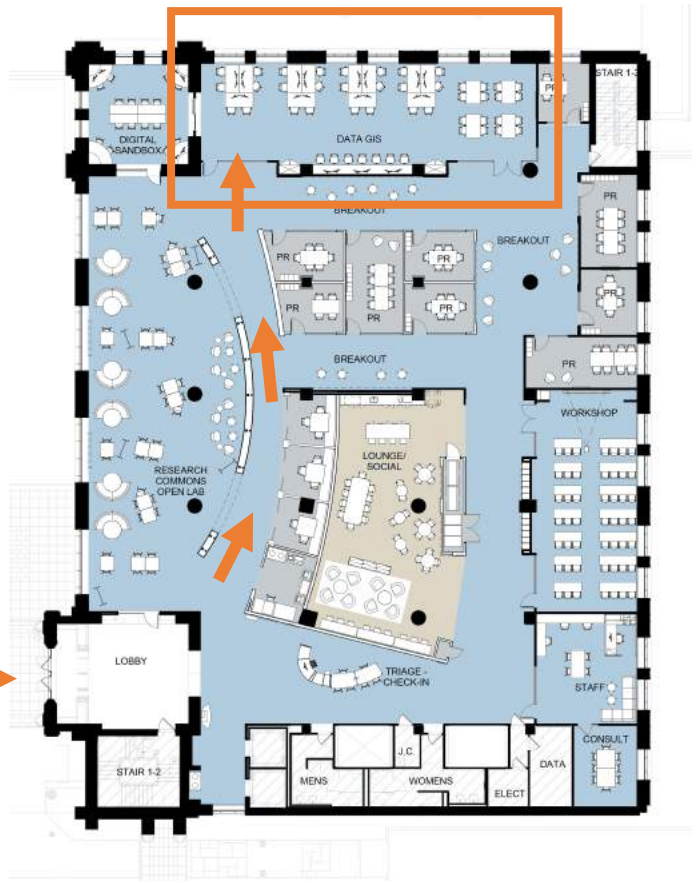


# Brandaleone Family Lab for Data and Visualization Services

http://library.duke.edu/data/about/lab

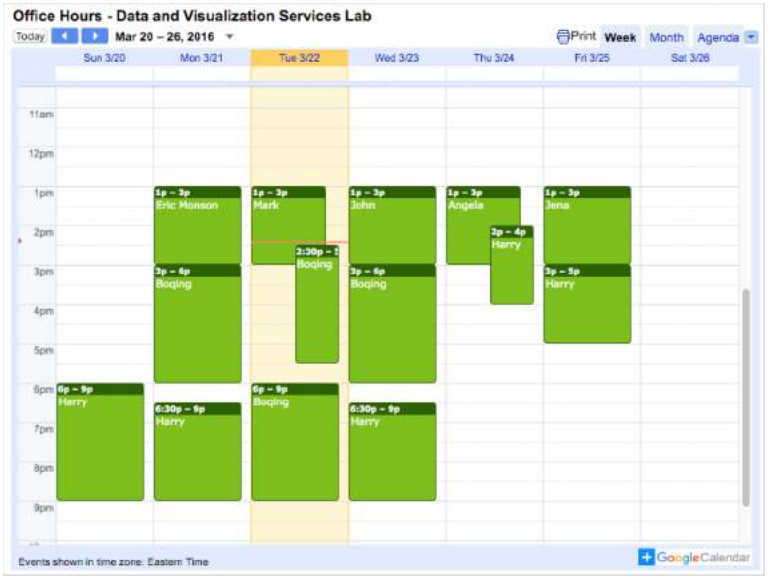
- **The Edge** *(1st floor of Bostock)*
- Open whenever the library is open
- 12 high-powered Dell workstations
- 3 Bloomberg financial workstations
- Software for data analysis, GIS, and visualization

Data and Visualization Lab




Entrance to Bostock

# Consulting

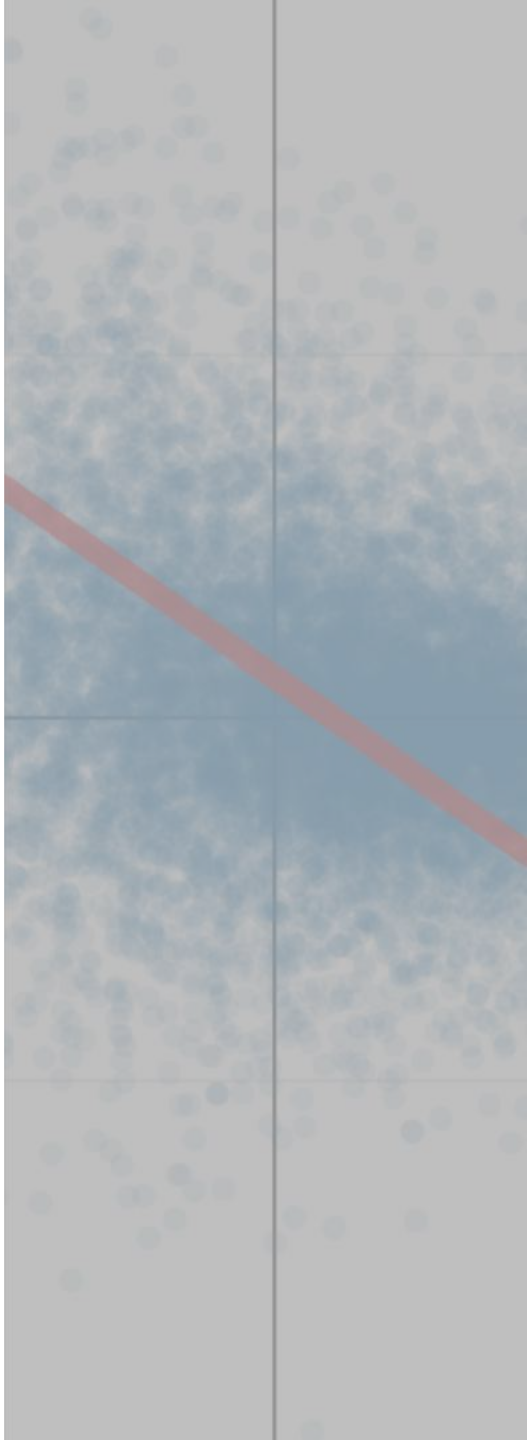



http://library.duke.edu/data/about/schedule

…or email
askdata@duke.edu
for an appointment

# Types of visualization consulting

- Look at data and brainstorm about the best visualization
- Recommend appropriate tools
- Troubleshoot software problems
- Help with cleaning and structuring data
- Offer graphic design advice for figures, diagrams, slides and posters



# Workshops

http://library.duke.edu/data/workshops

- Typically toward the beginning of the semester
- Covering: visualization, data processing, GIS/mapping
- 1-2 hours, often hands-on

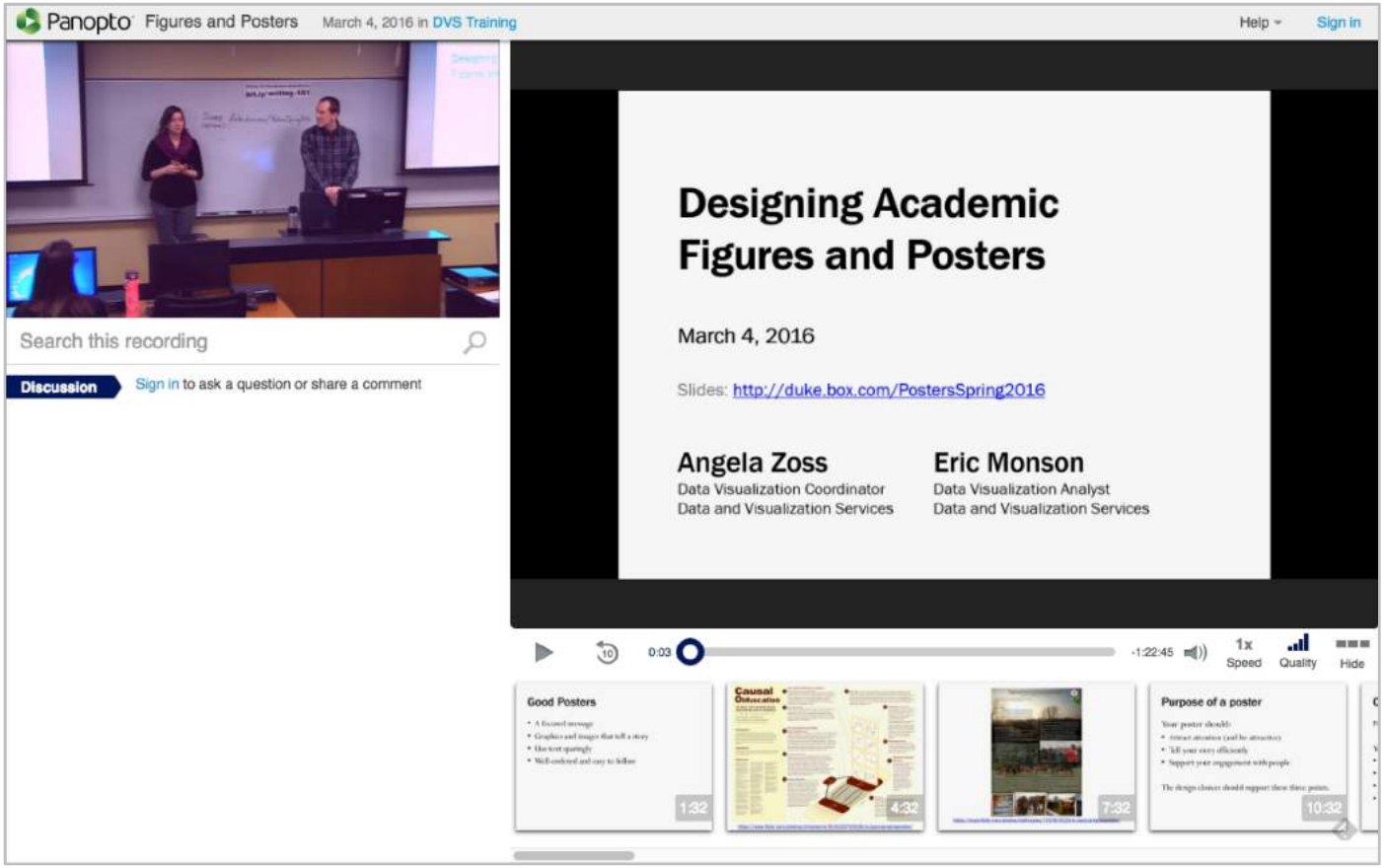
For announcements, sign up for our listserv:
https://lists.duke.edu/sympa/subscribe/dvs-announce

