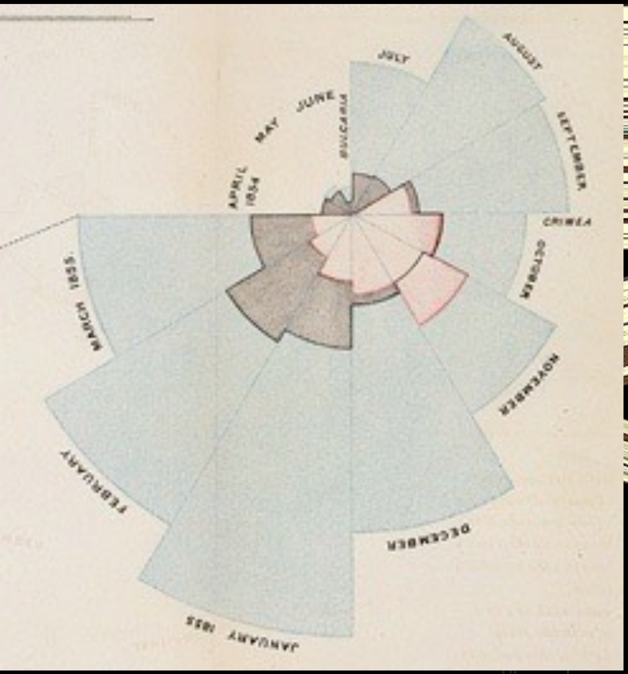
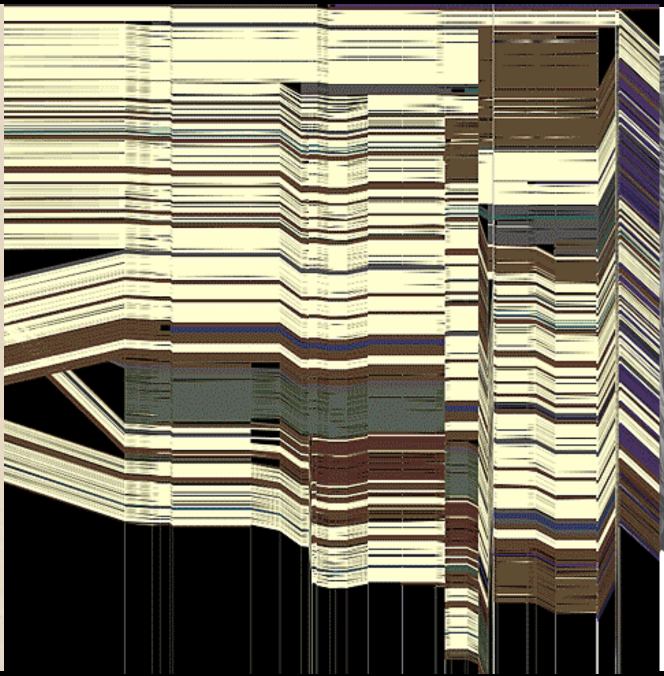
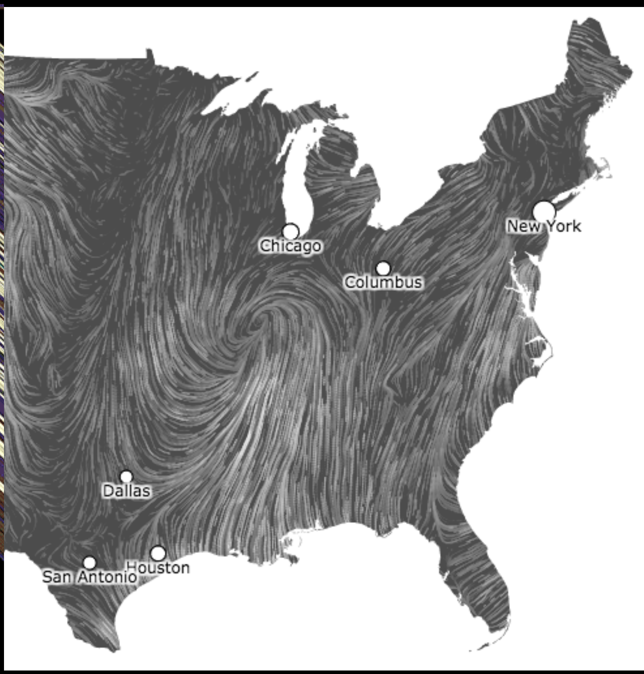
CSE 442 - Data Visualization

Visual Encoding Design







Jeffrey Heer University of Washington

A Design Space of Visual Encodings

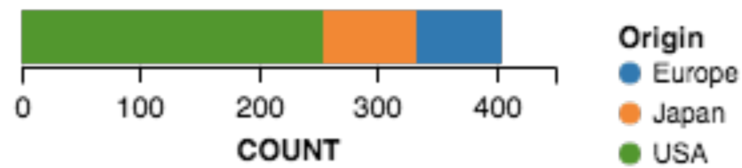
Mapping Data to Visual Variables

Assign **data fields** (e.g., with *N, O, Q* types) to **visual channels** (*x, y, color, shape, size, …*) for a chosen **graphical mark** type (*point, bar, line, …*).

Additional concerns include choosing appropriate **encoding parameters** (*log scale, sorting, …*) and **data transformations** (*bin*, *group, aggregate, …*).

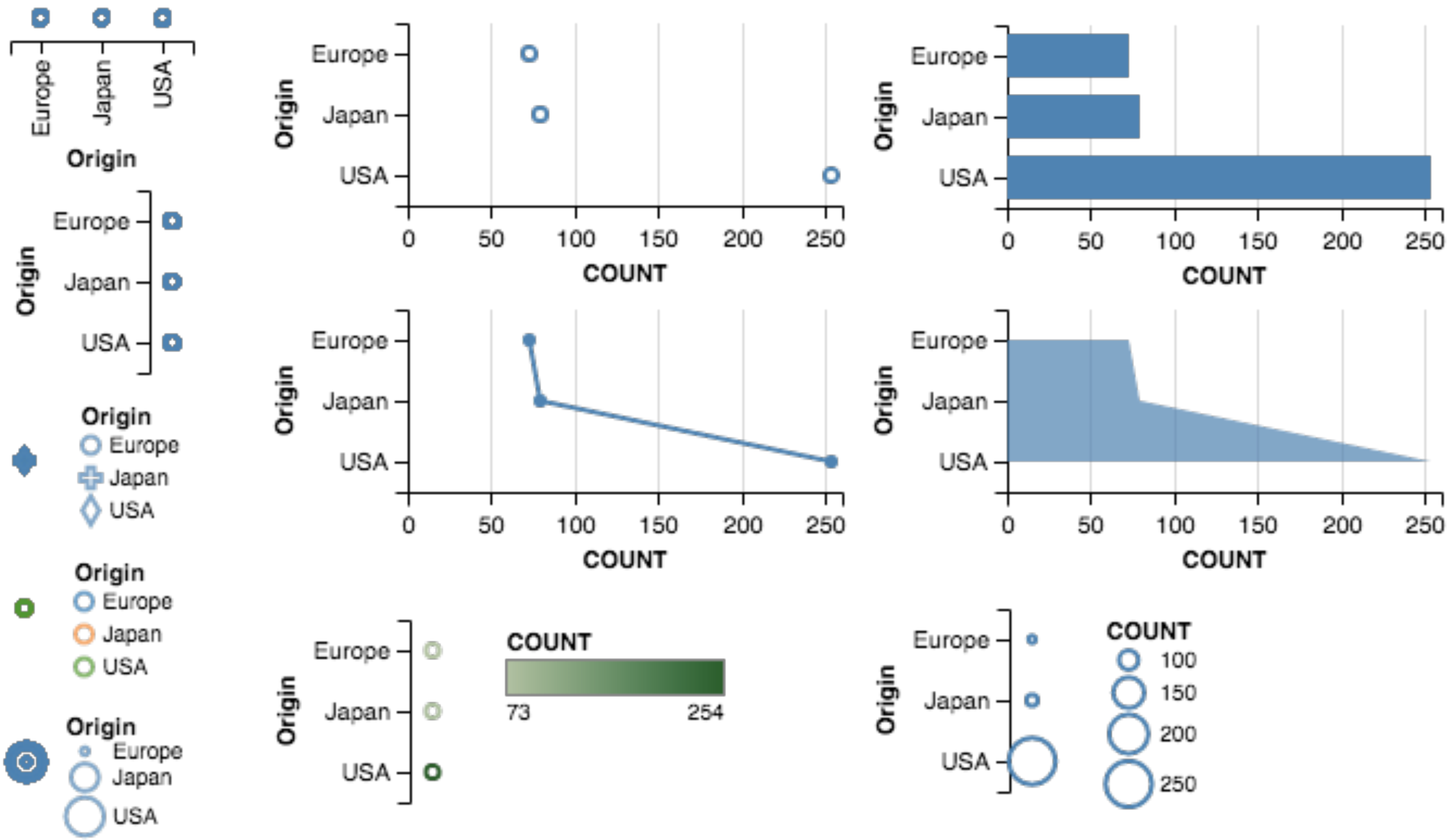
These options define a large combinatorial space, containing both useful and questionable charts!

1D: Nominal

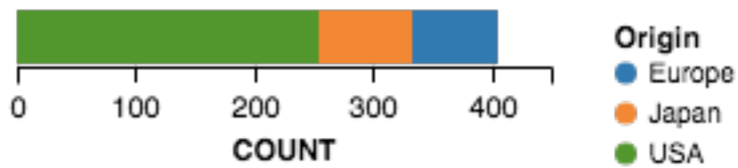


Raw

Aggregate (Count)

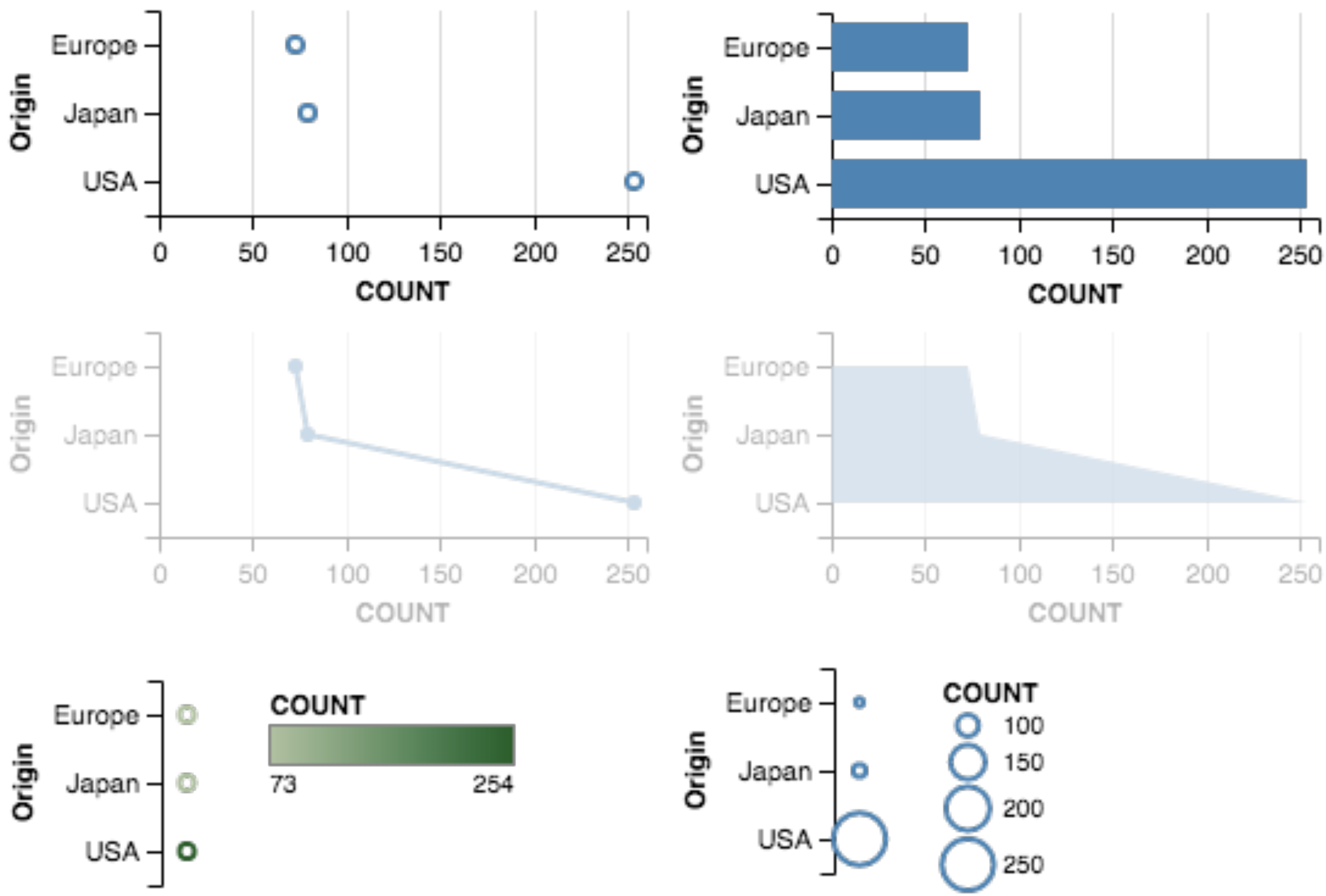


Expressive?



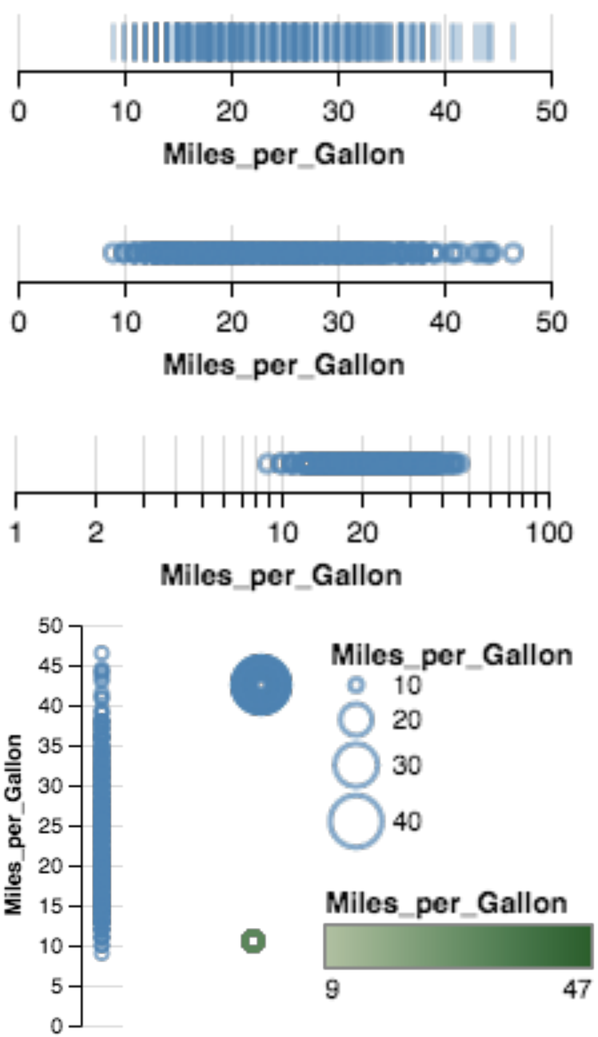
Raw

Aggregate (Count)

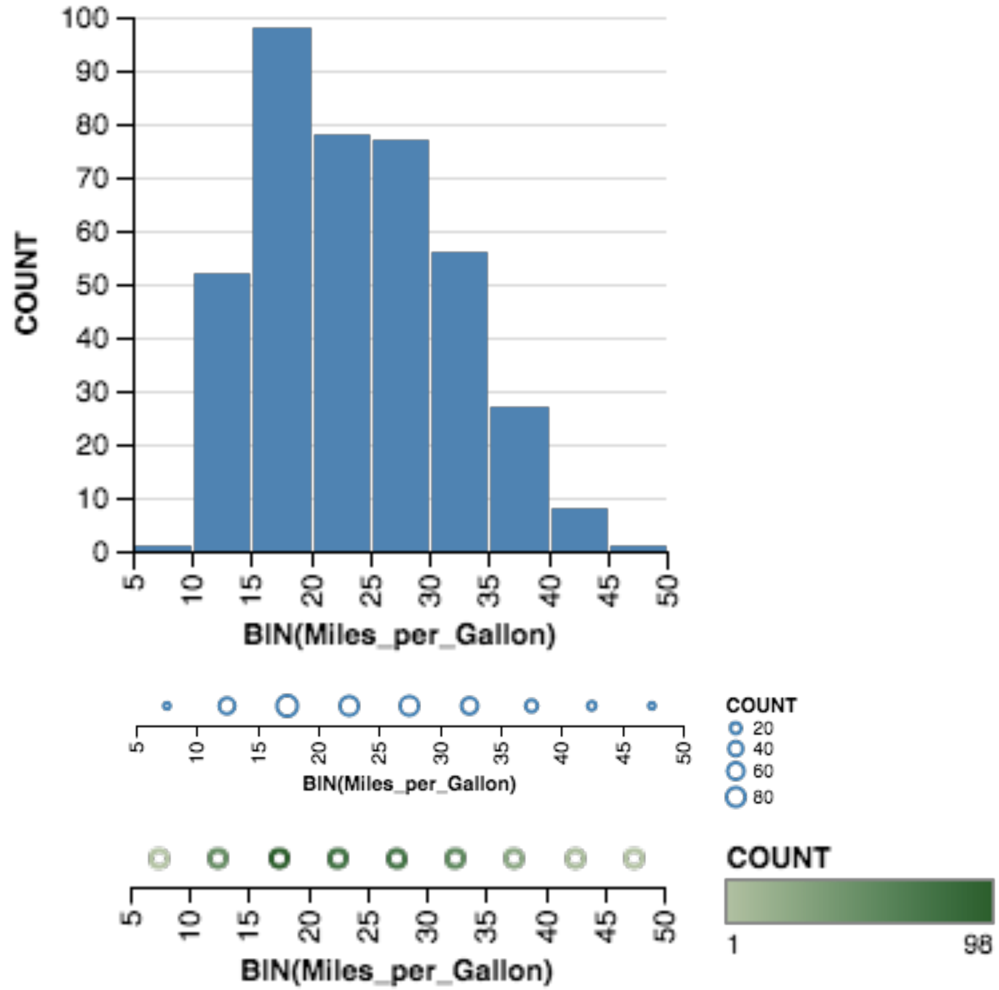


1D: Quantitative

Raw

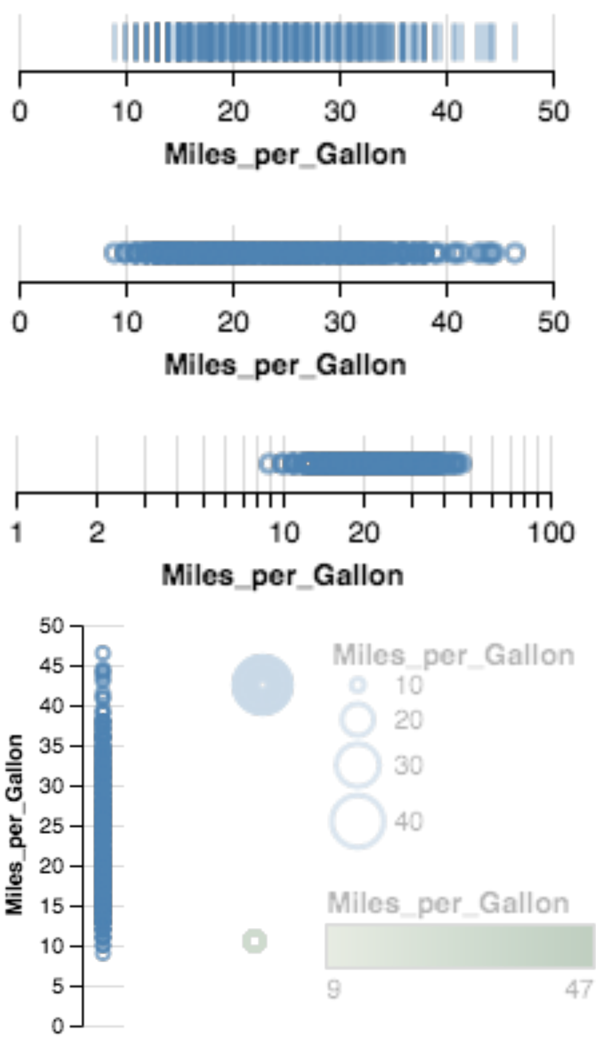


Aggregate (Count)

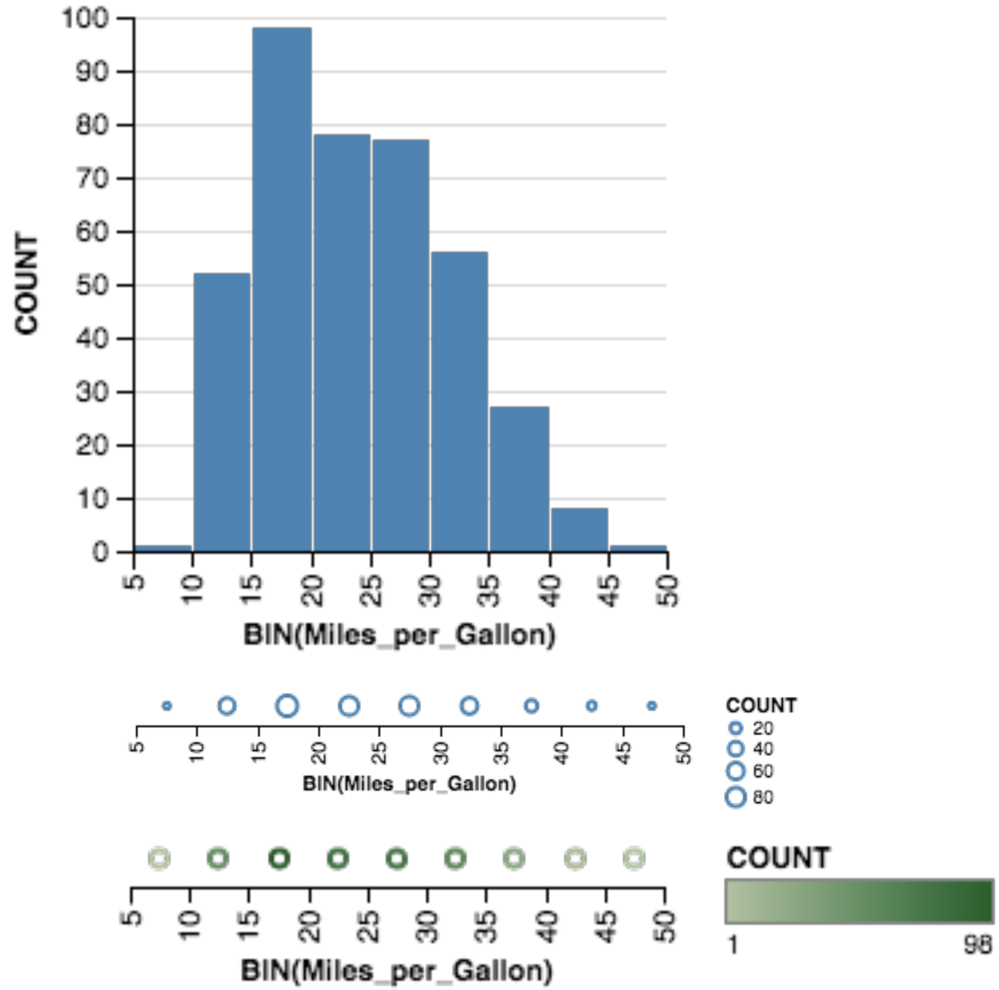


Expressive?

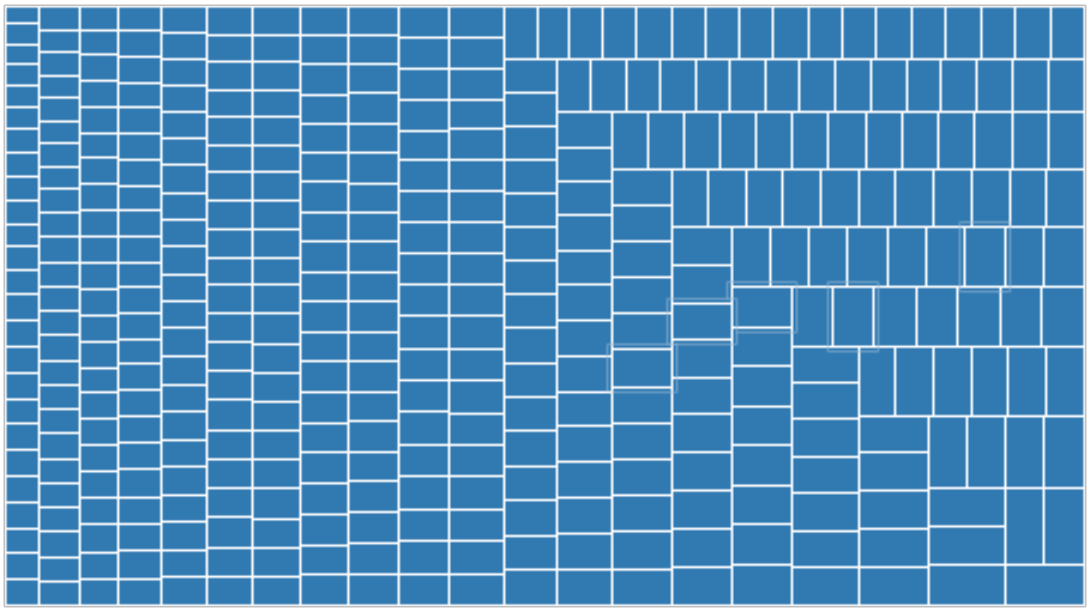
Raw



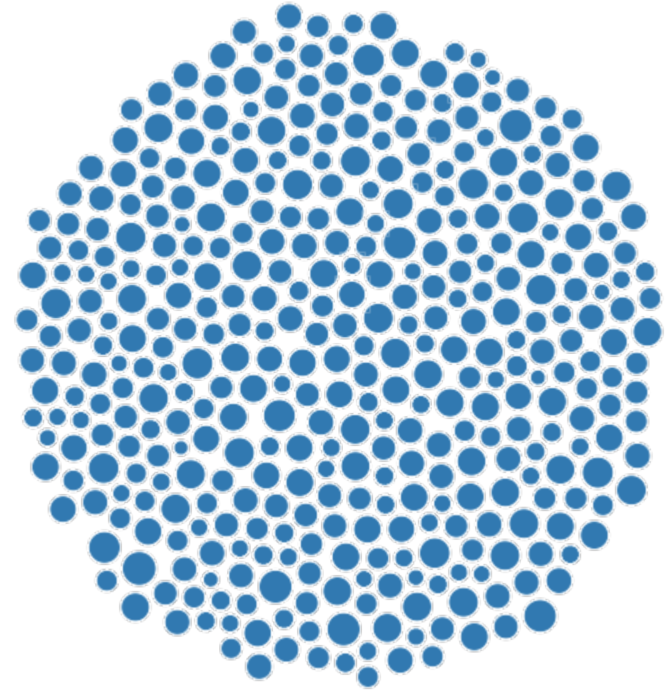
Aggregate (Count)



Raw (with Layout Algorithm)

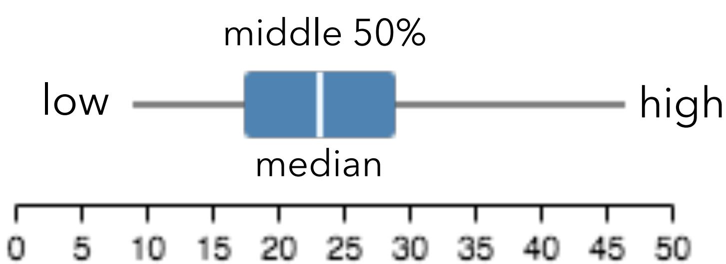


Treemap

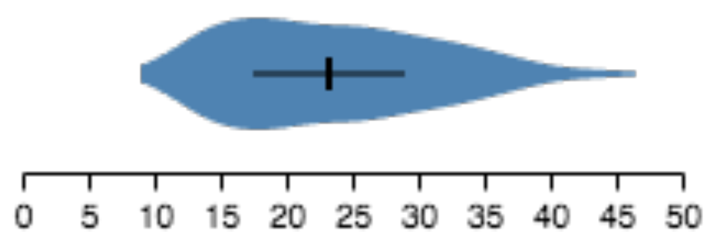


Bubble Chart

Aggregate (Distributions)



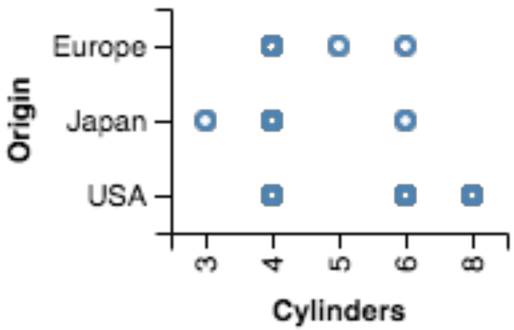
Box Plot

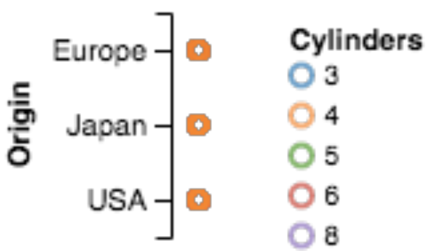


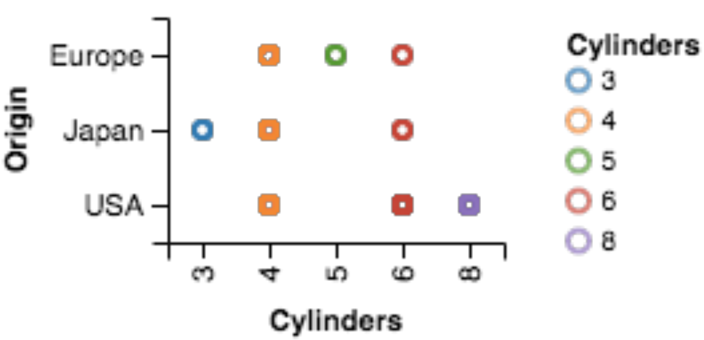
Violin Plot

2D: Nominal x Nominal

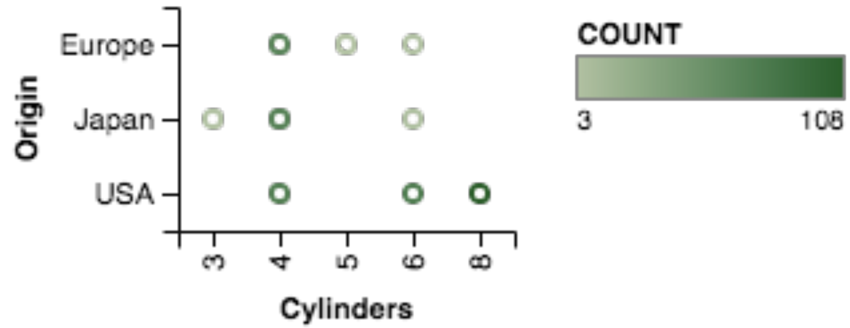
Raw

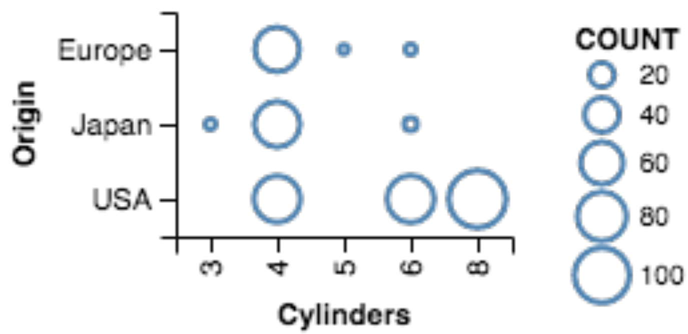


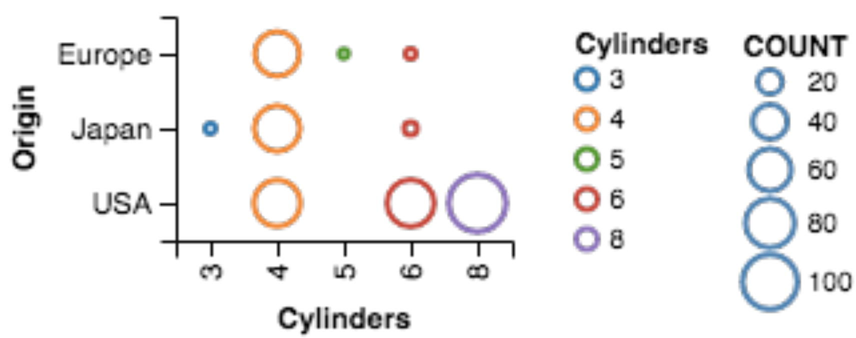




Aggregate (Count)

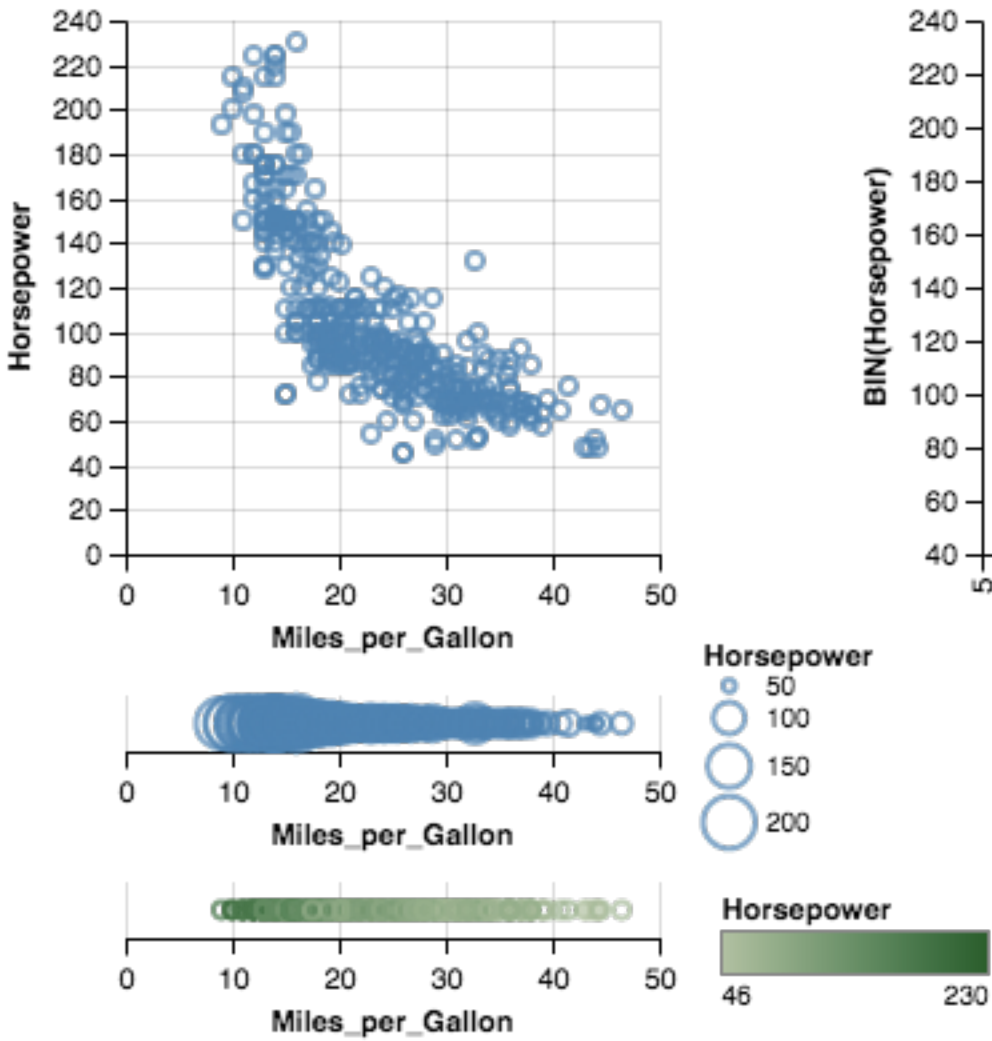




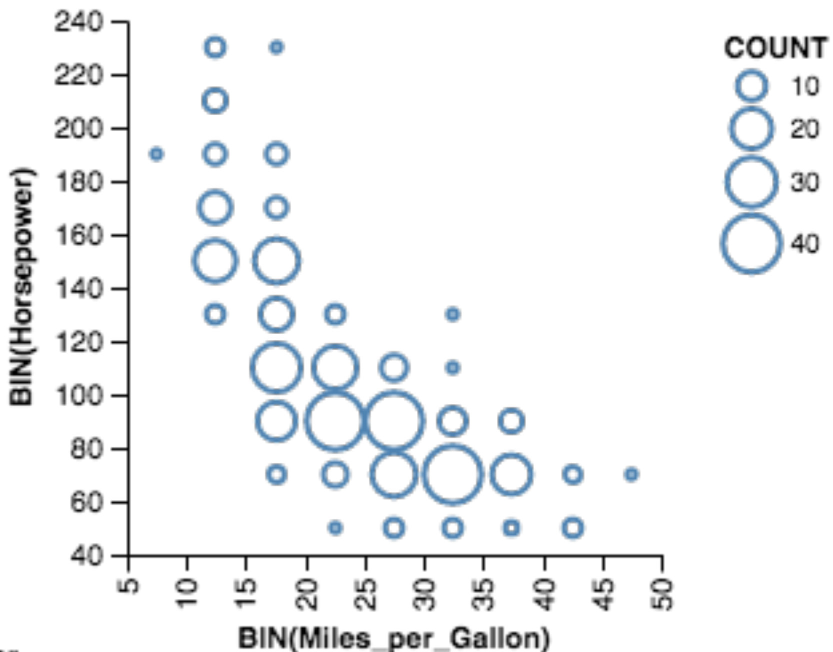


2D: Quantitative x Quantitative

Raw

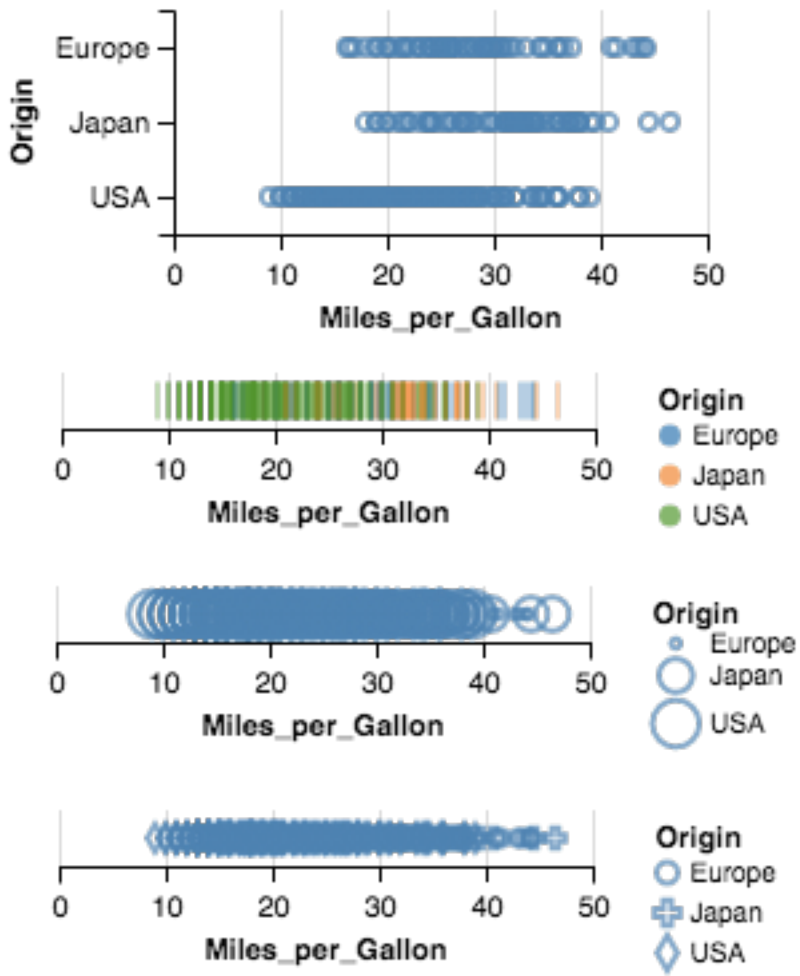


Aggregate (Count)

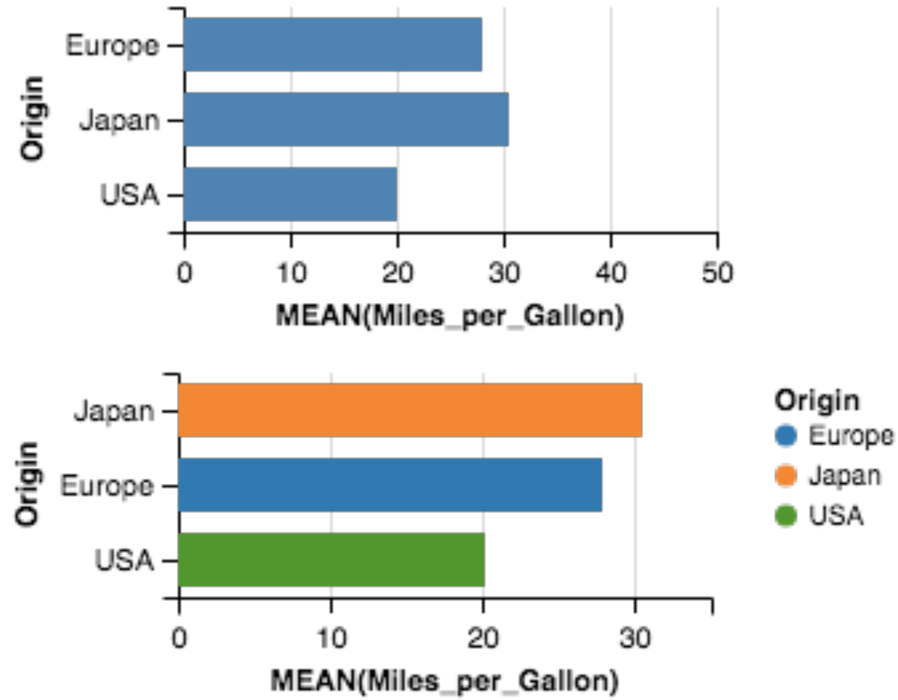


2D: Nominal x Quantitative

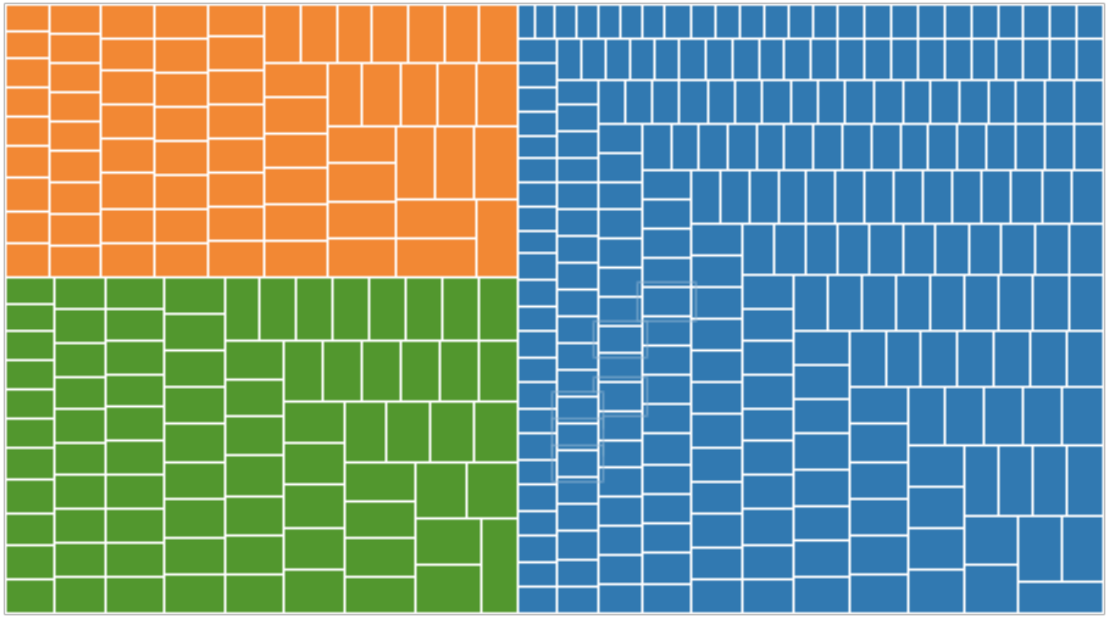
Raw



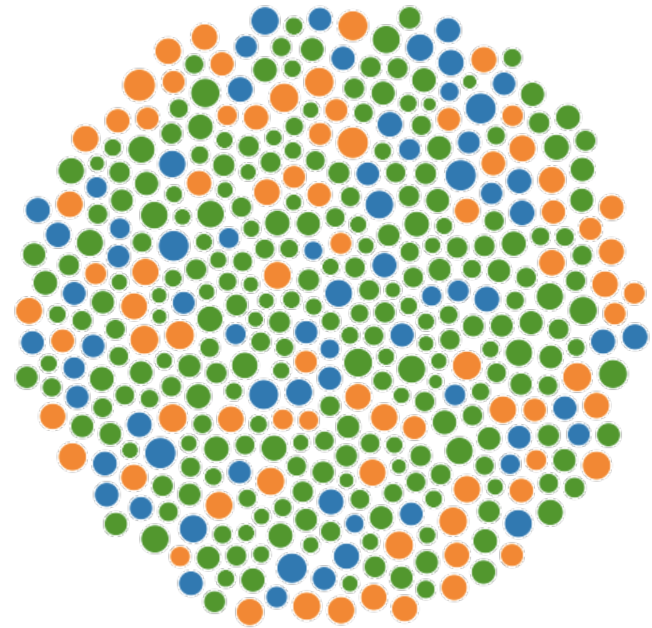
Aggregate (Mean)