# Spring 2019 visualization workshops

- Intro to ArcGIS Pro · Jan 24
- Rfun: Visualization in R using ggplot2 · Jan 25
- Rfun: Mapping with R · Jan 29
- Web Mapping · Jan 31
- Intro to QGIS · Feb 6
- Intro to Tableau – Easy Charts and Maps · Feb 7
- Introduction to GIS · Feb 12
- Story Maps · Feb 13
- Visualization in Python with Altair · Feb 19
- Map Design · Feb 21
- Rfun: Interactive Dashboards Visualizations with R · Feb 26
- Adobe Illustrator for Modifying Charts and Graphs · Mar 7

# Videos of past workshops

http://bit.ly/DVSvideos



# Visualization Friday Forum

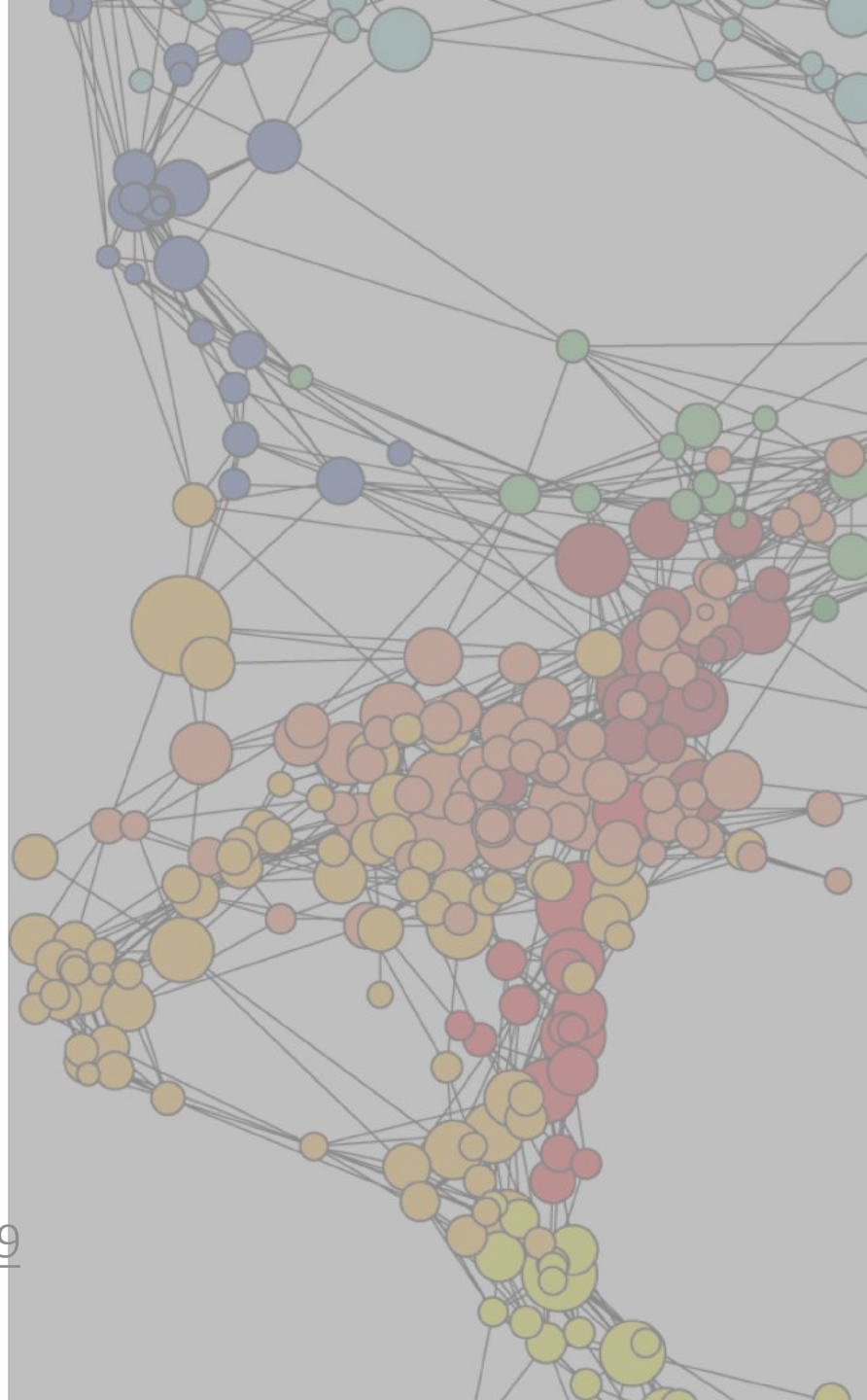
https://vis.duke.edu/FridayForum

- Every Friday during the semester
- Noon in LSRC D106
- Free lunch (sssh!)
- Live streamed and recorded
- Email me to get on the mailing list