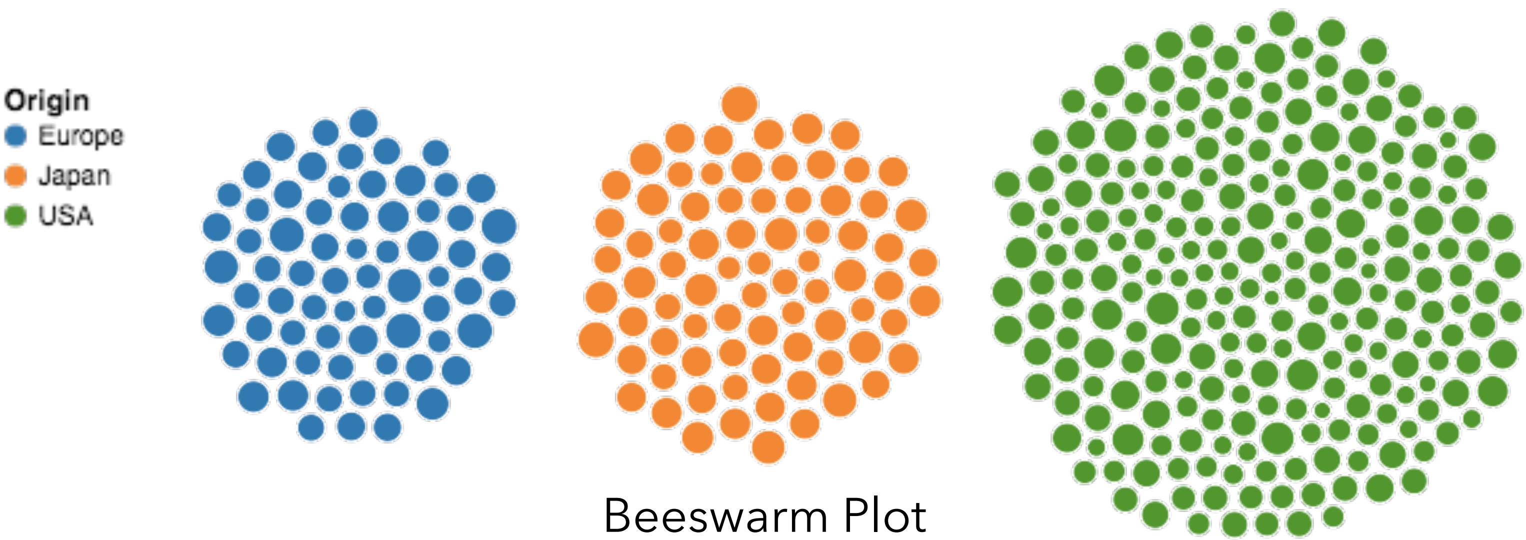
Raw (with Layout Algorithm)



Treemap



Bubble Chart



Beeswarm Plot

3D and Higher

Two variables [x,y]

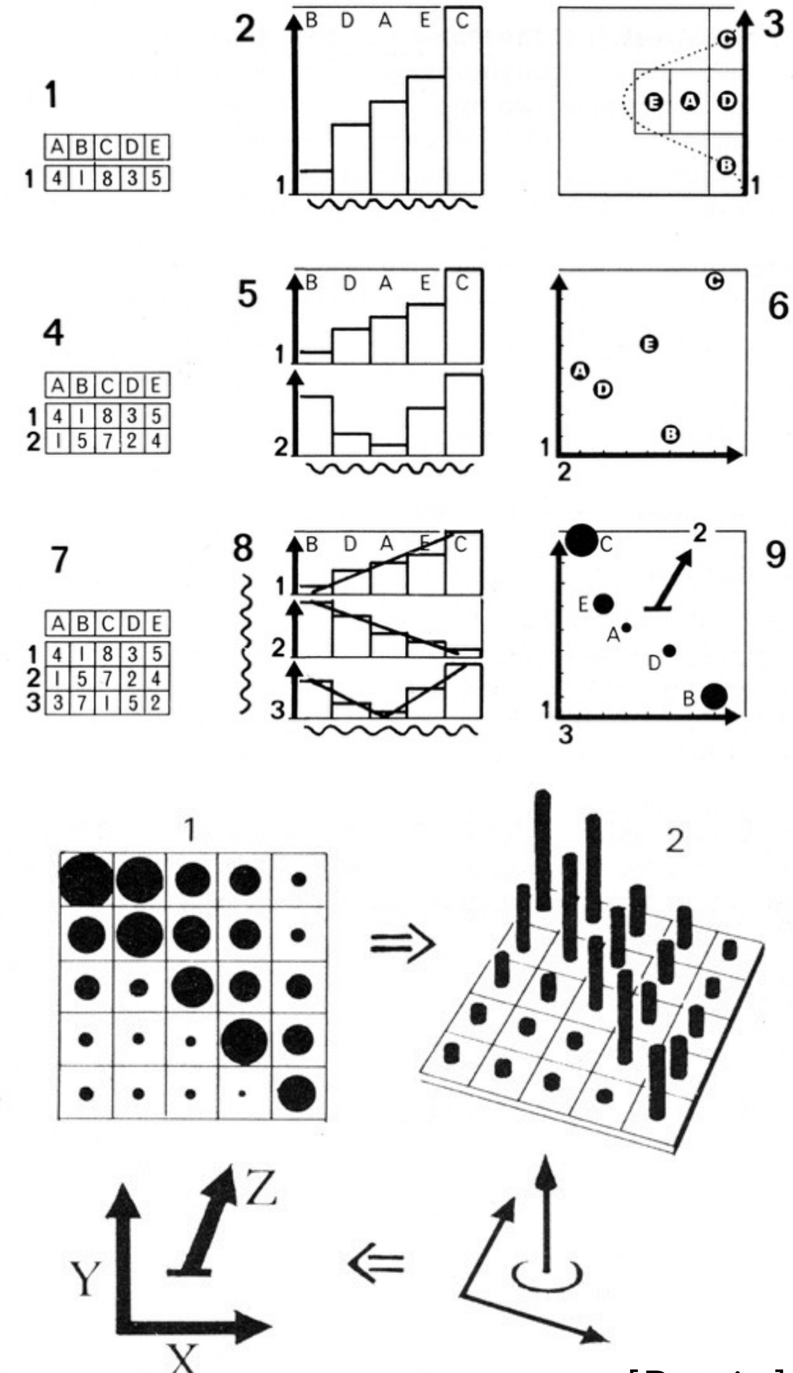
Can map to 2D points.

Scatterplots, maps, …

Third variable [z]

Often use one of size, color, opacity, shape, *etc*. Or, one can further partition space.

What about 3D rendering?



[Bertin]

Other Visual Encoding Channels?

Encoding Effectiveness

Effectiveness Rankings [Mackinlay 86]

QUANTITATIVE	ORDINAL	NOMINAL
Position	Position	Position
Length	Density (Value)	Color Hue
Angle	Color Sat	Texture
Slope	Color Hue	Connection
Area (Size)	Texture	Containment
Volume	Connection	Density (Value)
Density (Value)	Containment	Color Sat
Color Sat	Length	Shape
Color Hue	Angle	Length
Texture	Slope	Angle
Connection	Area (Size)	Slope
Containment	Volume	Area
Shape	Shape	Volume

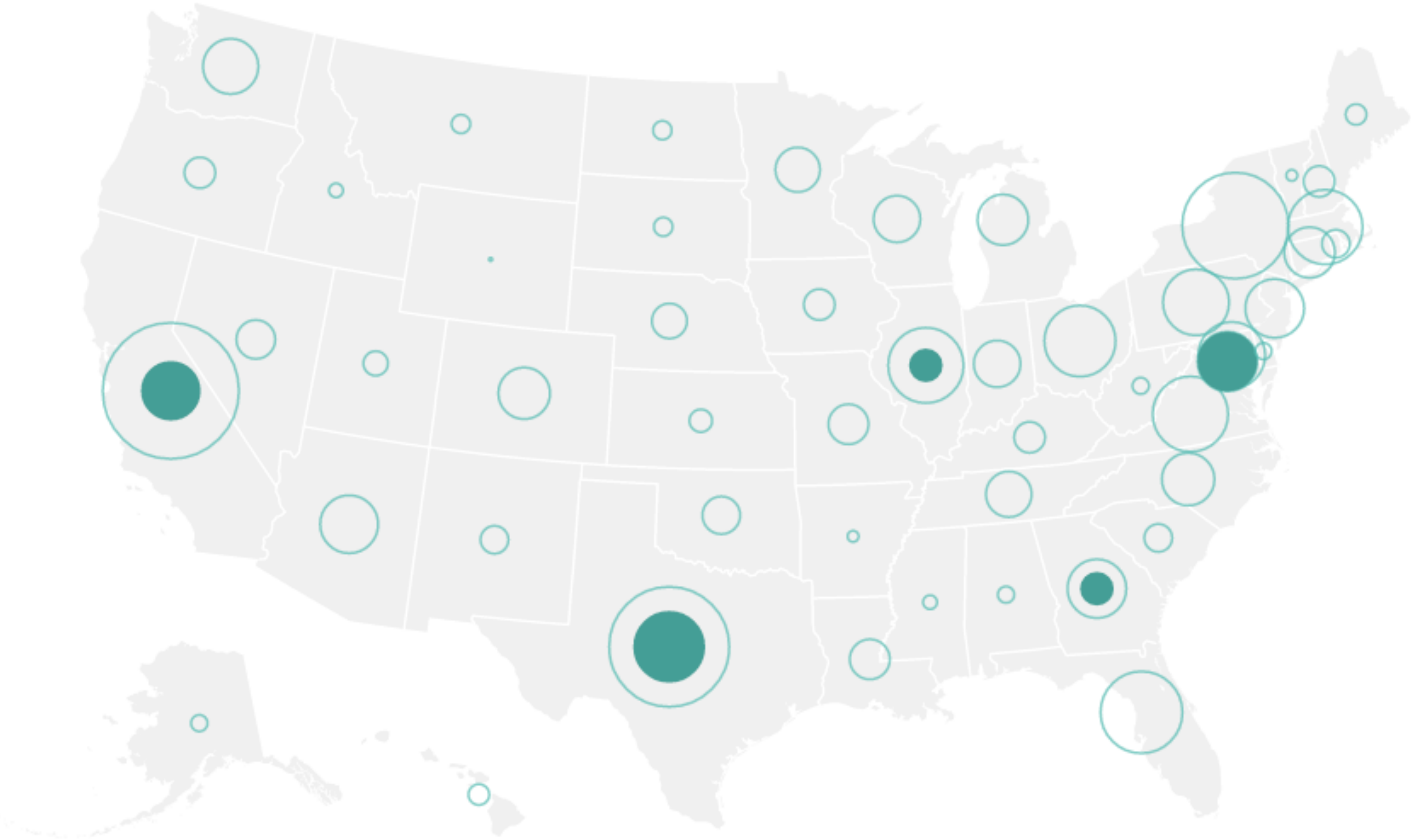
Effectiveness Rankings [Mackinlay 86]

QUANTITATIVE	ORDINAL	NOMINAL
Position	**Position**	**Position**
Length	Density (Value)	Color Hue
Angle	Color Sat	Texture
Slope	Color Hue	Connection
Area (Size)	Texture	Containment
Volume	Connection	Density (Value)
Density (Value)	Containment	Color Sat
Color Sat	Length	Shape
Color Hue	Angle	Length
Texture	Slope	Angle
Connection	Area (Size)	Slope
Containment	Volume	Area
Shape	Shape	Volume

Effectiveness Rankings [Mackinlay 86]

QUANTITATIVE	ORDINAL	NOMINAL
Position	Position	Position
Length	Density (Value)	**Color Hue**
Angle	Color Sat	Texture
Slope	**Color Hue**	Connection
Area (Size)	Texture	Containment
Volume	Connection	Density (Value)
Density (Value)	Containment	Color Sat
Color Sat	Length	Shape
Color Hue	Angle	Length
Texture	Slope	Angle
Connection	Area (Size)	Slope
Containment	Volume	Area
Shape	Shape	Volume

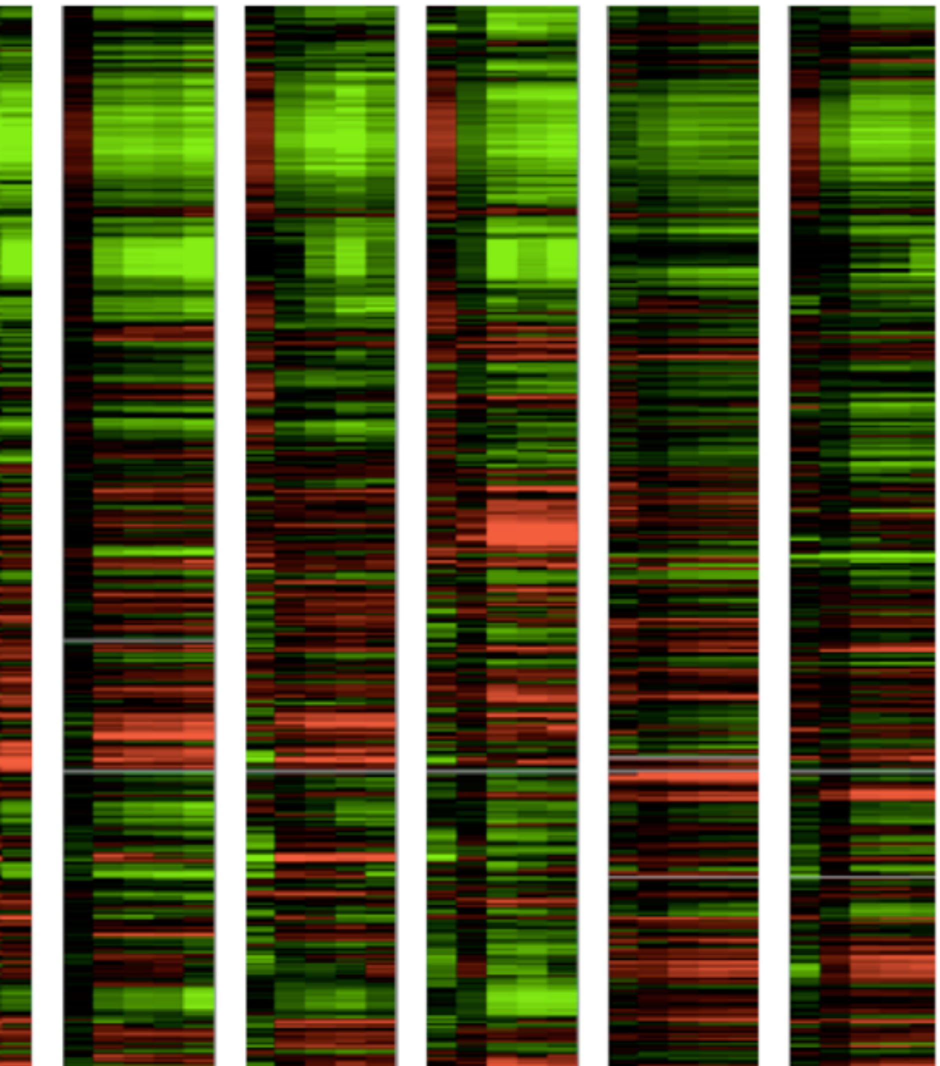
Color Encoding



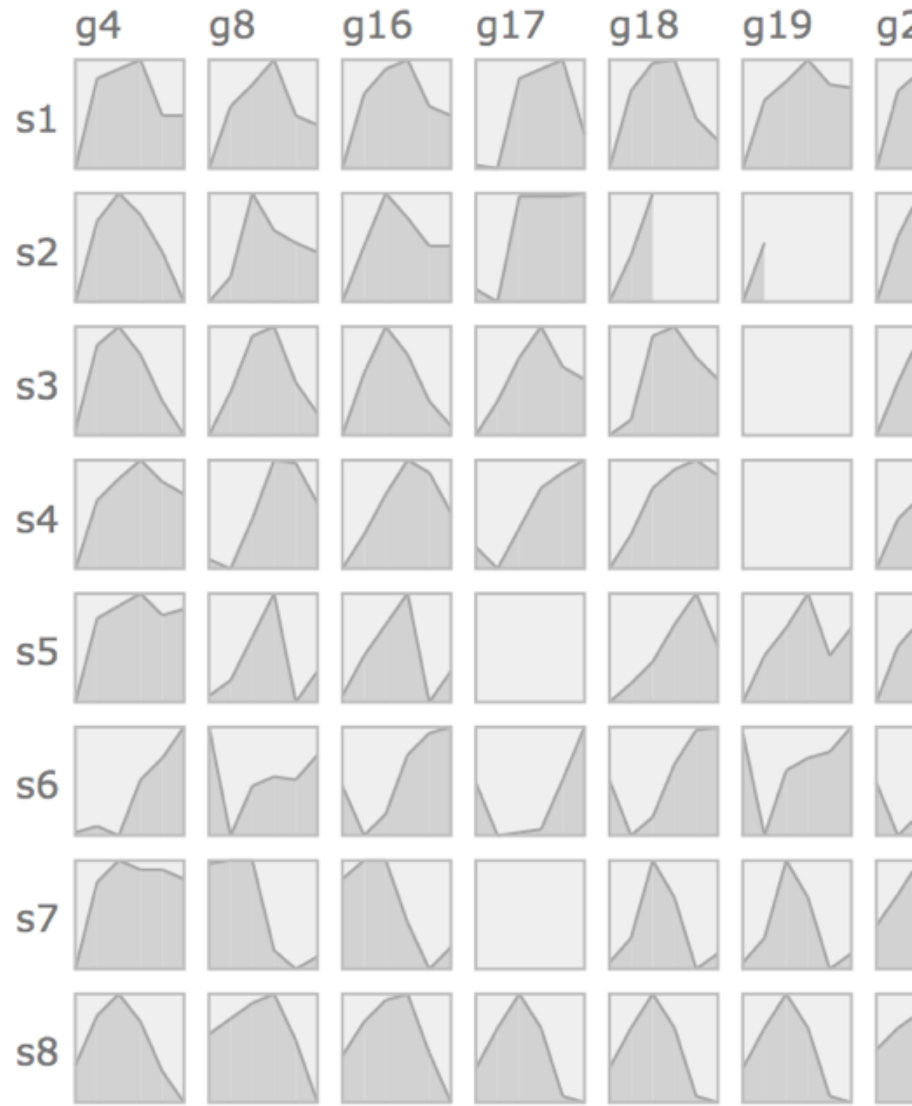
Area Encoding

Gene Expression Time-Series [Meyer et al '11]

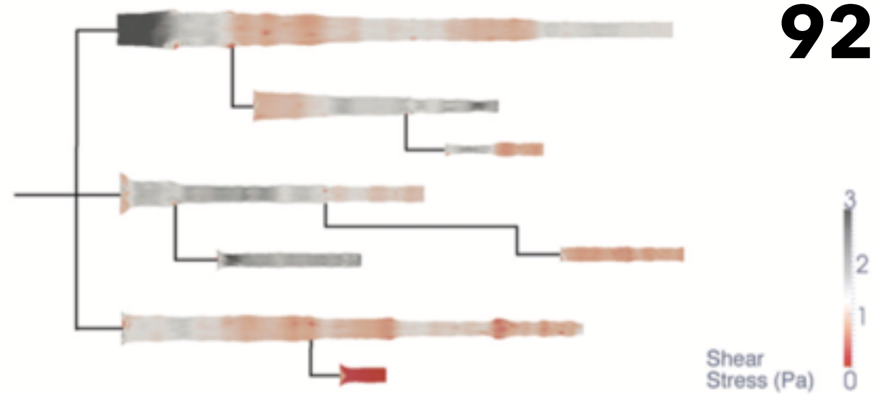
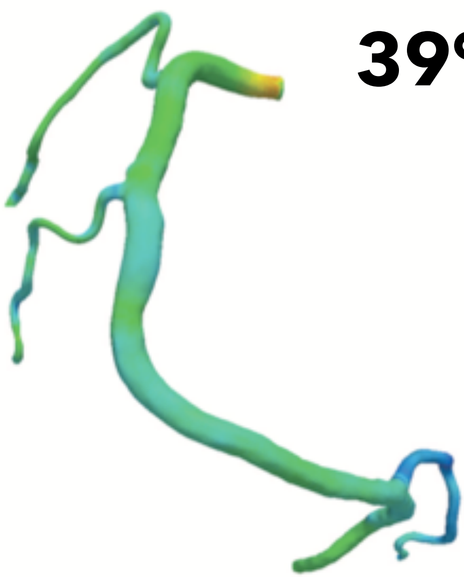
Color Encoding



Position Encoding



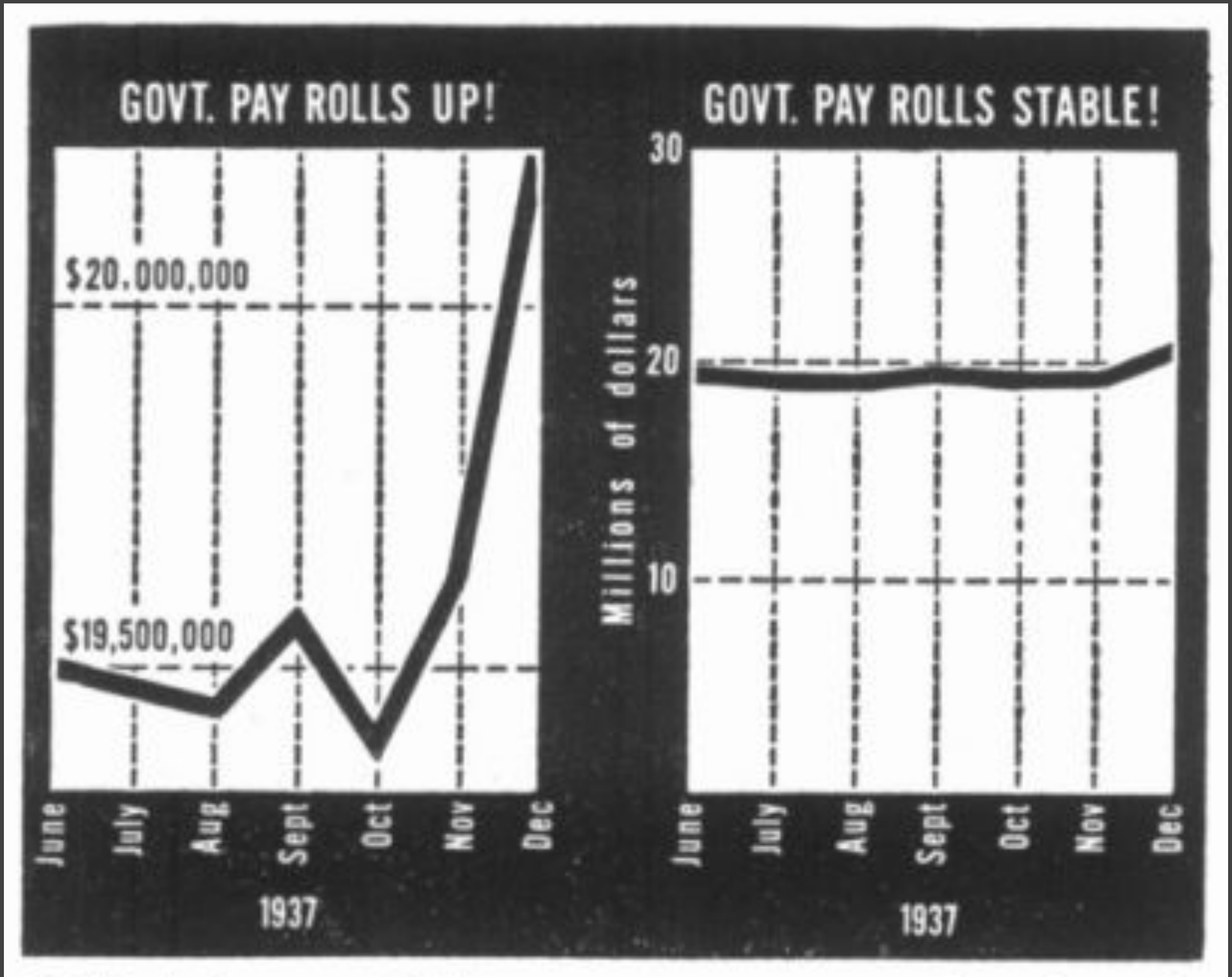
Artery Visualization [Borkin et al '11]

	Rainbow Palette	Diverging Palette
2D	**62%** 	**92%** 
3D	**39%** 	**71%** 

Using Space Effectively

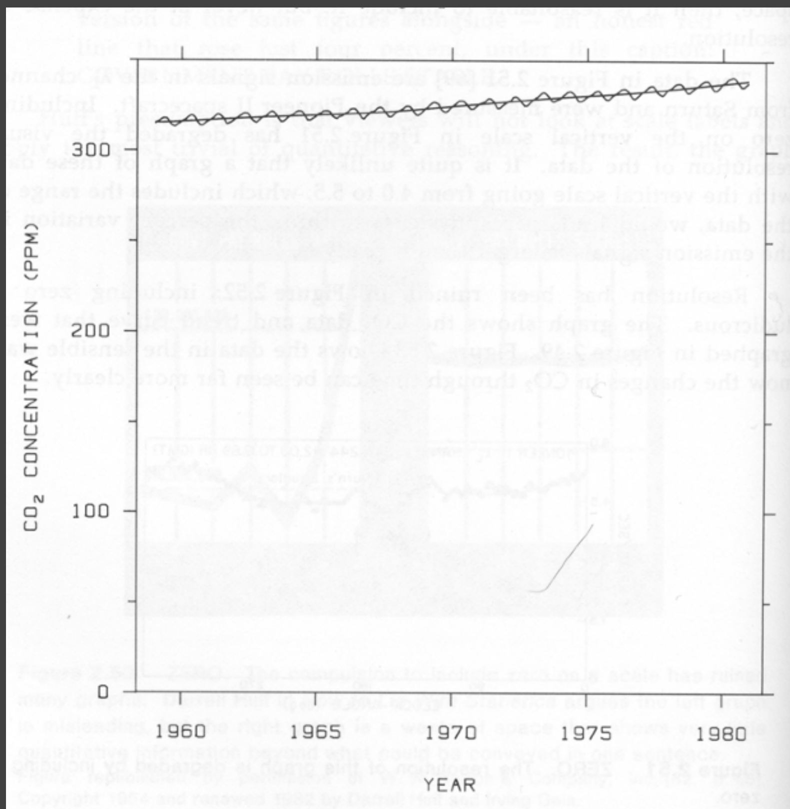
Scales & Axes

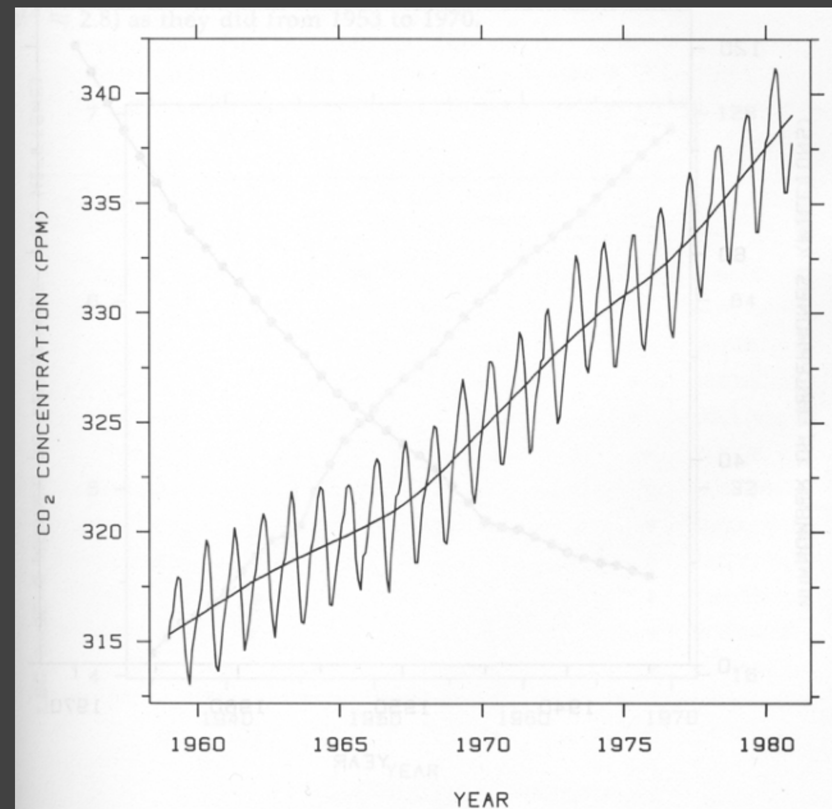
Include Zero in Axis Scale?



Government payrolls in 1937 [How To Lie With Statistics. Huff]

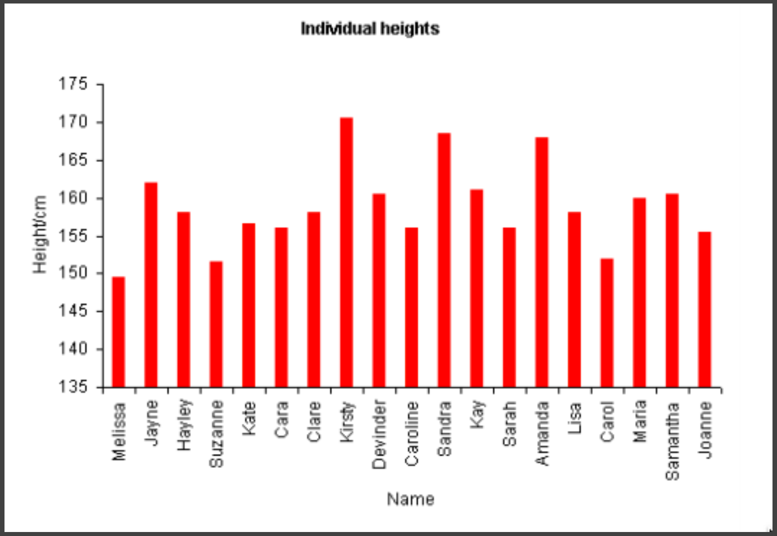
Include Zero in Axis Scale?





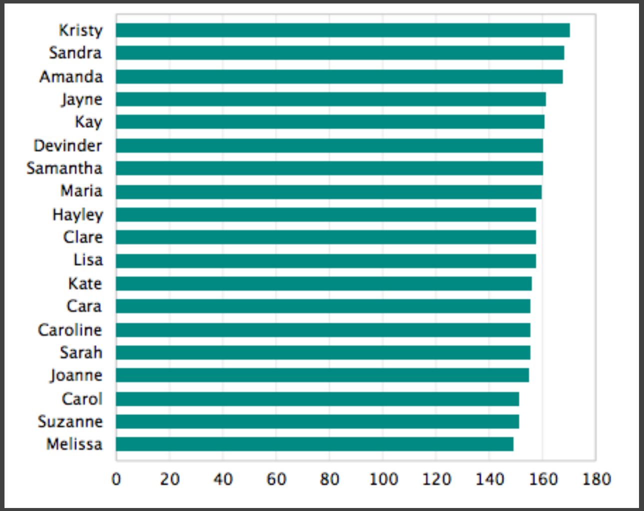
Yearly CO_2 concentrations [Cleveland 85]

Include Zero in Axis Scale?

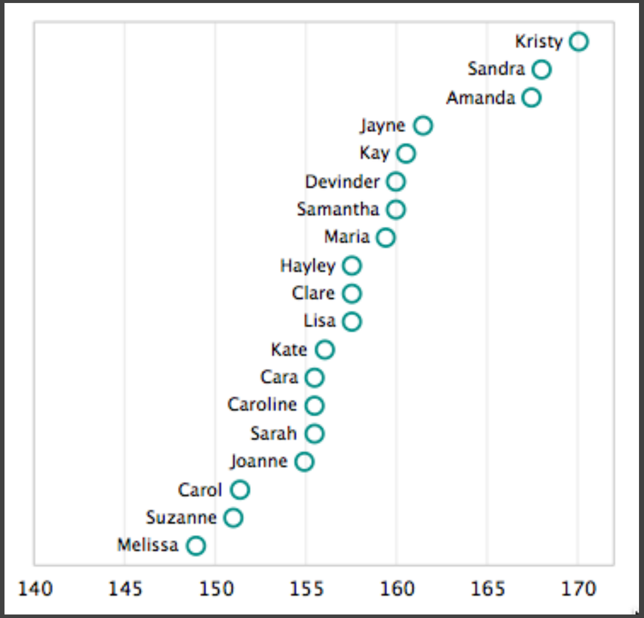


Violates Expressiveness Principle!

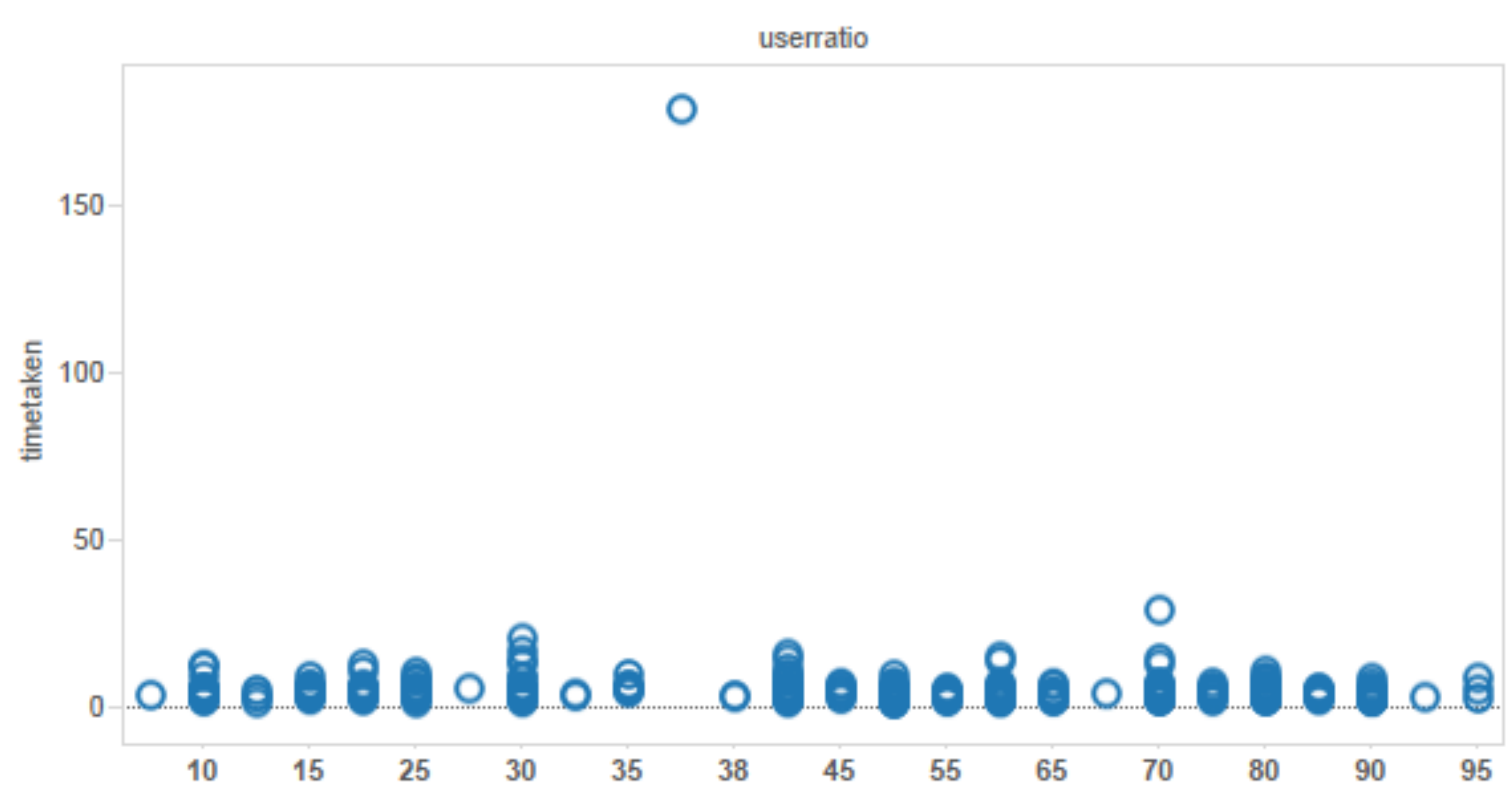
Compare Proportions (Q-Ratio)



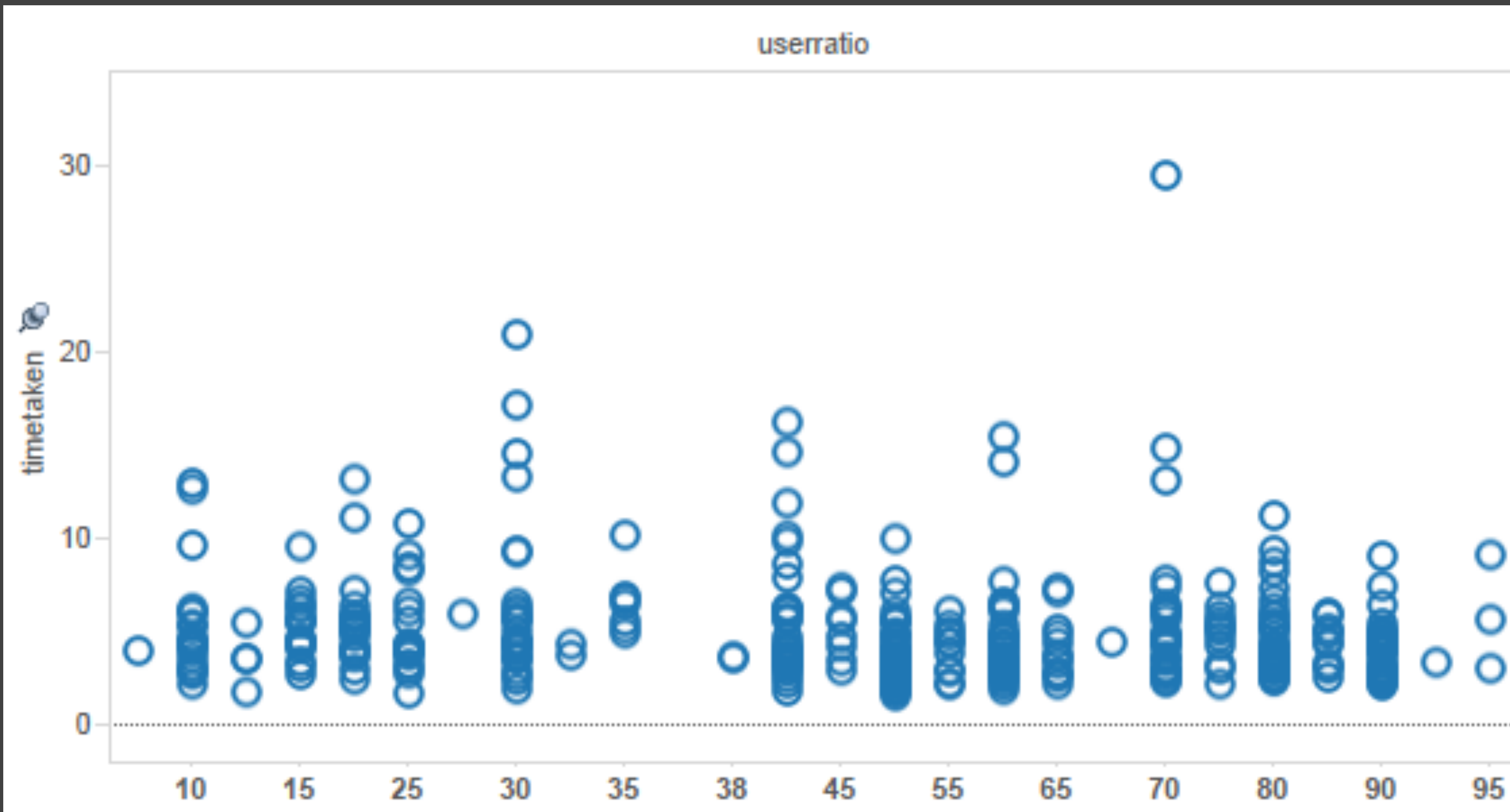
Compare Relative Position (Q-Interval)



How to Scale the Axis?