# Questions

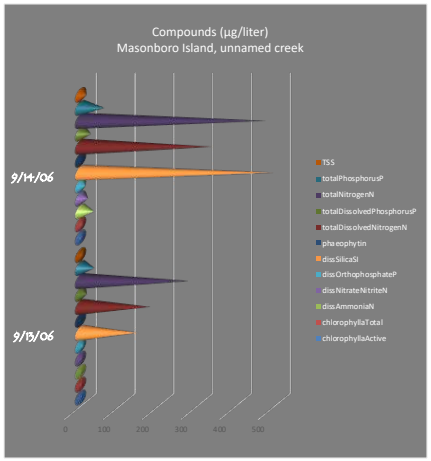
askdata@duke.edu

Slides: https://bit.ly/STA199visSpring2019

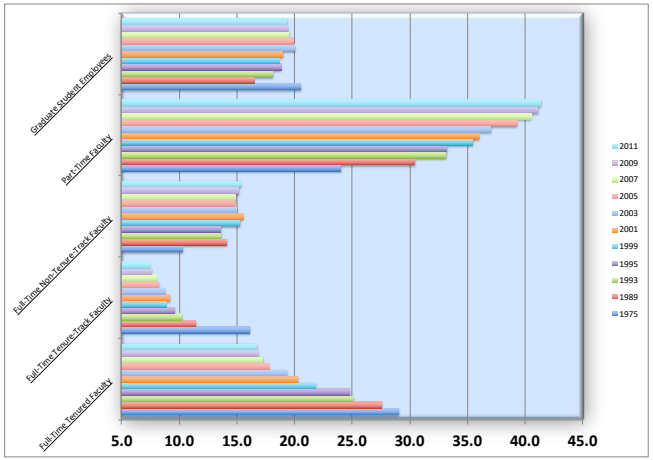


# Visualization Reworks Activity

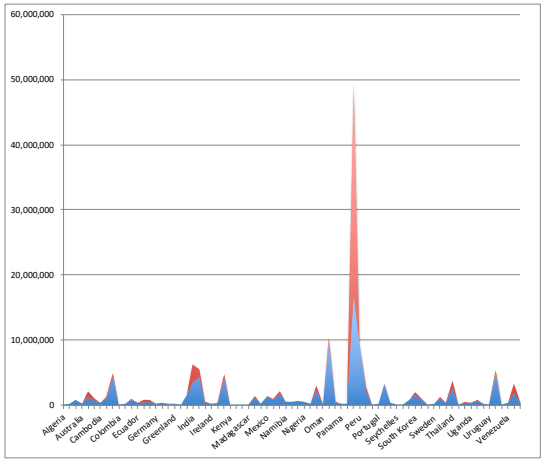
## NERRS Nutrients




## Instructional Staff Employment

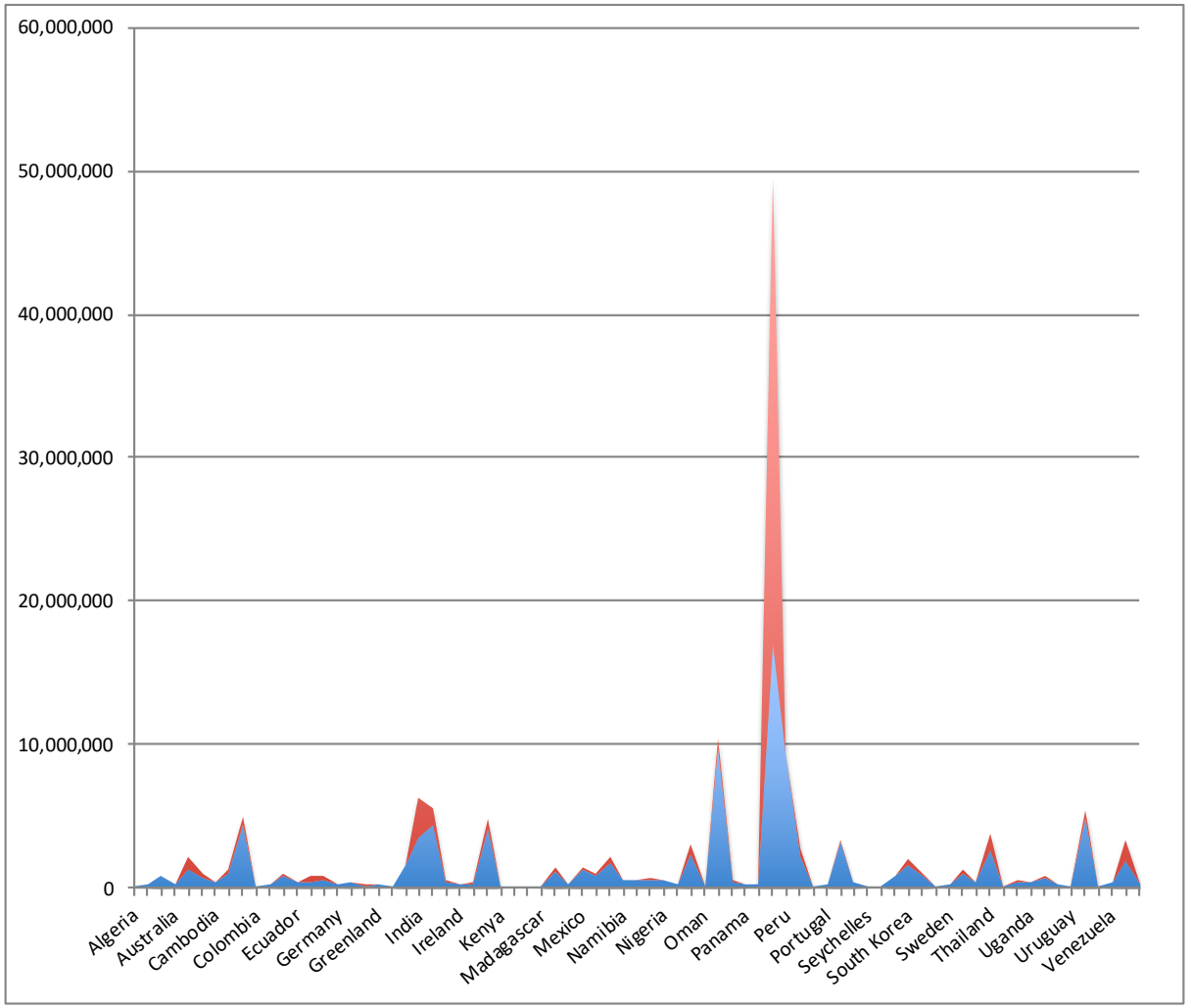


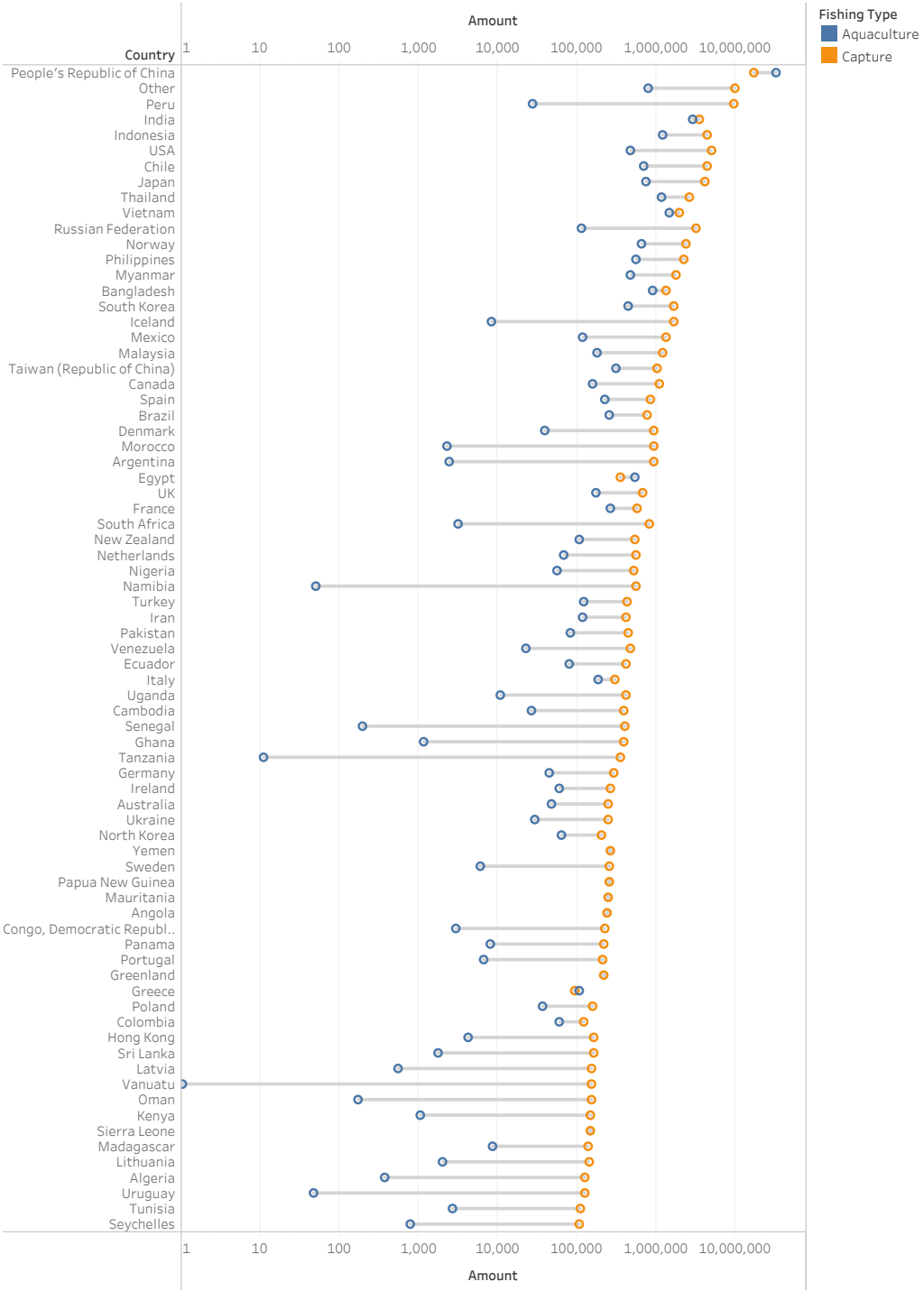

## Fishing Industry



# Rework activity

# Fishing industry by country




Amount
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Country
People's Republic of China
Other
Peru
India
Indonesia
USA
Chile
Japan
Thailand
Vietnam
Russian Federation
Norway
Philippines
Myanmar
Bangladesh
South Korea
Iceland
Mexico
Malaysia
Taiwan (Republic of China)
Canada
Spain
Brazil
Denmark
Morocco
Argentina
Egypt
UK
France
South Africa
New Zealand
Netherlands
Nigeria
Namibia
Turkey
Iran
Pakistan
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Sweden
Papua New Guinea
Mauritania
Angola
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Panama
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Poland
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Hong Kong
Sri Lanka
Latvia
Vanuatu
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Sierra Leone
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Lithuania
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Uruguay
Tunisia
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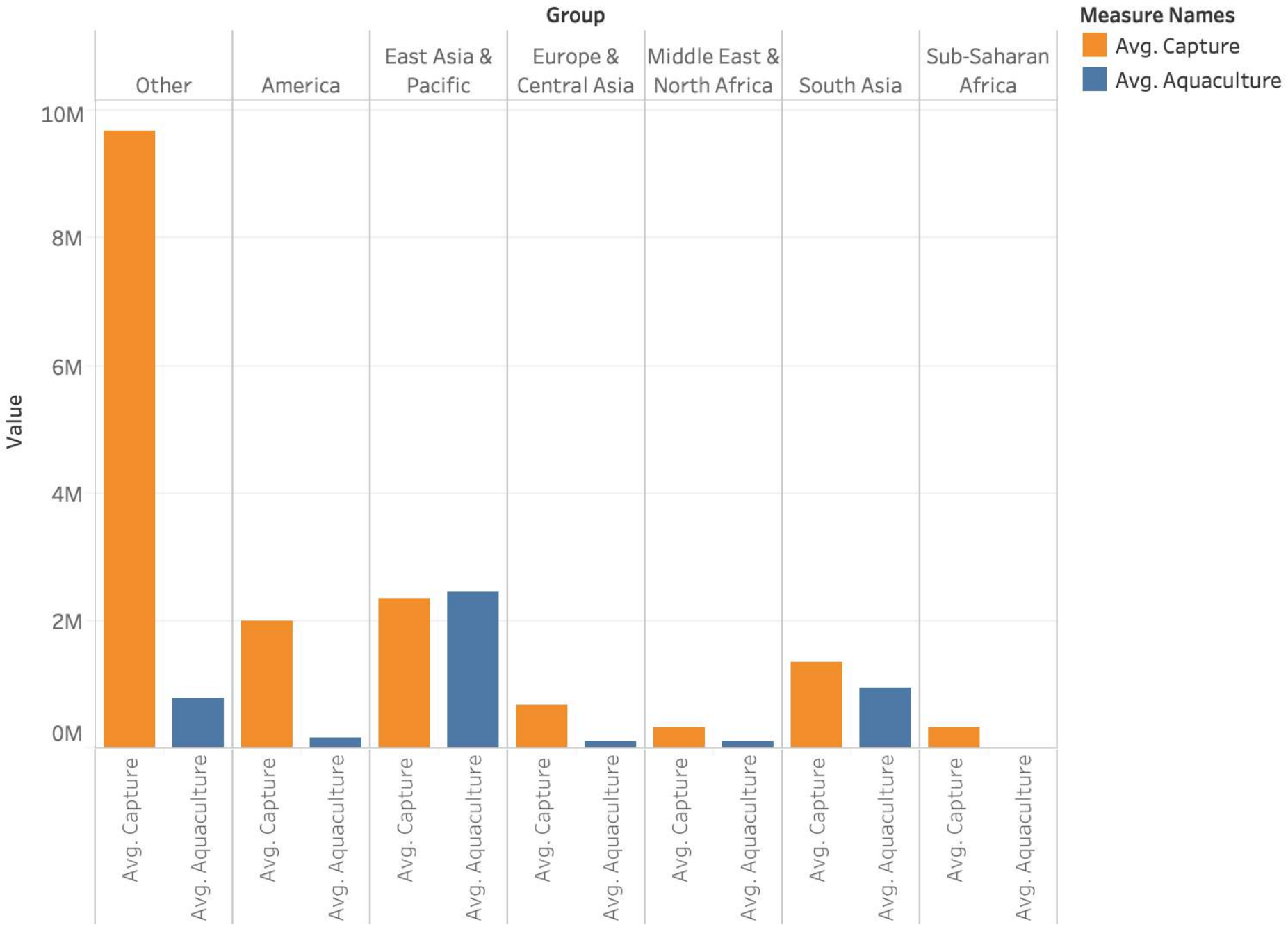
Amount
Fishing Type
Aquaculture
Capture