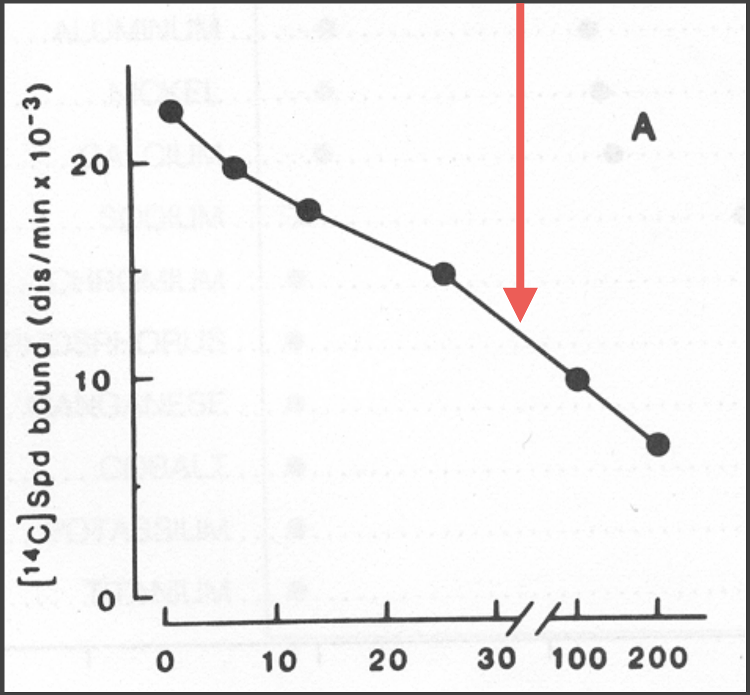


One Option: Clip Outliers

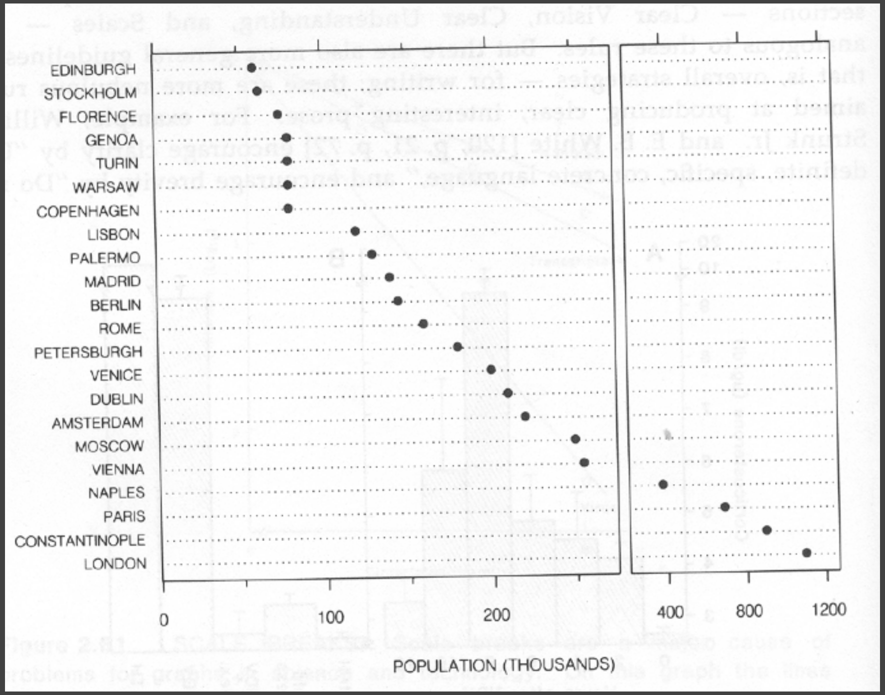


Clearly Mark Scale Breaks

Violates Expressiveness Principle!

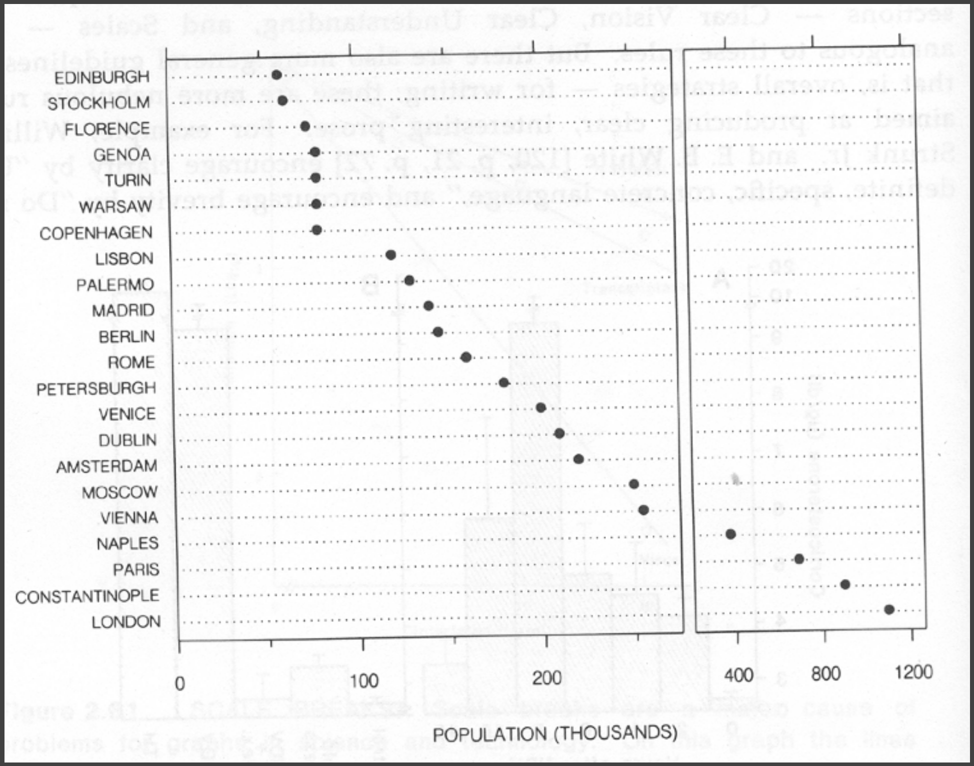


Poor scale break [Cleveland 85]

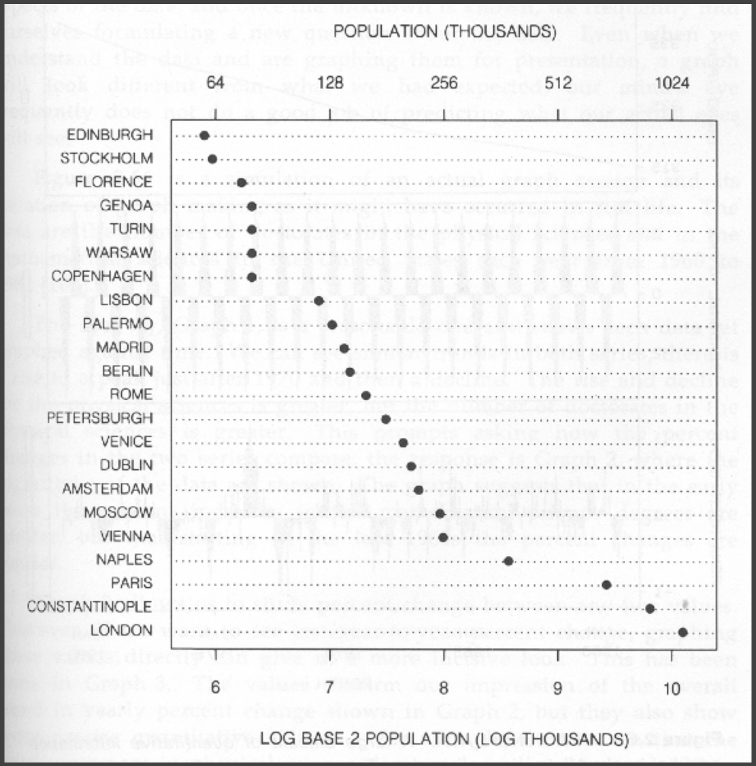


Well-marked scale break [Cleveland 85]

Scale Break vs. Log Scale



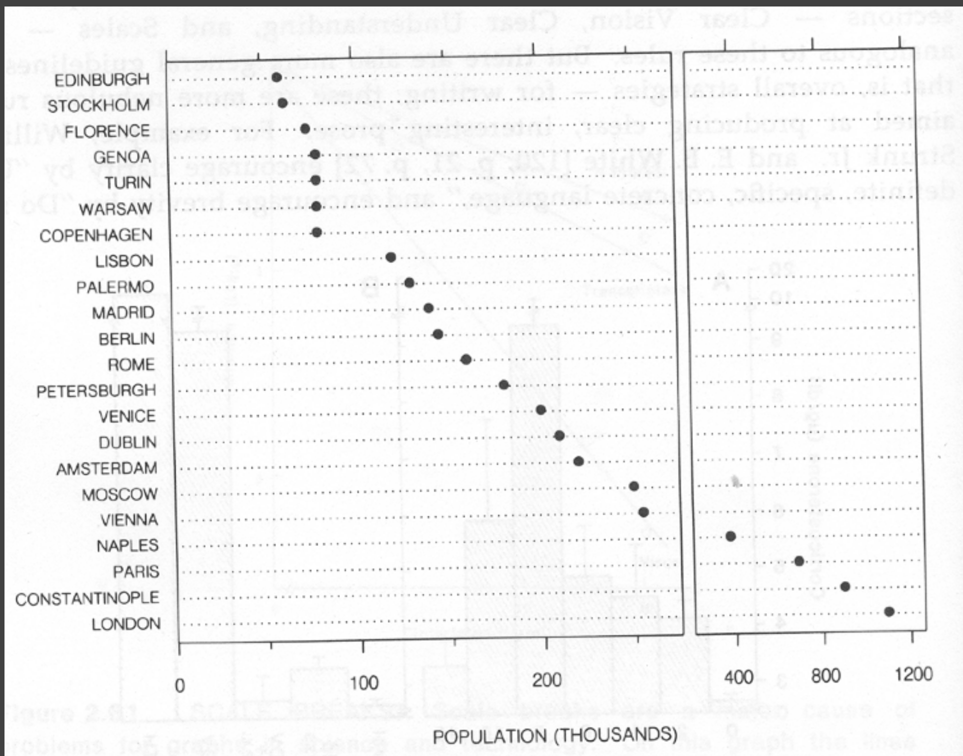
Scale Break

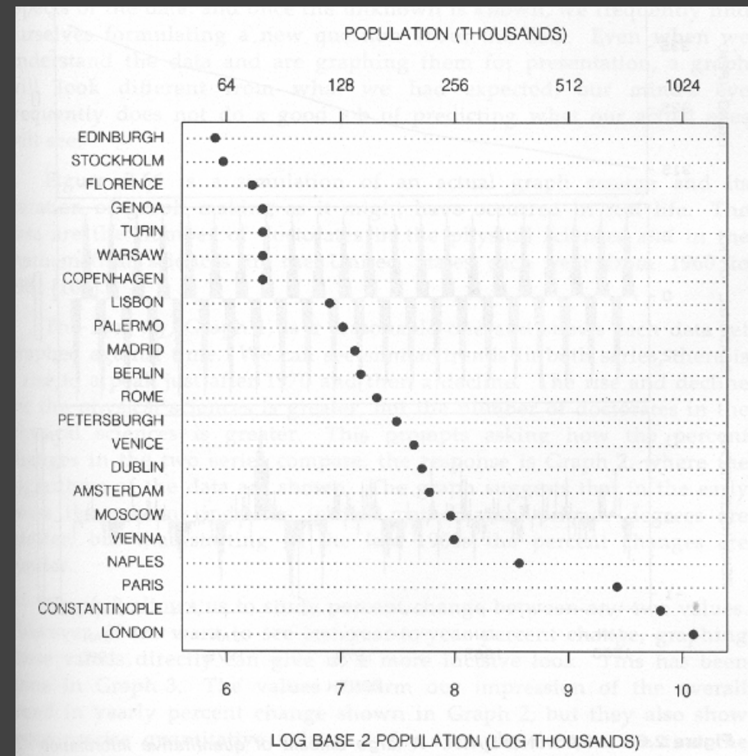


Log Scale

[Cleveland 85]

Scale Break vs. Log Scale





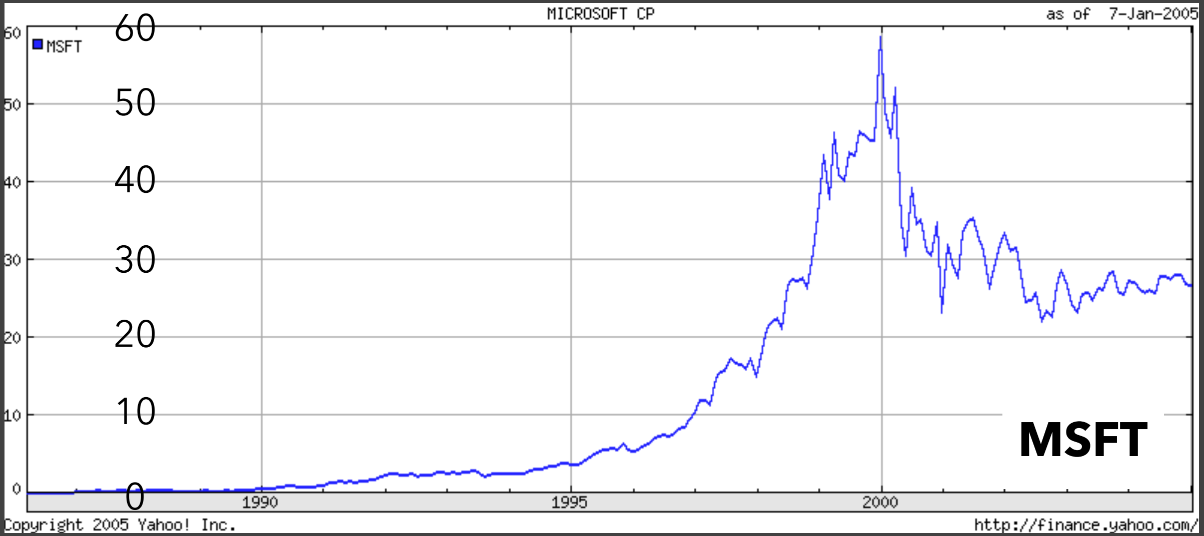
Both increase visual resolution

Scale break: difficult to compare (*cognitive* – not *perceptual* – work)

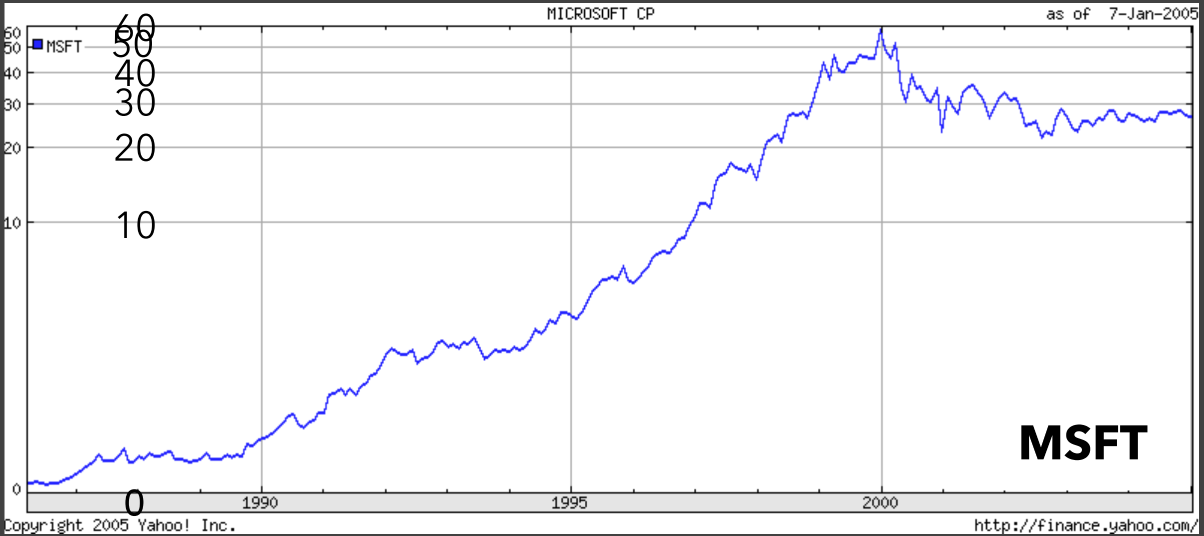
Log scale: direct comparison of all data

Linear Scale vs. Log Scale

Linear Scale



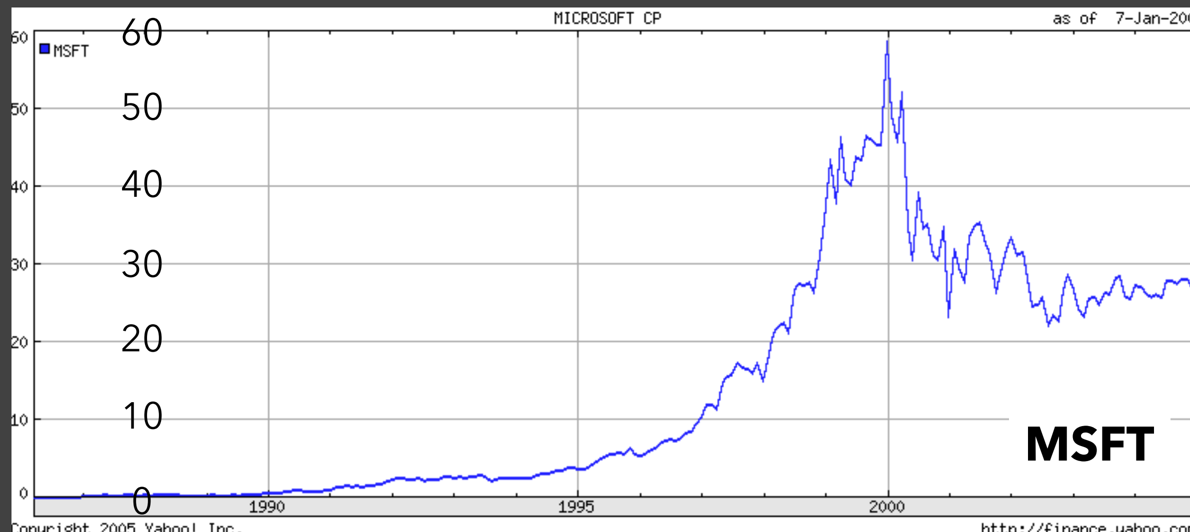
Log Scale



Linear Scale vs. Log Scale

Linear Scale

Absolute change

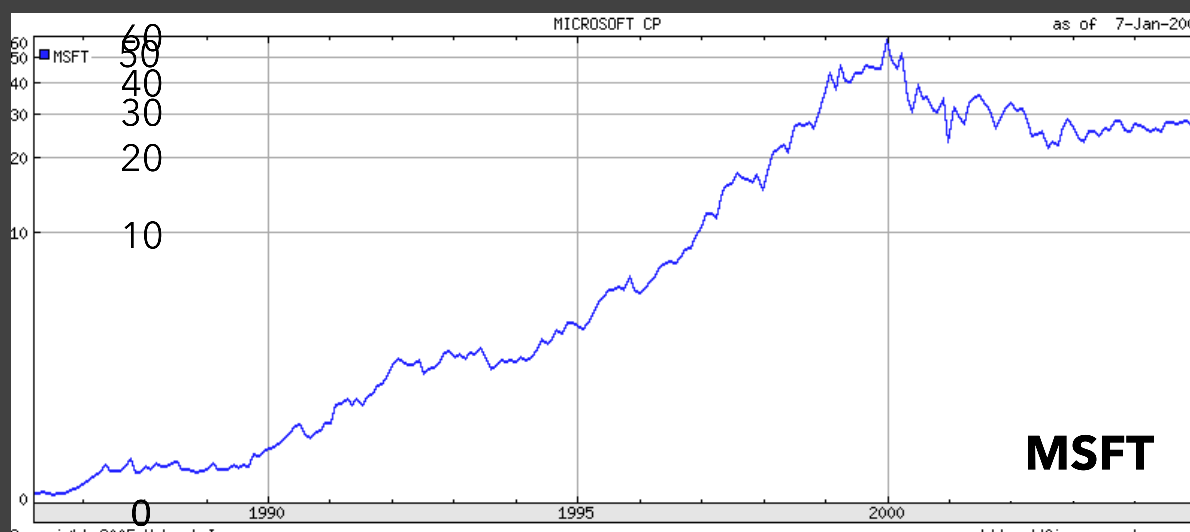


Log Scale

Small fluctuations

Percent change

d(10,20) = d(30,60)



When To Apply a Log Scale?

Address data skew (e.g., long tails, outliers)

Enables comparison within and across multiple orders of magnitude.

Focus on multiplicative factors (not additive)

Recall that the logarithm transforms **×** to **+**!

Percentage change, not absolute value.

Constraint: **positive, non-zero values**

Constraint: **audience familiarity?**

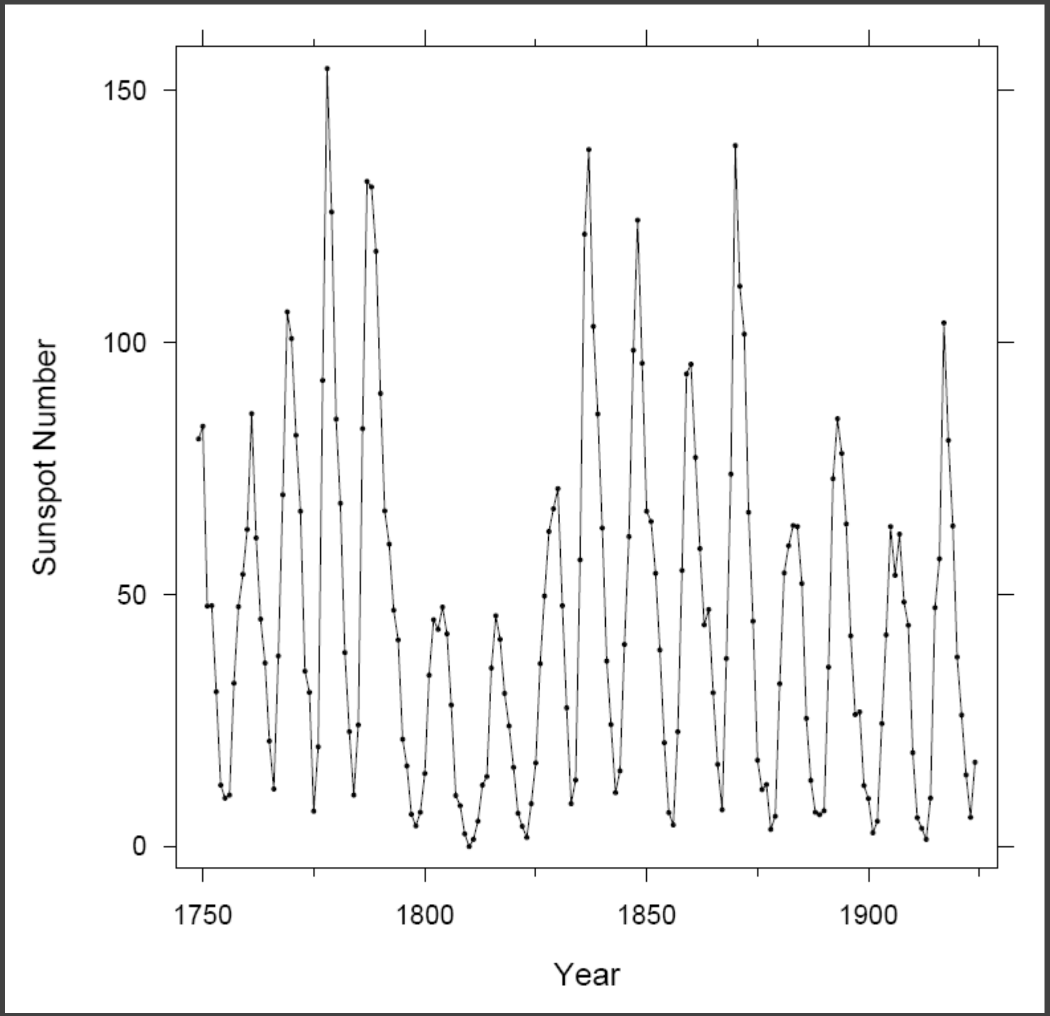
Optimizing Design

Chart Design Parameters

Given a visual encoding (e.g., line chart), what aspects might affect graphical perception?

Physical Size
Aspect Ratio
Ticks, Labels, Gridlines
Line Width
Data Points (e.g., dots)

How might we determine optimized choices?



Optimization-Based Design

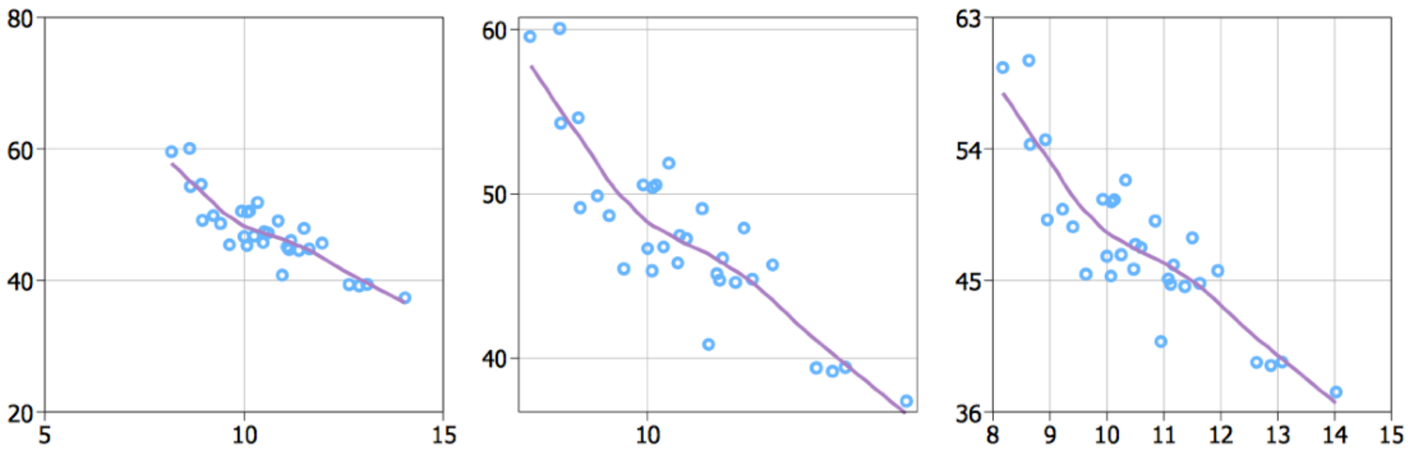
Determine *error* or *energy* functions for measuring the "quality" of a visualization.

Treat as an optimization *objective* and then *solve* (or *search*) for better chart parameters.

Examples:
Selecting axis ticks
Determining chart aspect ratio

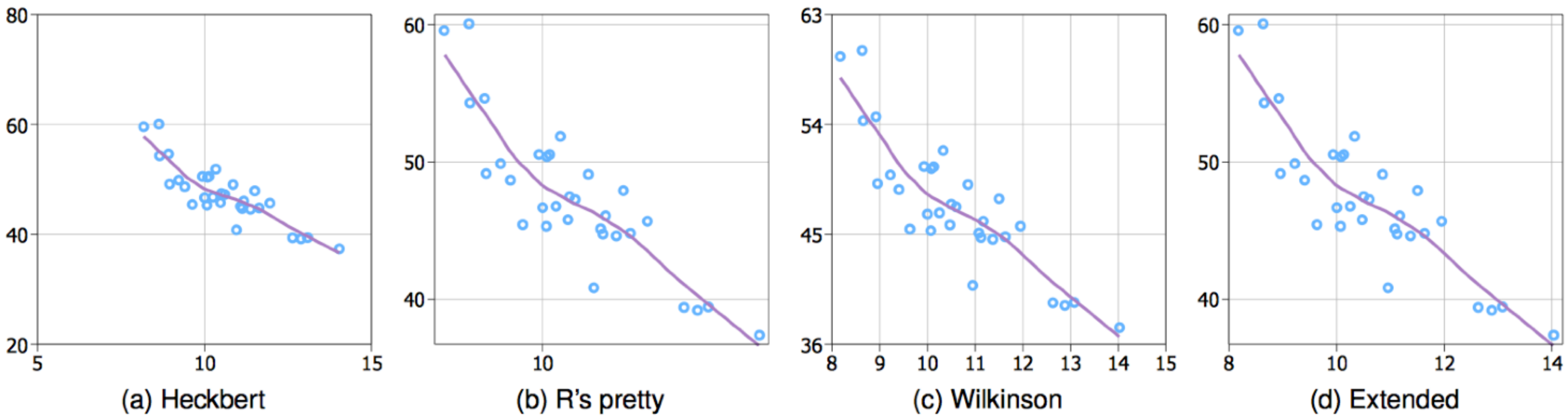
Axis Ticks

Tick Mark Selection



What are some properties of "good" tick marks?

Tick Mark Selection



What are some properties of “good” tick marks?

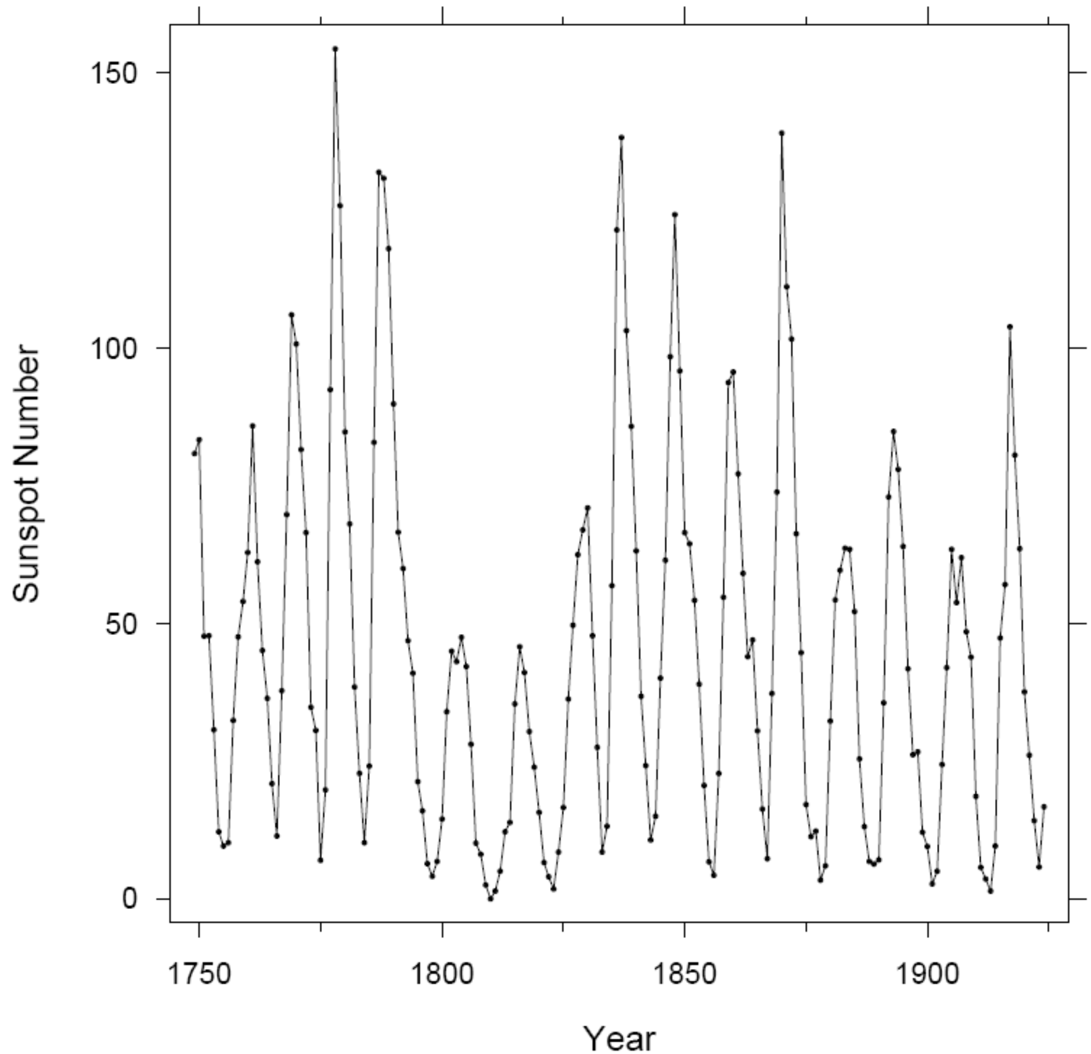
Tick Mark Criteria

Simplicity - numbers are multiples of 10, 5, 2
Coverage - ticks near the ends of the data
Density - not too many, nor too few
Legibility - whitespace, horizontal text, size

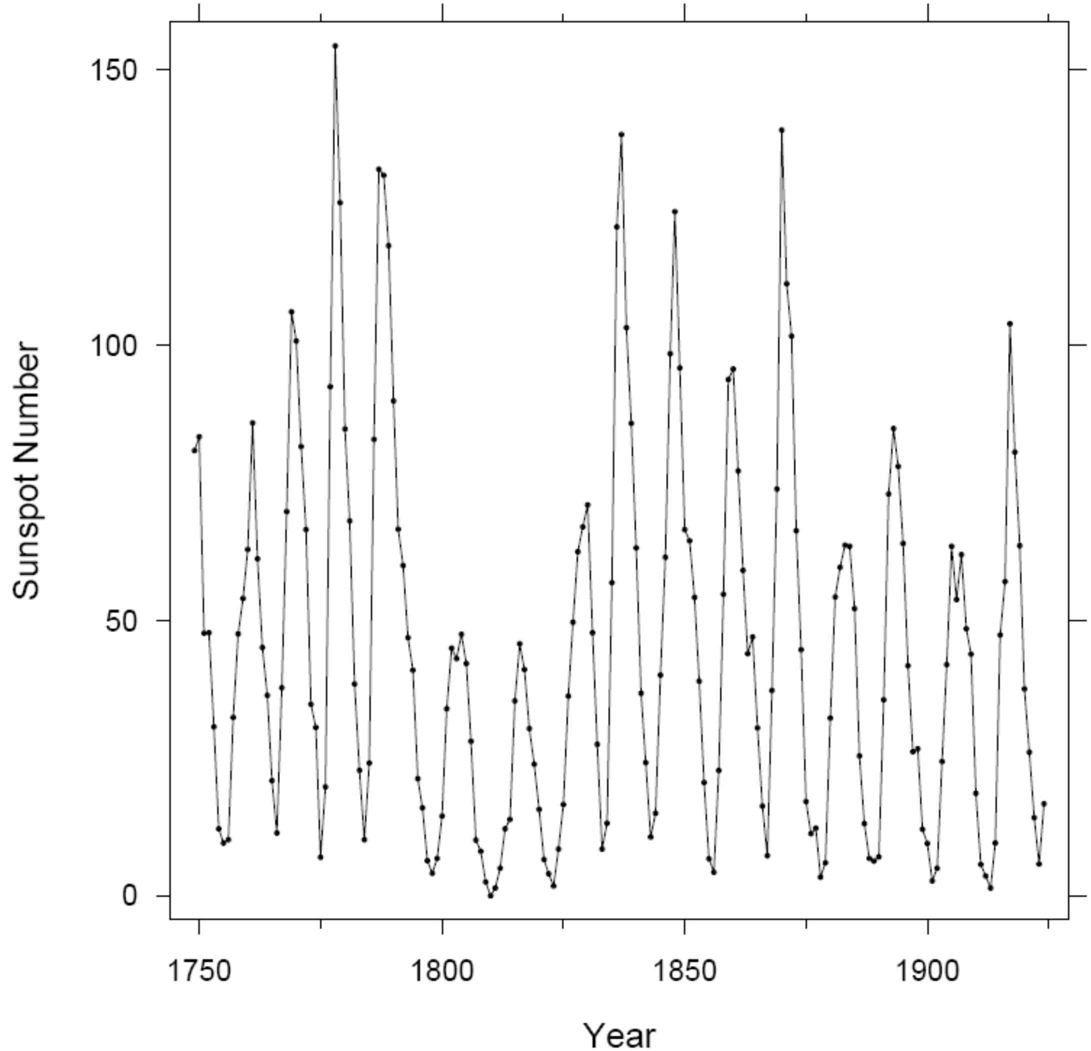
Optimization
Talbot et al ’10 use a search procedure that optimizes criteria in turn (e.g., find simple numbers first, then adjust coverage, *etc.*).

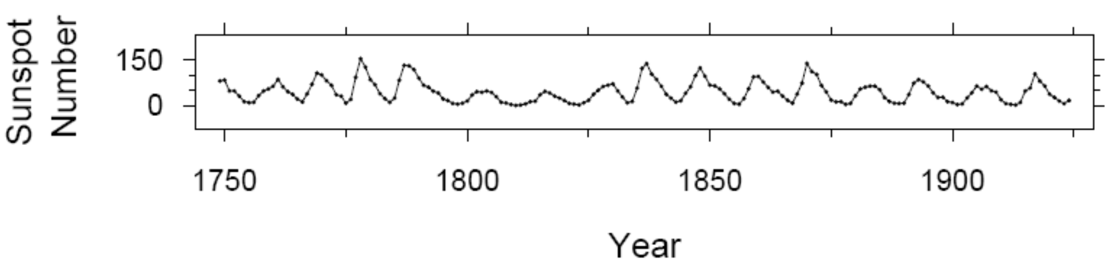
S = 0.2 *simplicity* + 0.25 *coverage* + 0.5 *density* + 0.05 *legibility*

Aspect Ratio



William S. Cleveland
The Elements of Graphing Data

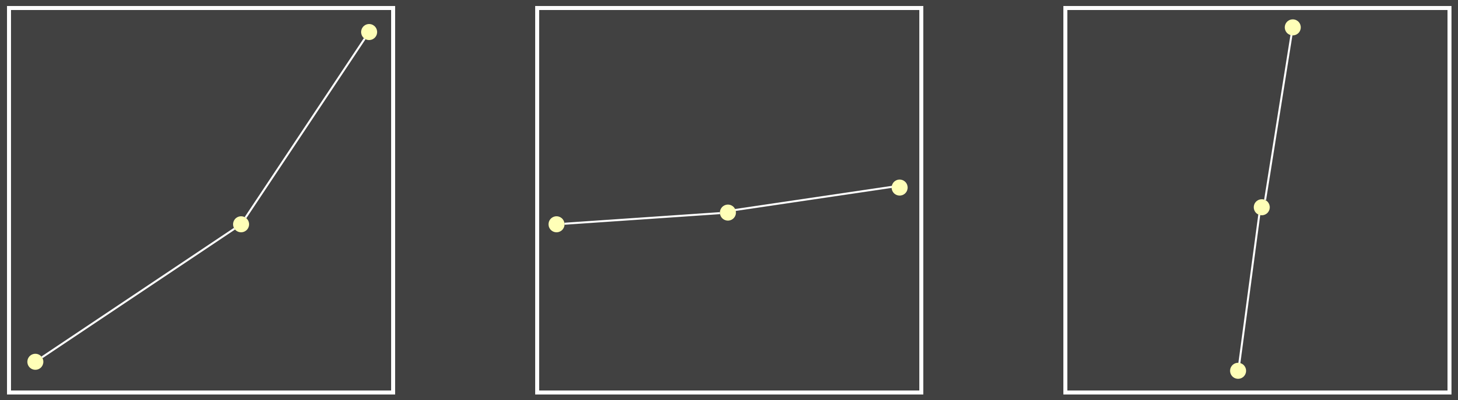




William S. Cleveland
The Elements of Graphing Data

Banking to 45° [Cleveland]

To facilitate perception of trends, maximize the discriminability of line segment orientations

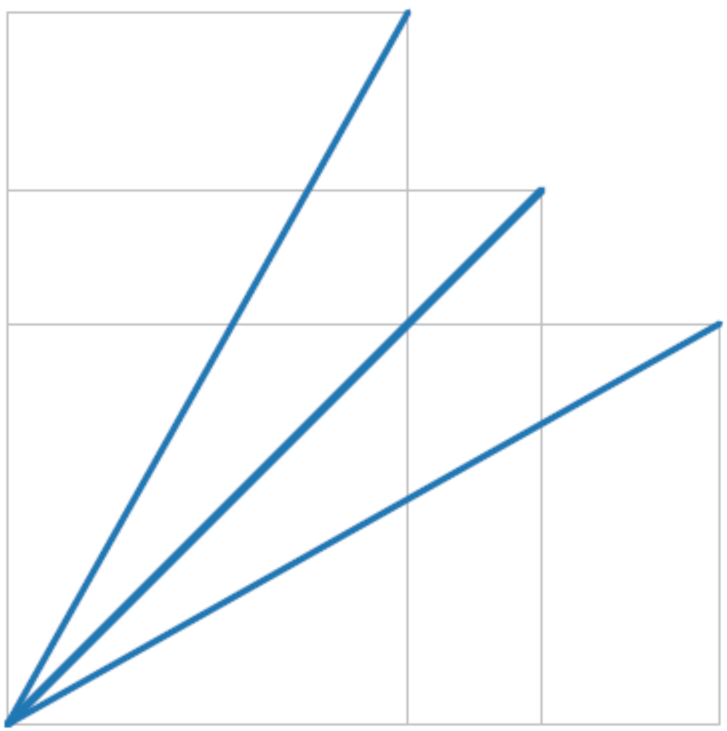


Two line segments are maximally discriminable when their average absolute angle is 45°

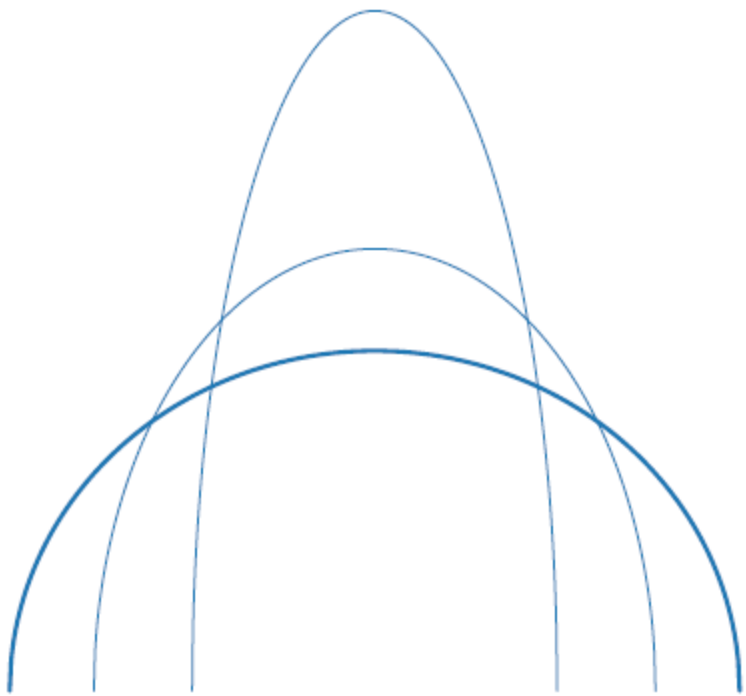
Insight: to optimize the aspect ratio, bank to 45°