Group
Other
America
East Asia & Pacific
Europe & Central Asia
Middle East & North Africa
South Asia
Sub-Saharan Africa
Measure Names
Avg. Capture
Avg. Aquaculture
Value
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8M
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4M
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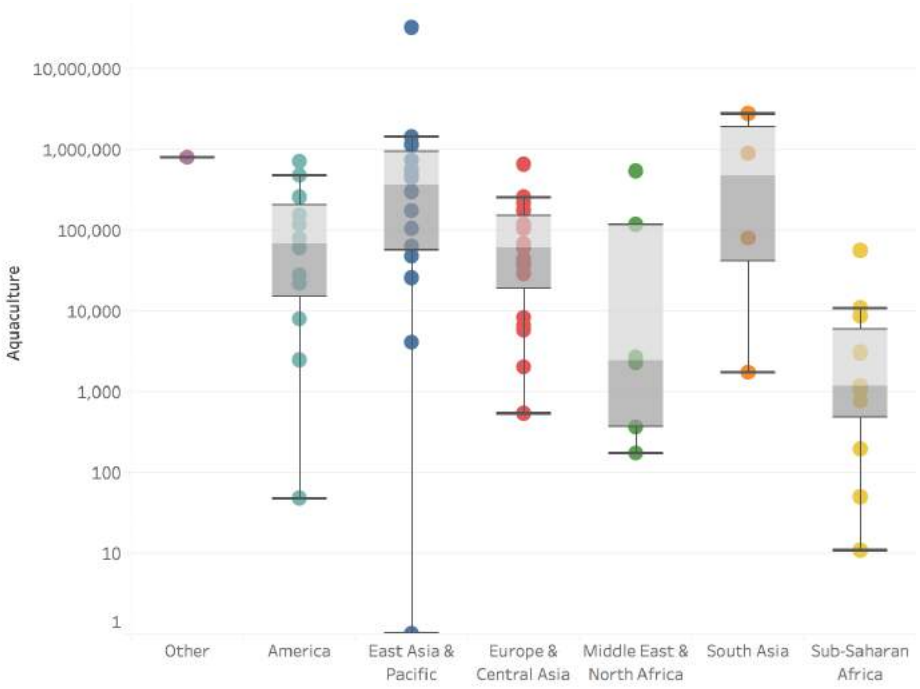
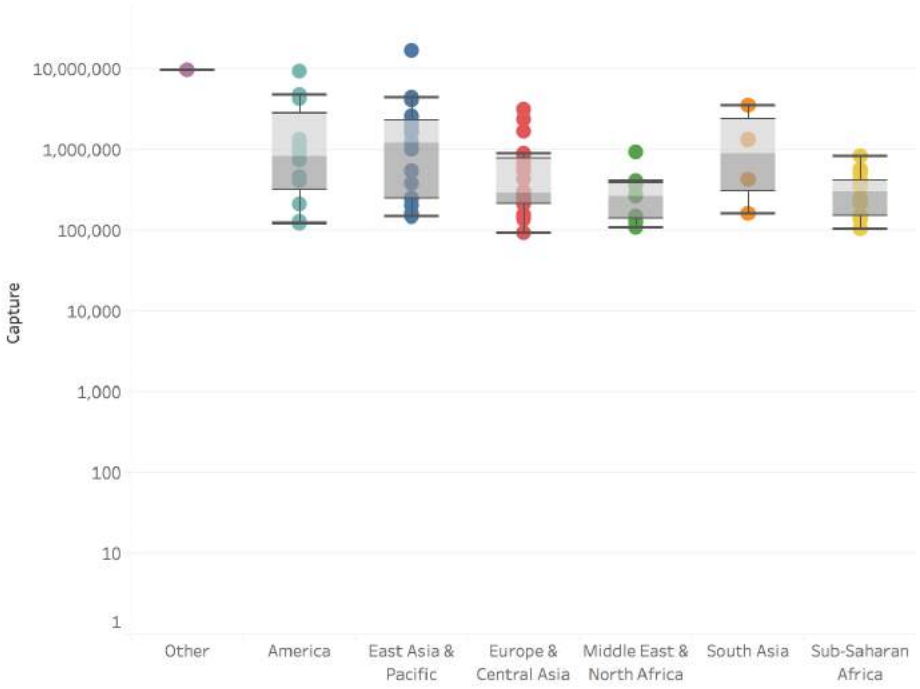
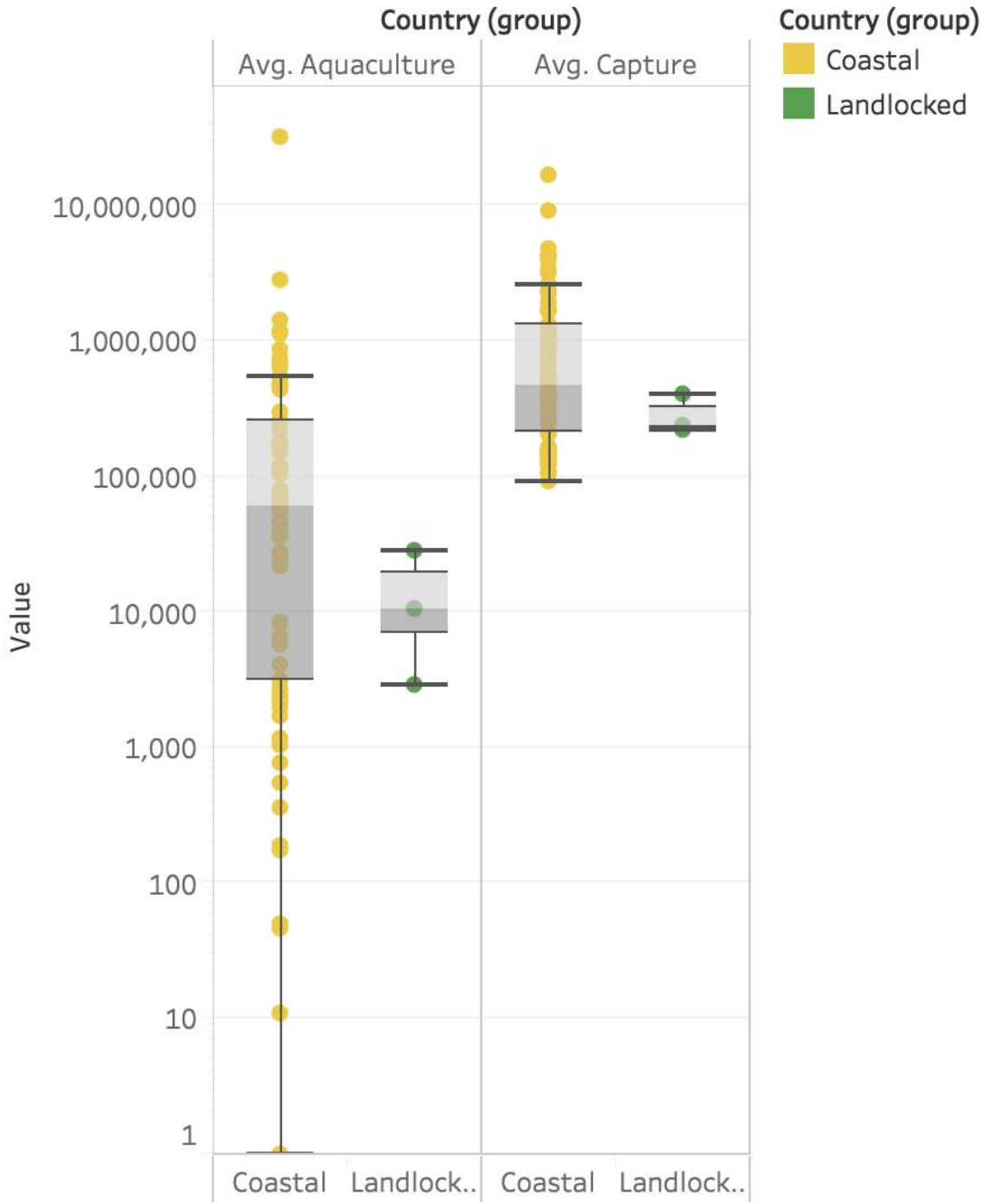
Avg. Capture
Avg. Aquaculture

## Aquaculture




## Capture




Country (group)
Country (group)
Coastal
Landlocked
Avg. Aquaculture
Avg. Capture
Value
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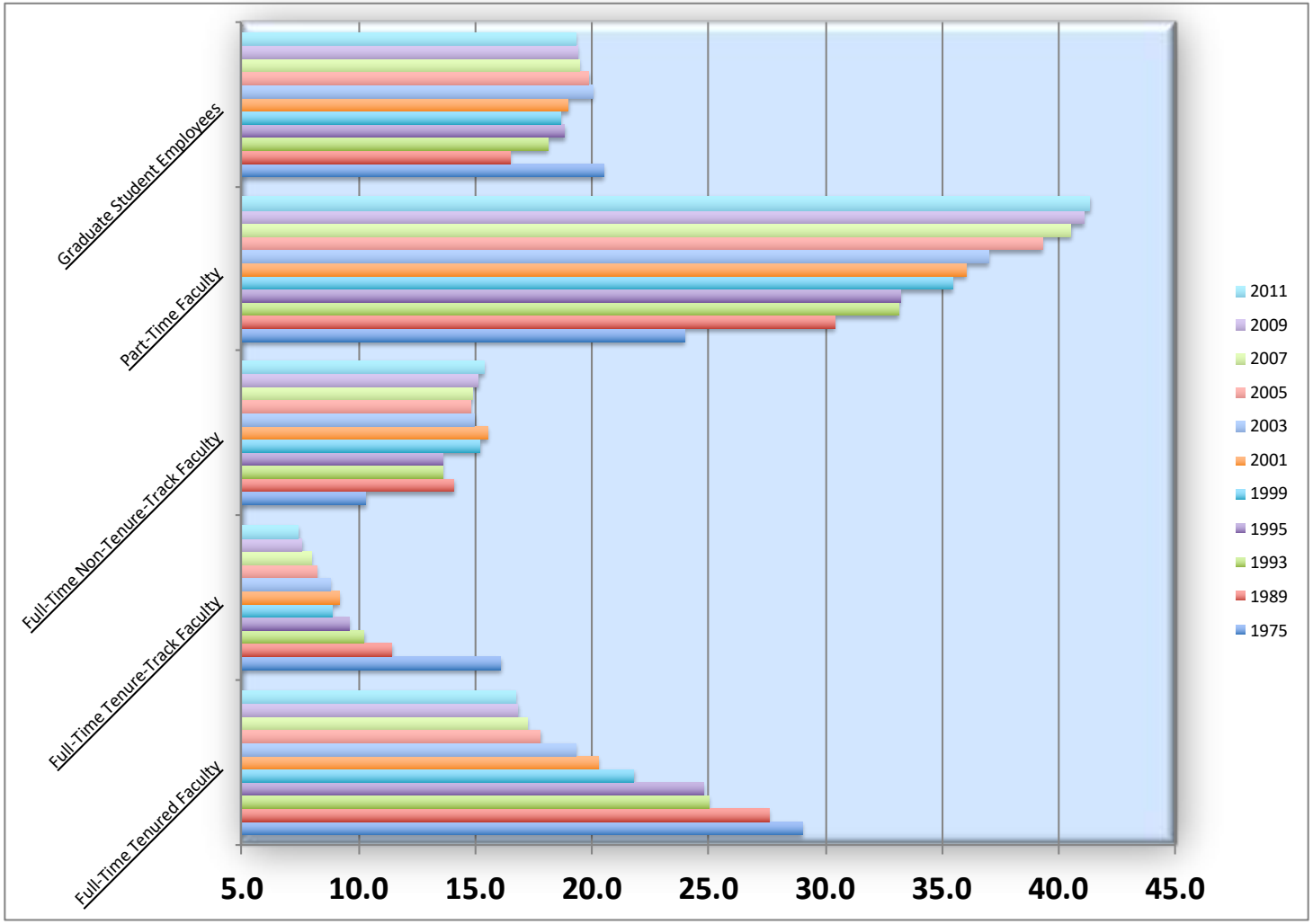
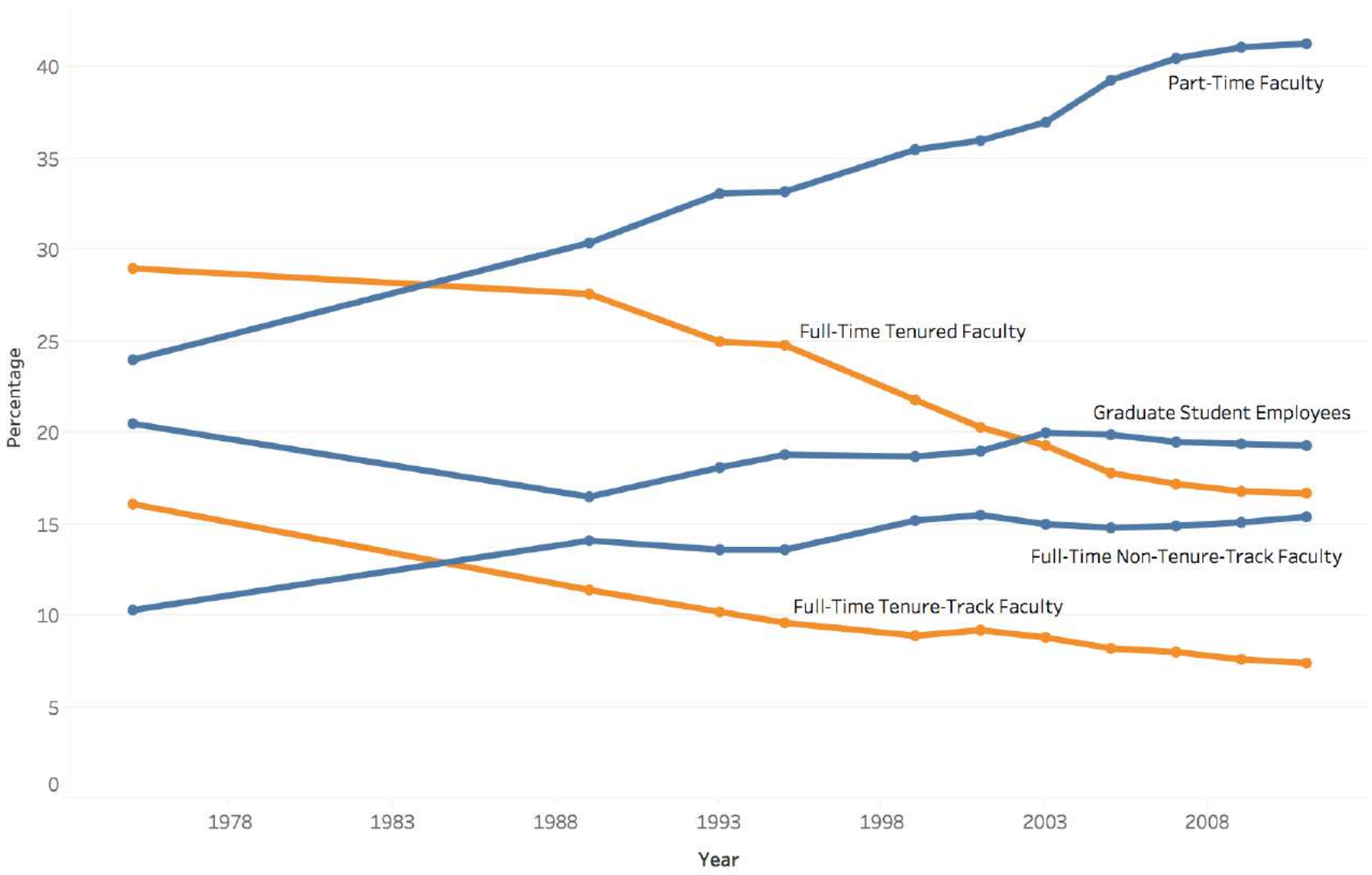
Coastal
Landlock..
Coastal
Landlock..