Alternative: Minimize Arc Length

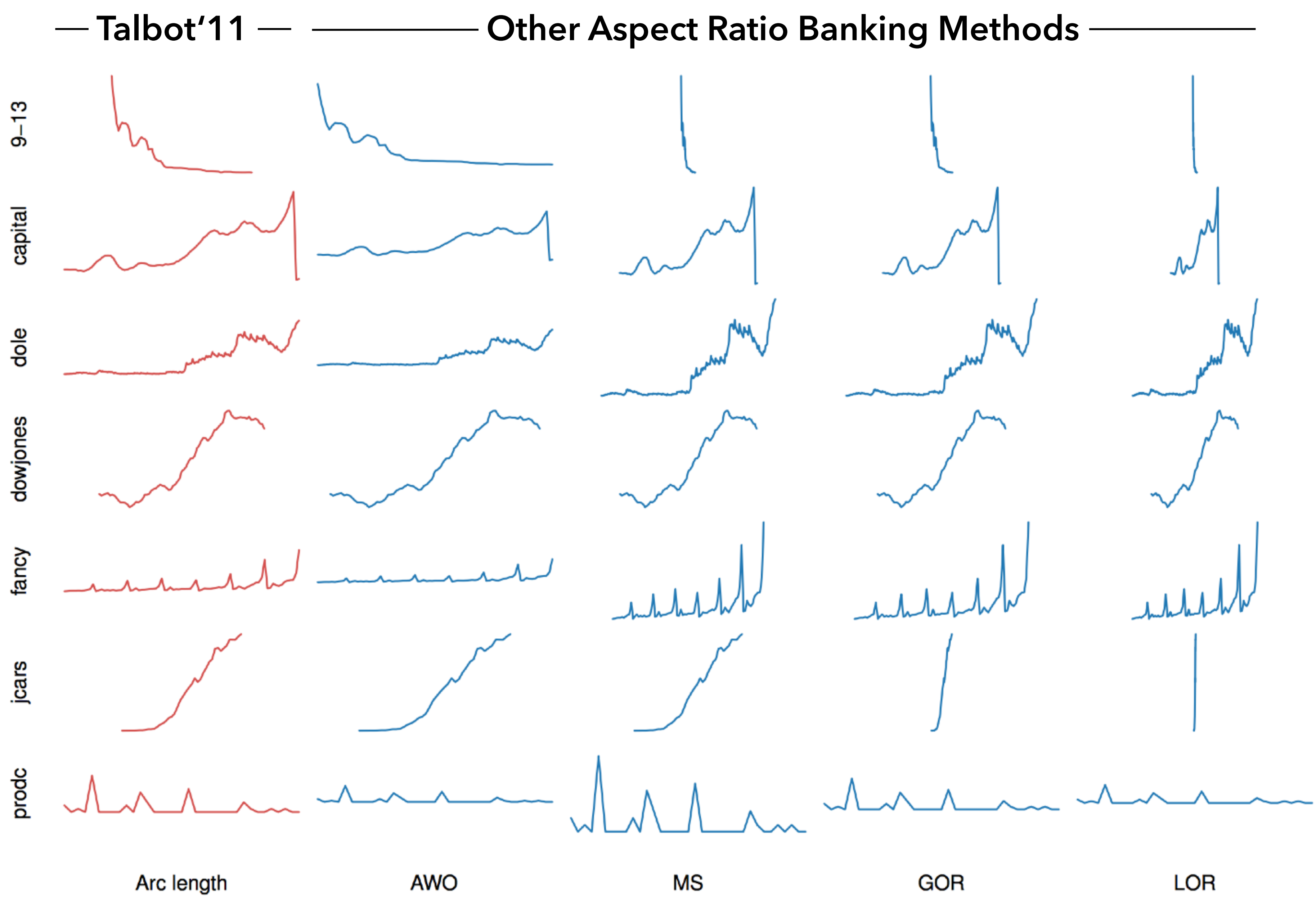
while holding area constant [Talbot et al. 2011]



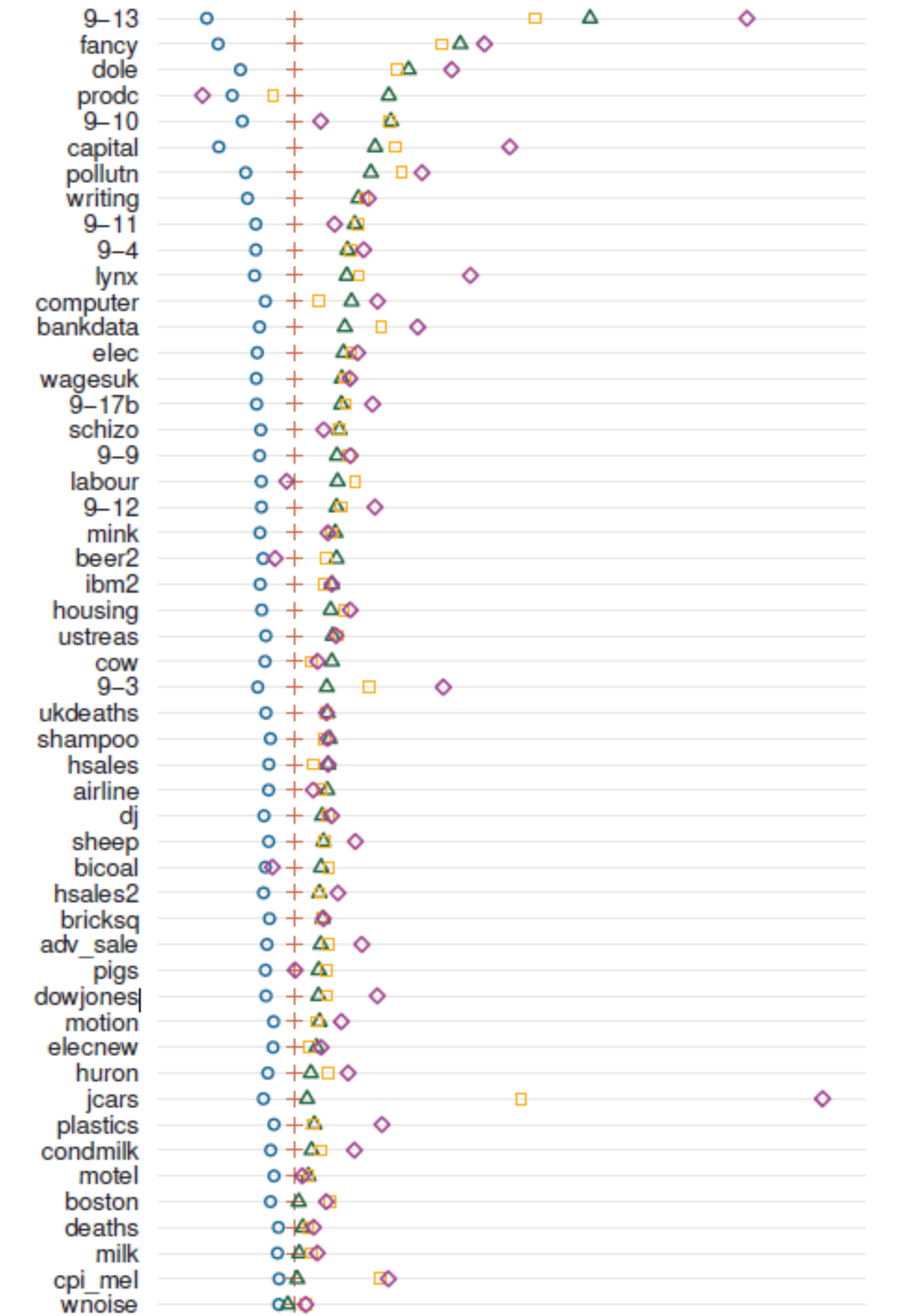
Straight line -> 45°



Ellipse -> Circle



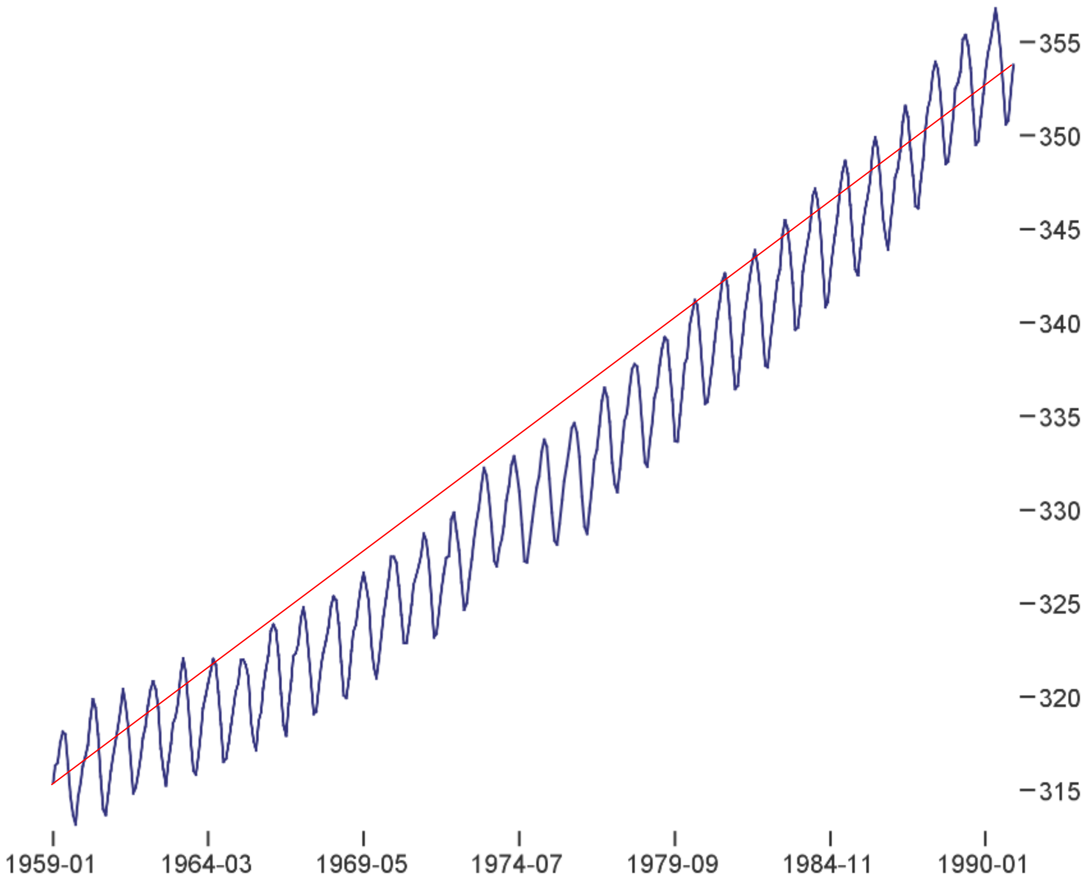
Talbot'11
Other Aspect Ratio Banking Methods
9–13
capital
dole
dowjones
fancy
jcars
prodc
Arc length
AWO
MS
GOR
LOR



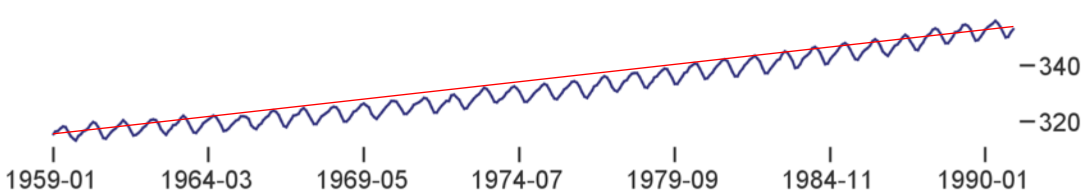
A Good Compromise

Arc-length banking produces aspect ratios in-between those produced by other methods.

[Talbot et al. 2011]



Aspect Ratio = 1.17



Aspect Ratio = 7.87

Trends may occur at different scales!

Apply banking to the original data *or* to fitted trend lines.

[Heer & Agrawala '06]

CO_2 Measurements

William S. Cleveland

Visualizing Data

Administrivia

A2: Exploratory Data Analysis

Use visualization software to form & answer questions

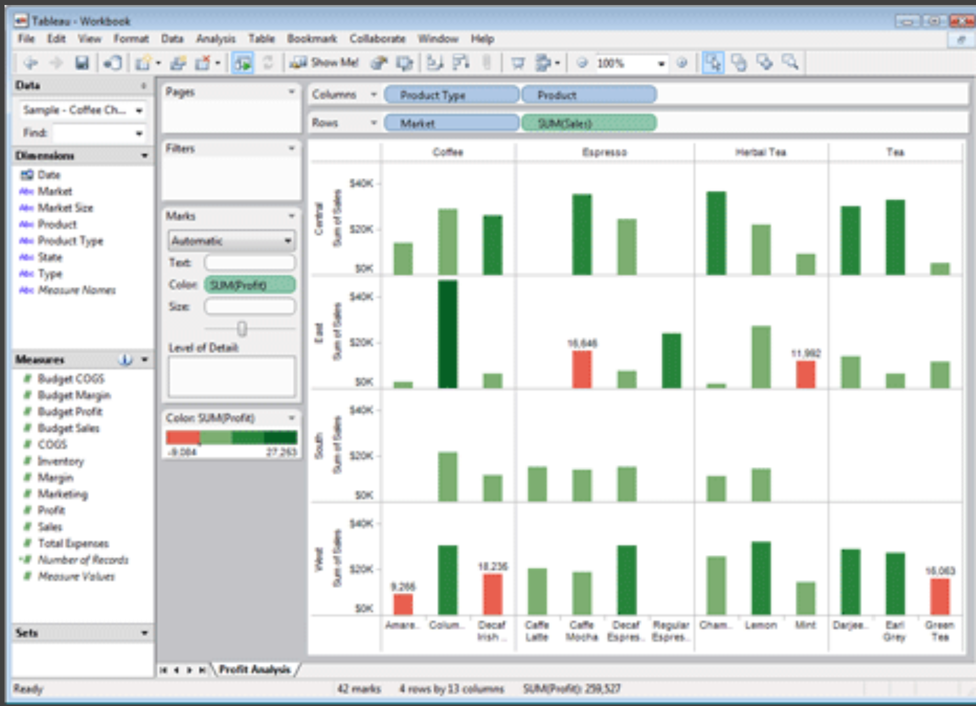
First steps:

Step 1: Pick domain & data

Step 2: Pose questions

Step 3: Profile the data

Iterate as needed



Create visualizations

Interact with data

Refine your questions

Author a report

Screenshots of most insightful views *(10+)*

Include titles and captions for each view

Due by 11:59pm

Friday, Apr 13

Technology Tutorial

Introduction to D3.js

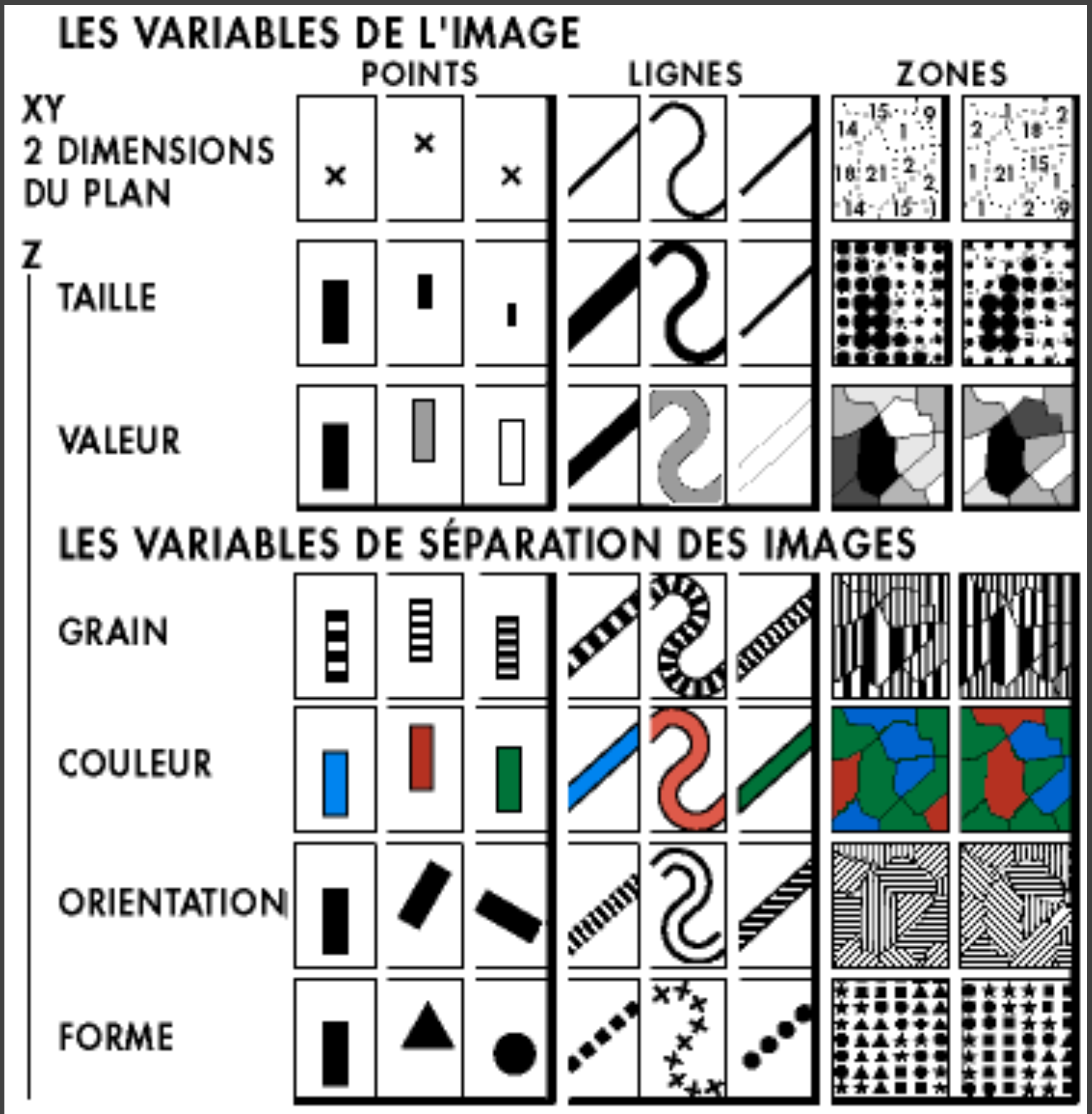
Thursday, April 19 - 4:30-6:30pm - Sieg 134

Multidimensional Data

Visual Encoding Variables

Position (X)
Position (Y)
Size
Value
Texture
Color
Orientation
Shape

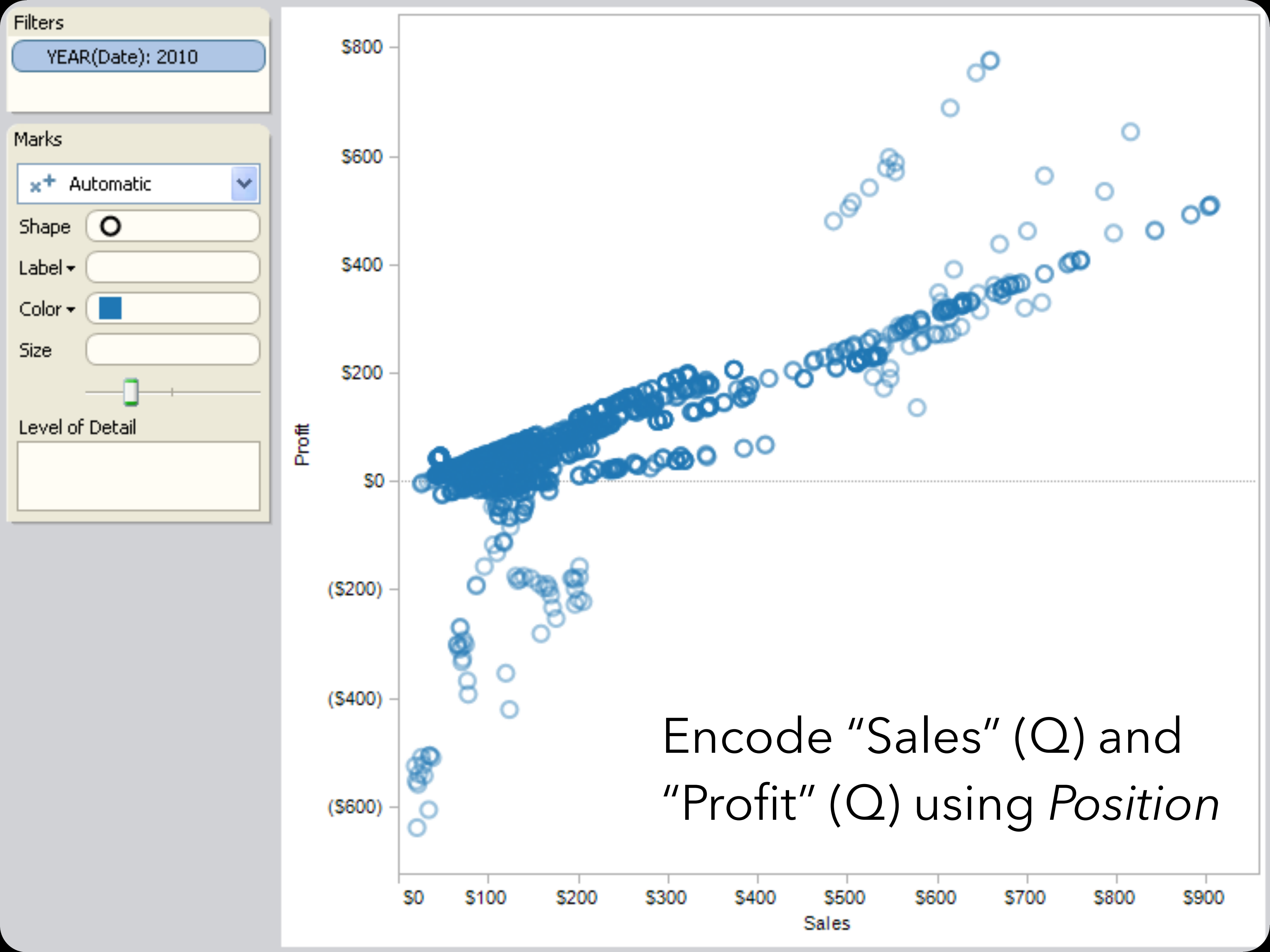
~8 dimensions?