Size: Total fishing – Color: Fraction capture

# Instructional staff trends




Percentage
40
35
30
25
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15
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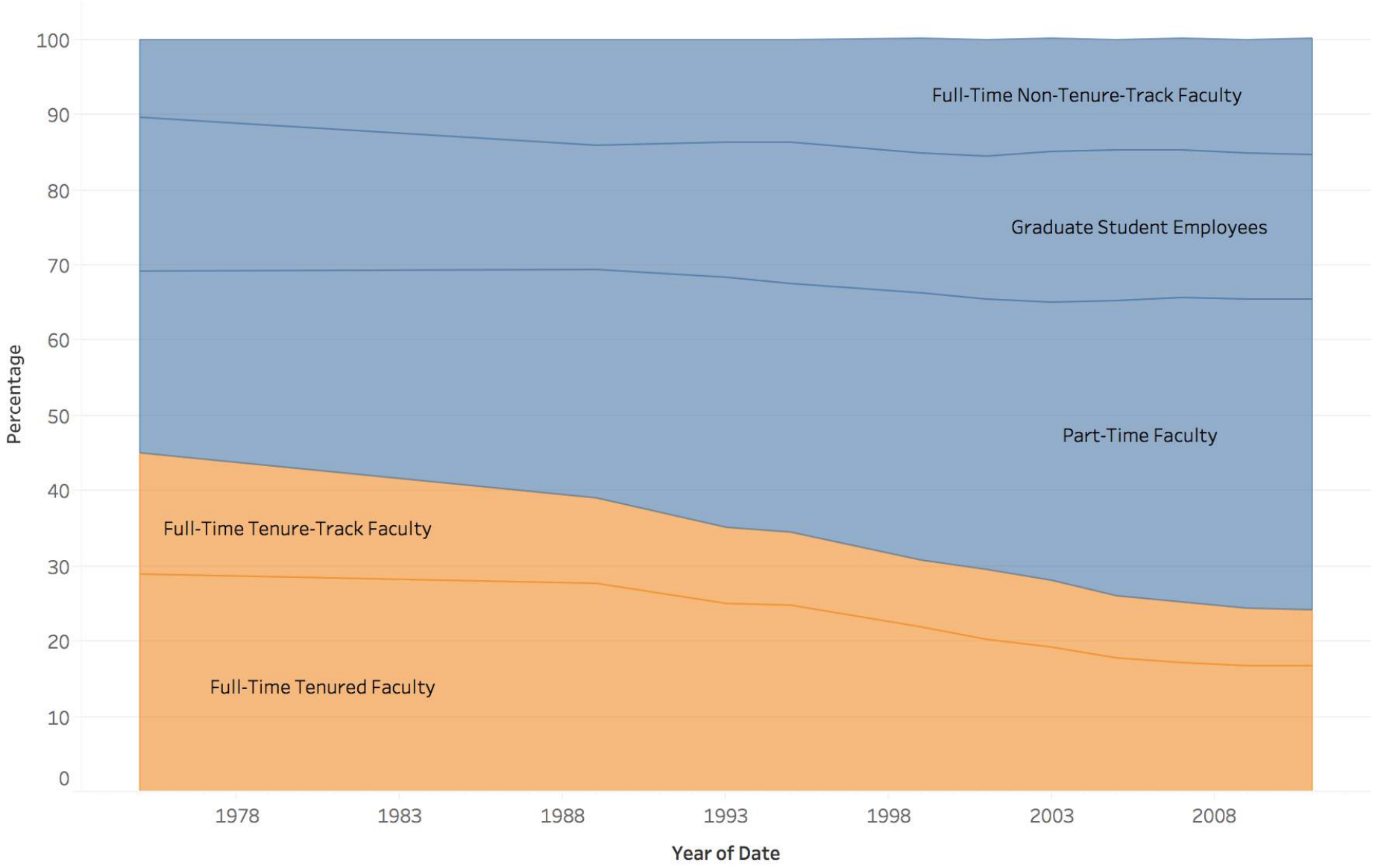
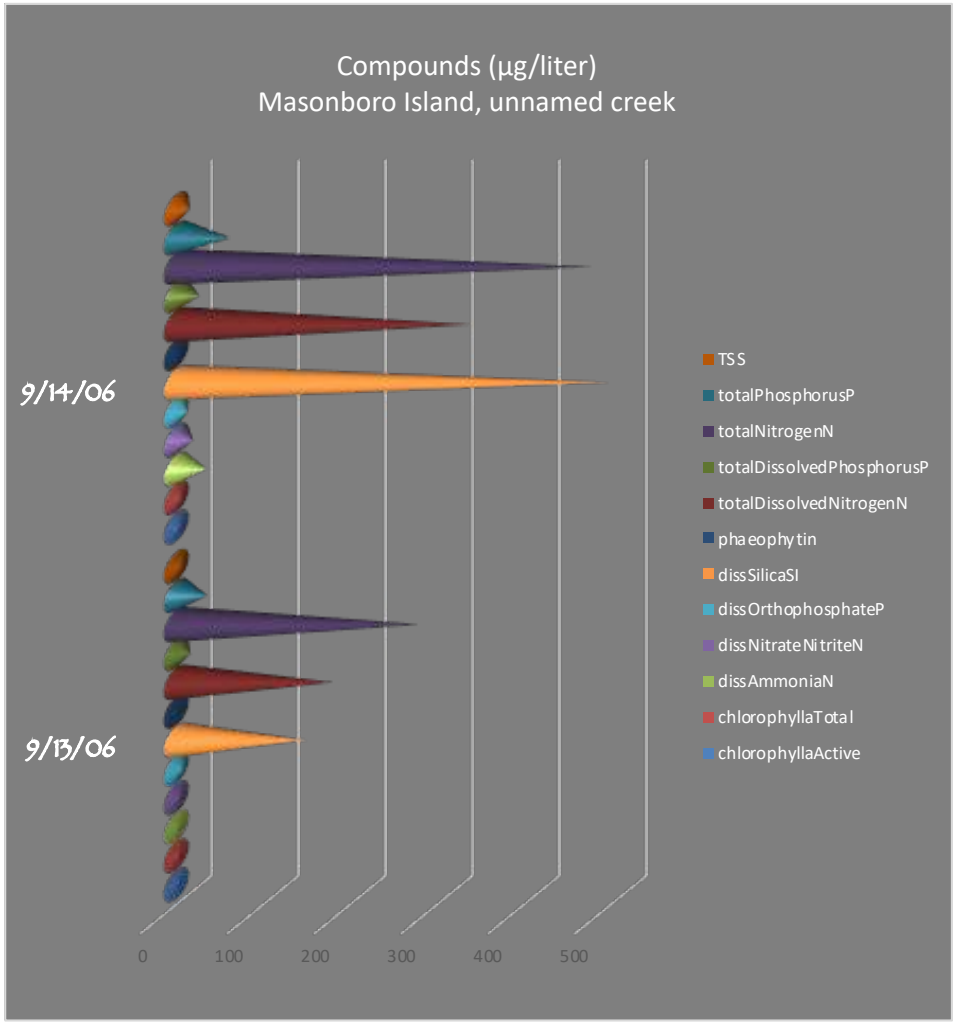
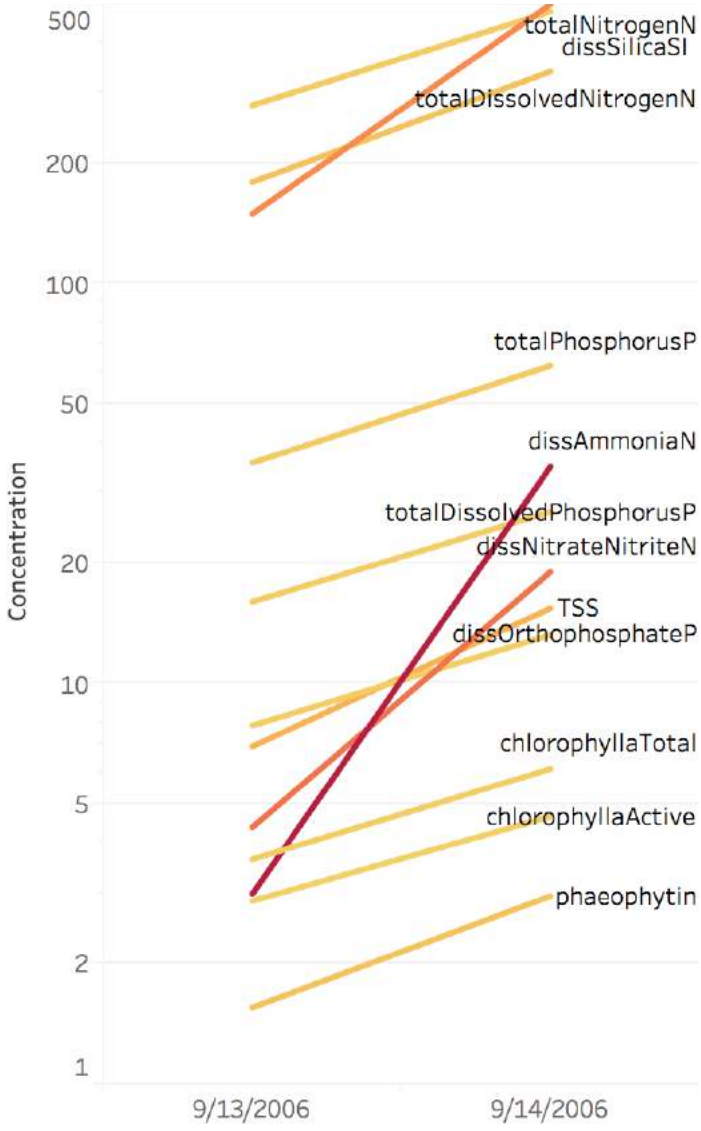
1978
1983
1988
1993
1998
2003
2008
Year
Part-Time Faculty
Full-Time Tenured Faculty
Graduate Student Employees
Full-Time Non-Tenure-Track Faculty
Full-Time Tenure-Track Faculty


Full-Time Non-Tenure-Track Faculty
Graduate Student Employees
Part-Time Faculty
Full-Time Tenure-Track Faculty
Full-Time Tenured Faculty
Percentage
100
90
80
70
60
50
40
30
20
10
0
1978
1983
1988
1993
1998
2003
2008
Year of Date

# NERRS nutrients

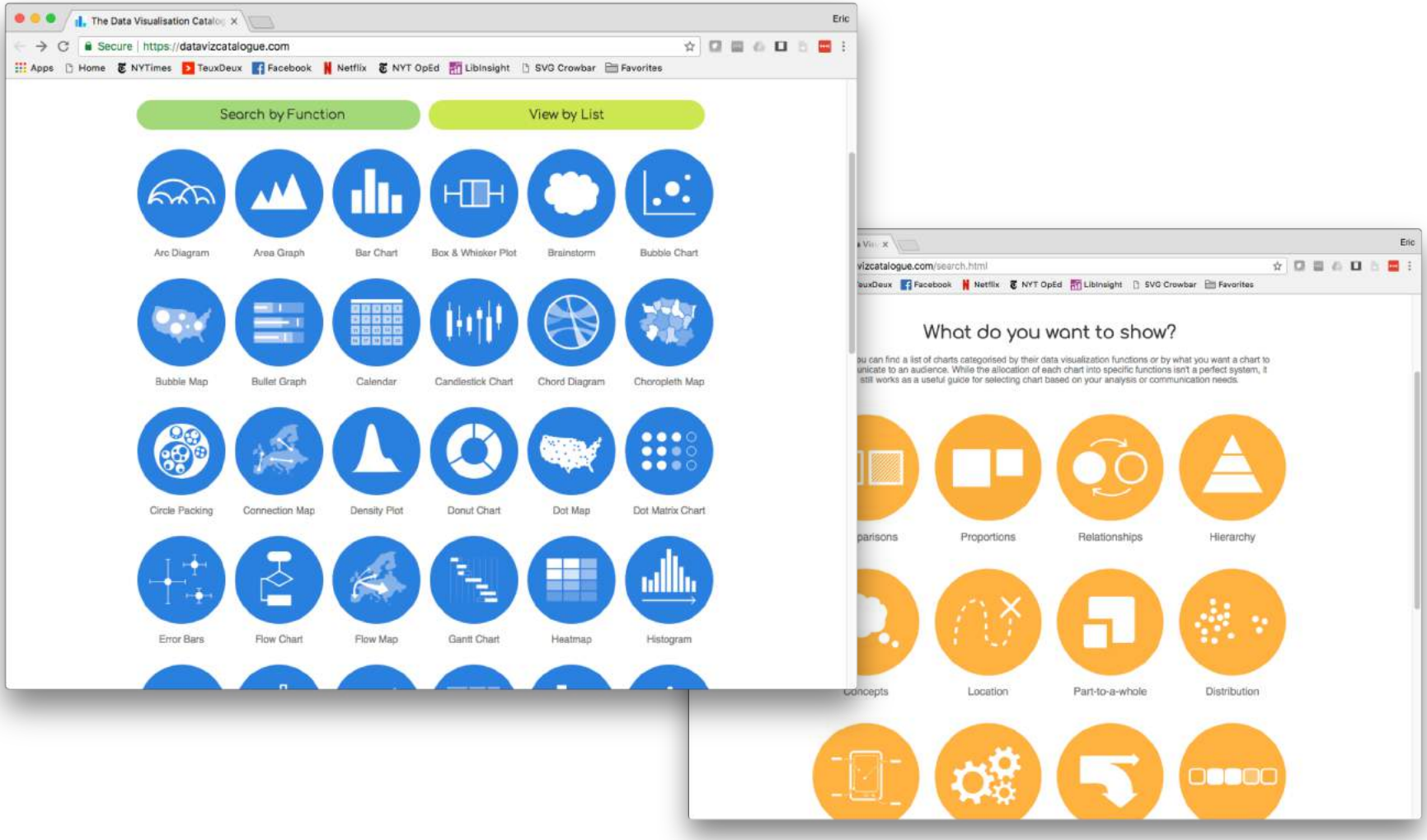



500
200
100
50
20
10
5
2
1
Concentration
totalNitrogenN
dissSilicaSI
totalDissolvedNitrogenN
totalPhosphorusP
dissAmmoniaN
totalDissolvedPhosphorusP
dissNitrateNitriteN
TSS
dissOrthophosphateP
chlorophyllaTotal
chlorophyllaActive
phaeophytin
9/13/2006
9/14/2006

# Chart chooser helper sites

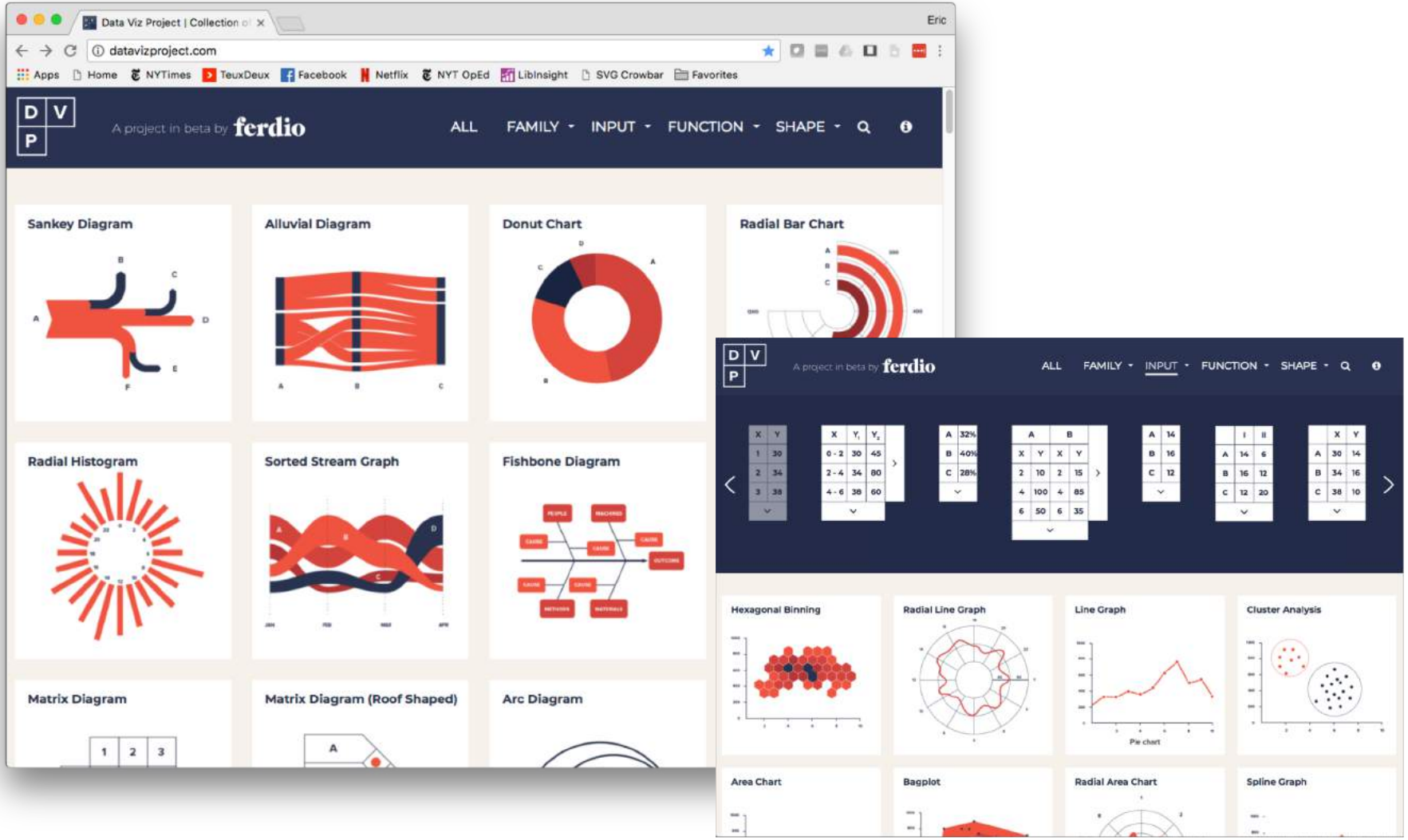
# Chart choosing helper sites

https://datavizcatalogue.com/



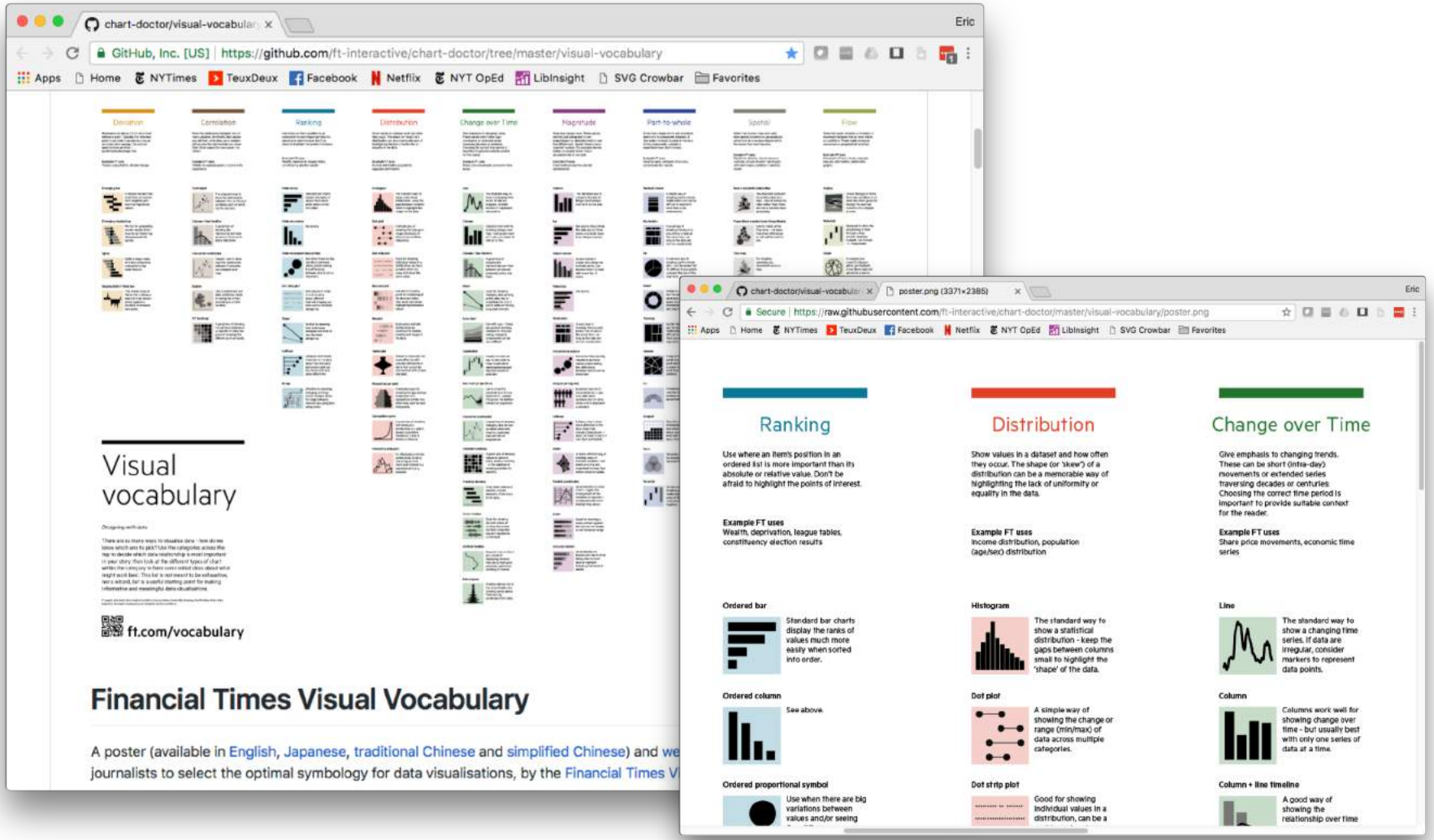
# Chart choosing helper sites

http://datavizproject.com/



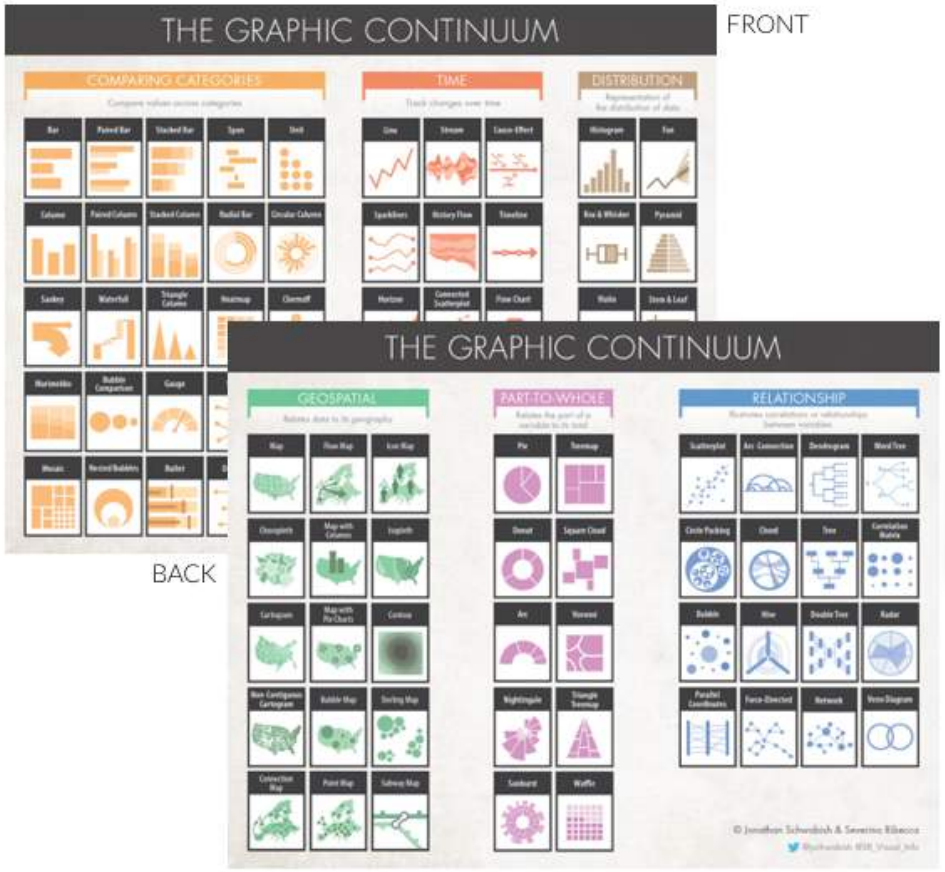
# Chart choosing helper sites

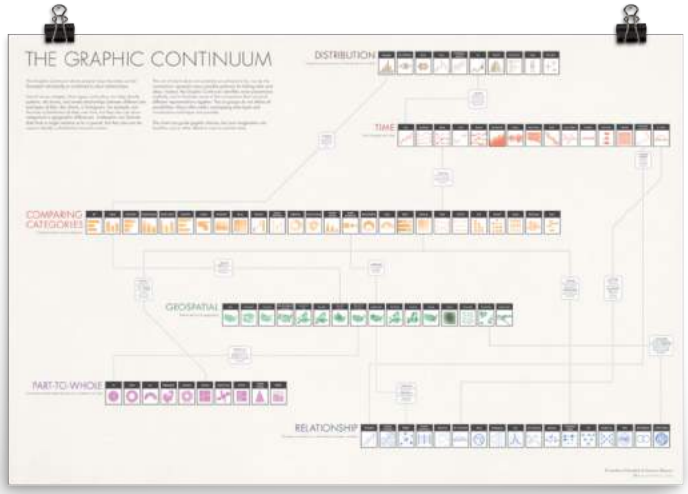
https://github.com/ft-interactive/chart-doctor/tree/master/visual-vocabulary



# Chart choosing helper sites

https://policyviz.com/shop/

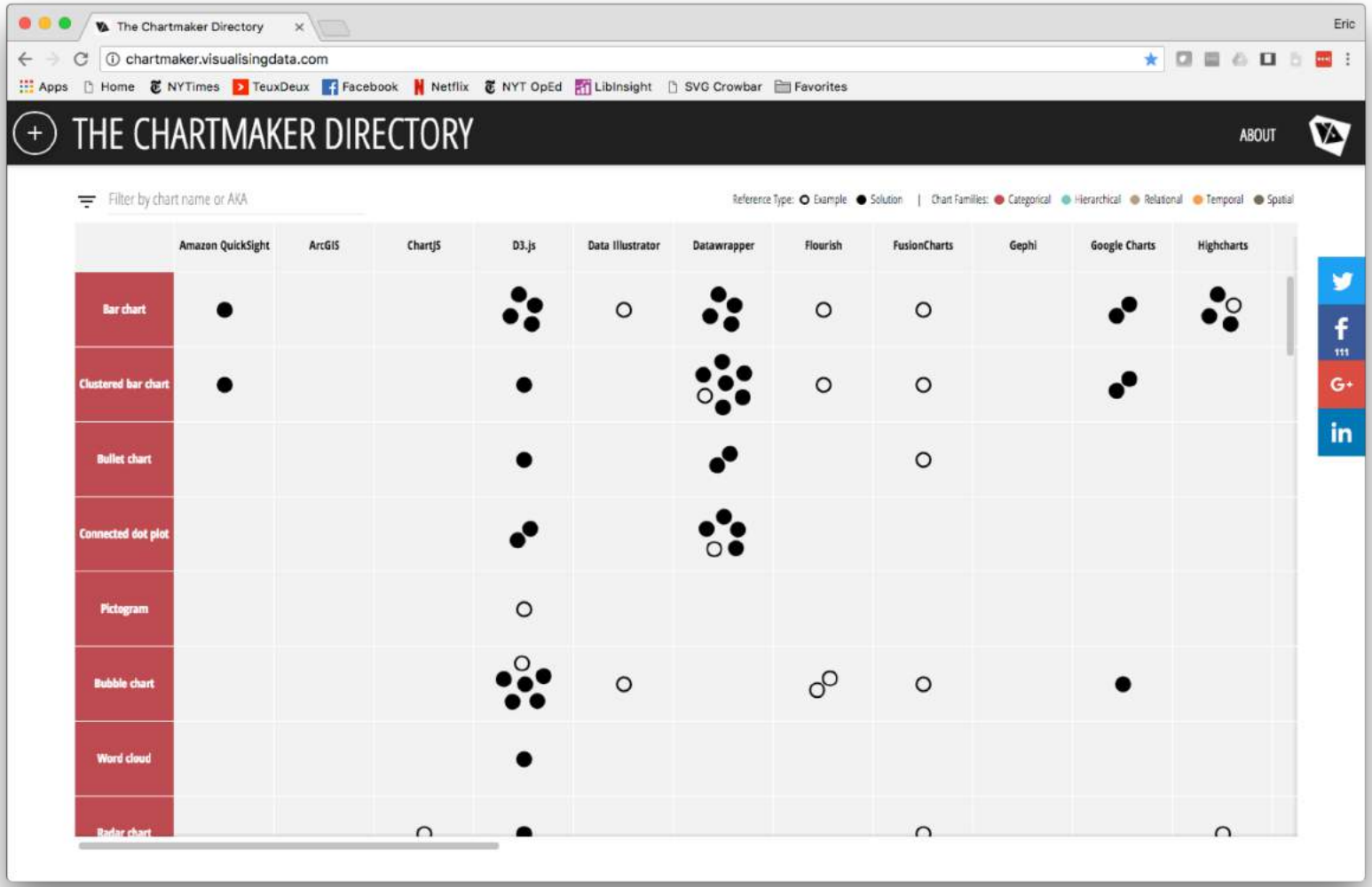




# Chart choosing helper sites

http://chartmaker.visualisingdata.com/



# Chart choosing helper sites

https://xeno.graphics/