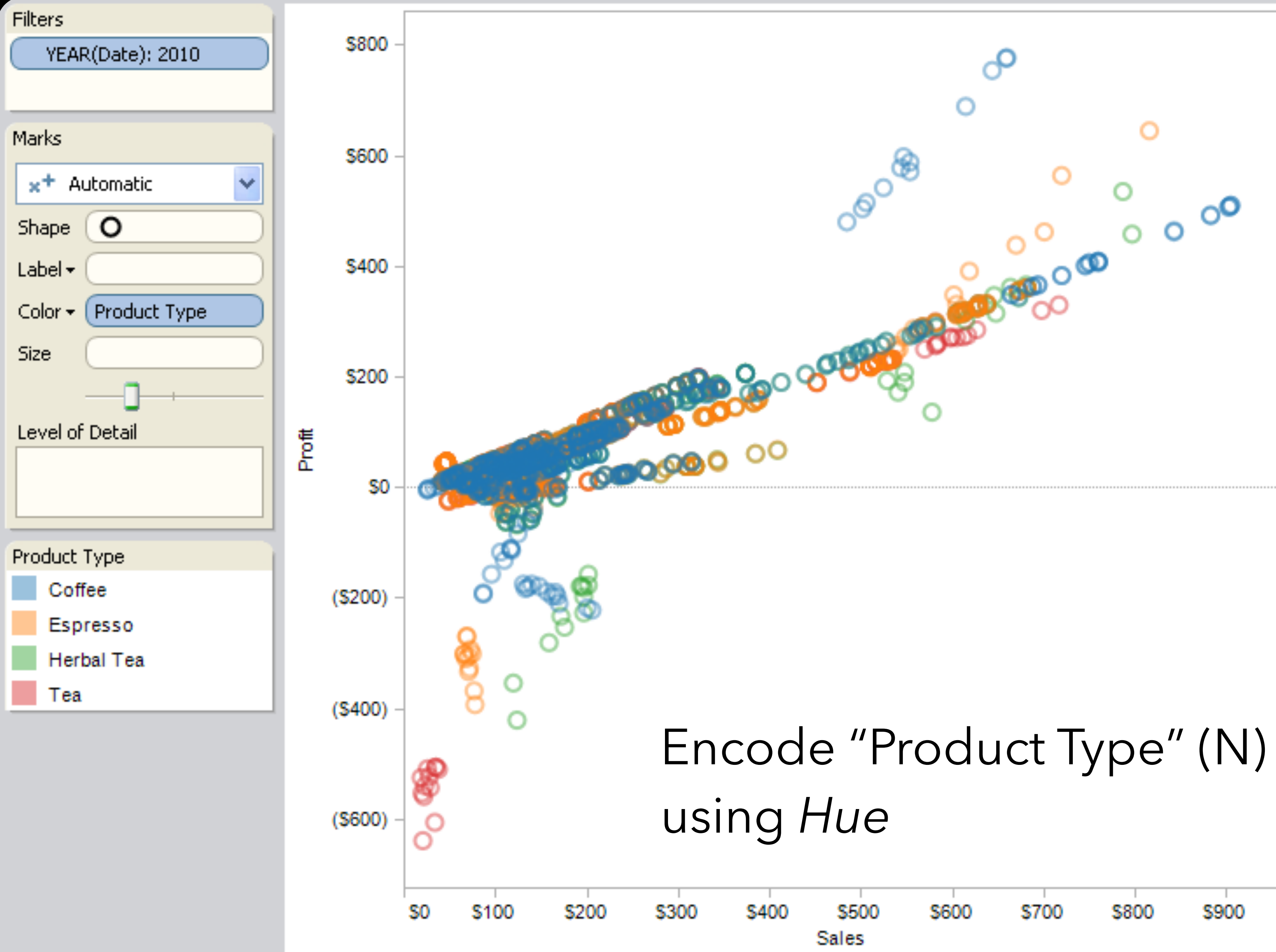
Example: Coffee Sales

Sales figures for a fictional coffee chain

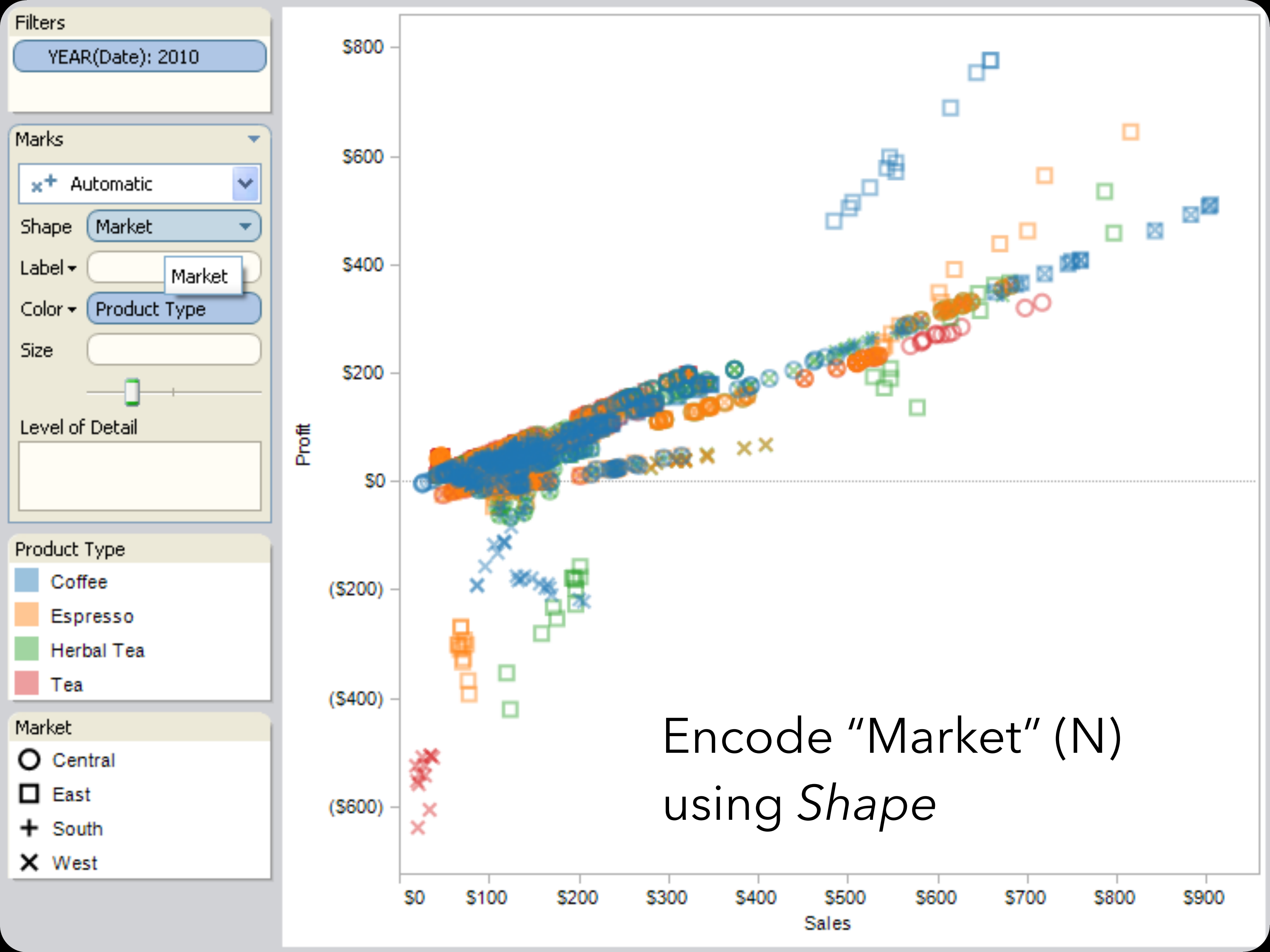
Sales	Q-Ratio
Profit	Q-Ratio
Marketing	Q-Ratio
Product Type	N {Coffee, Espresso, Herbal Tea, Tea}
Market	N {Central, East, South, West}

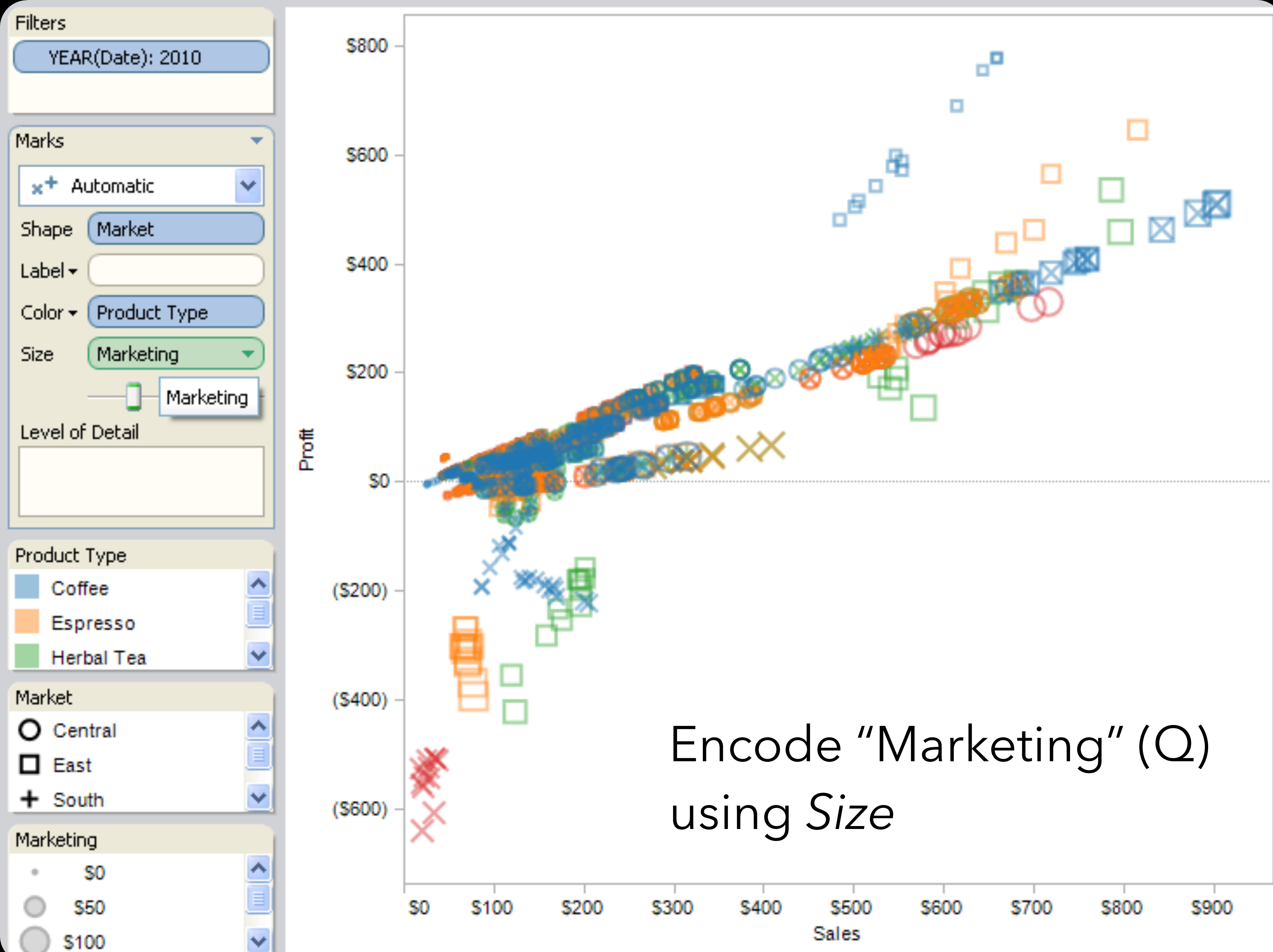


Encode "Sales" (Q) and "Profit" (Q) using *Position*



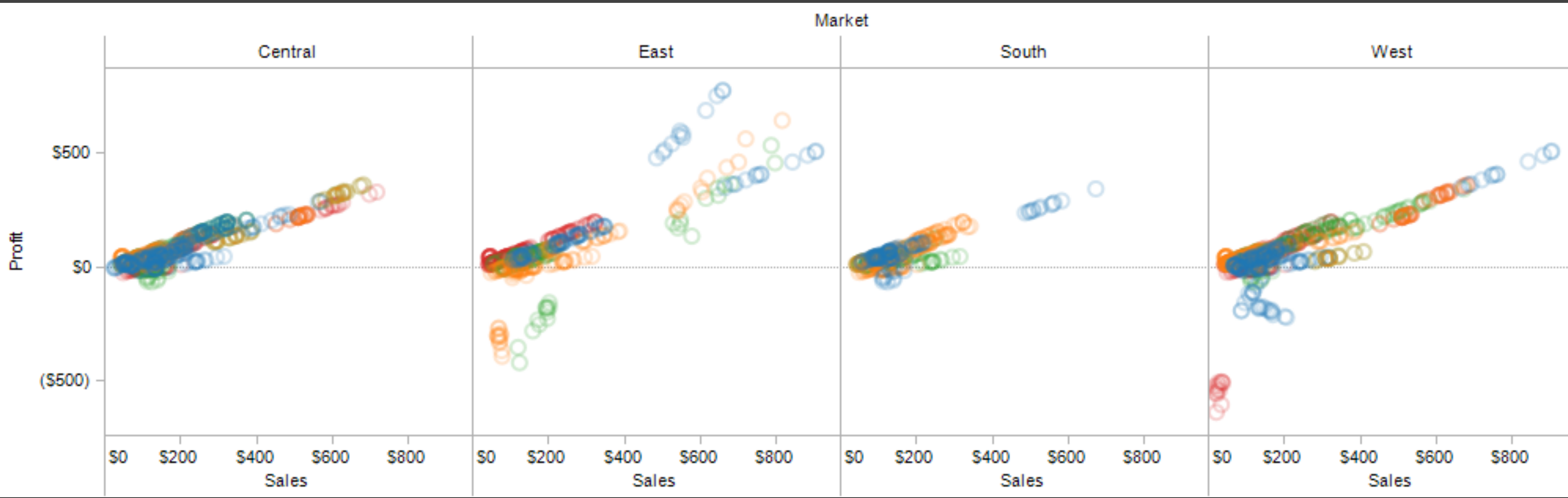
Encode “Product Type” (N) using *Hue*


Filters
YEAR(Date): 2010
Marks
Automatic
Shape
Market
Label
Market
Color
Product Type
Size
Level of Detail
Product Type
Coffee
Espresso
Herbal Tea
Tea
Market
Central
East
South
West
$800
$600
$400
$200
$0
($200)
($400)
($600)
Profit
$0
$100
$200
$300
$400
$500
$600
$700
$800
$900
Sales
Encode "Market" (N)
using *Shape*



Encode "Marketing" (Q) using *Size*

Trellis Plots



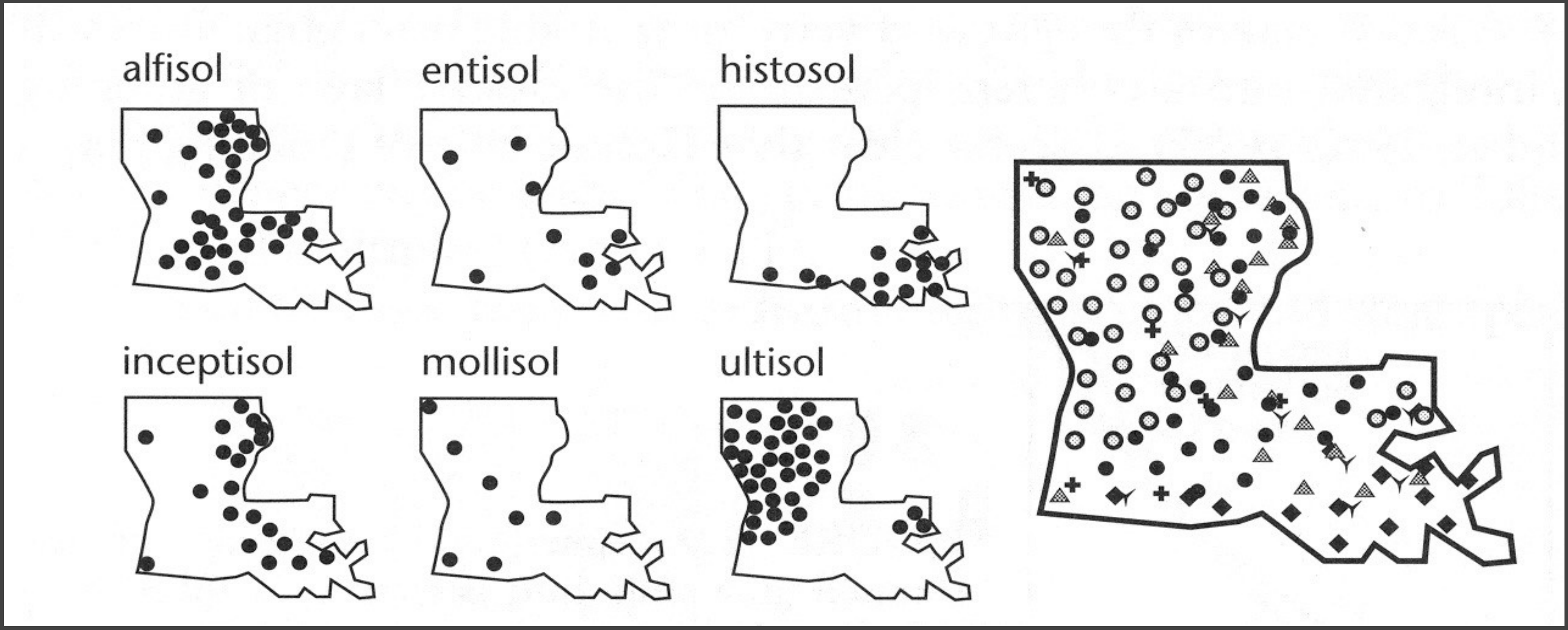
A *trellis plot* subdivides space to enable comparison across multiple plots.

Typically nominal or ordinal variables are used as dimensions for subdivision.

Small Multiples

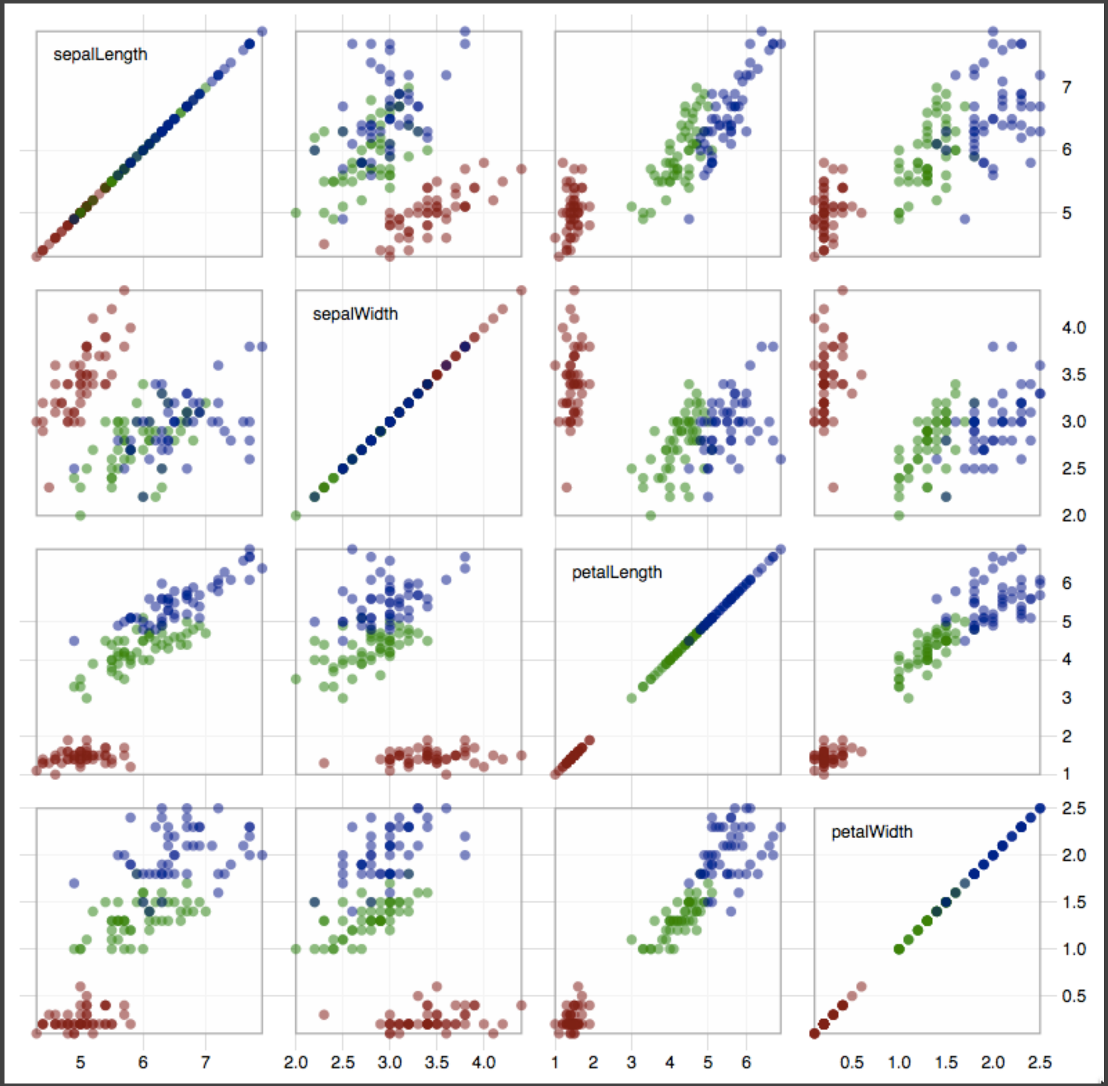
[MacEachren '95, Figure 2.11, p. 38]

Small Multiples



[MacEachren '95, Figure 2.11, p. 38]

Scatterplot Matrix (SPLOM)



Scatter plots for pairwise comparison of each data dimension.

Multiple Coordinated Views

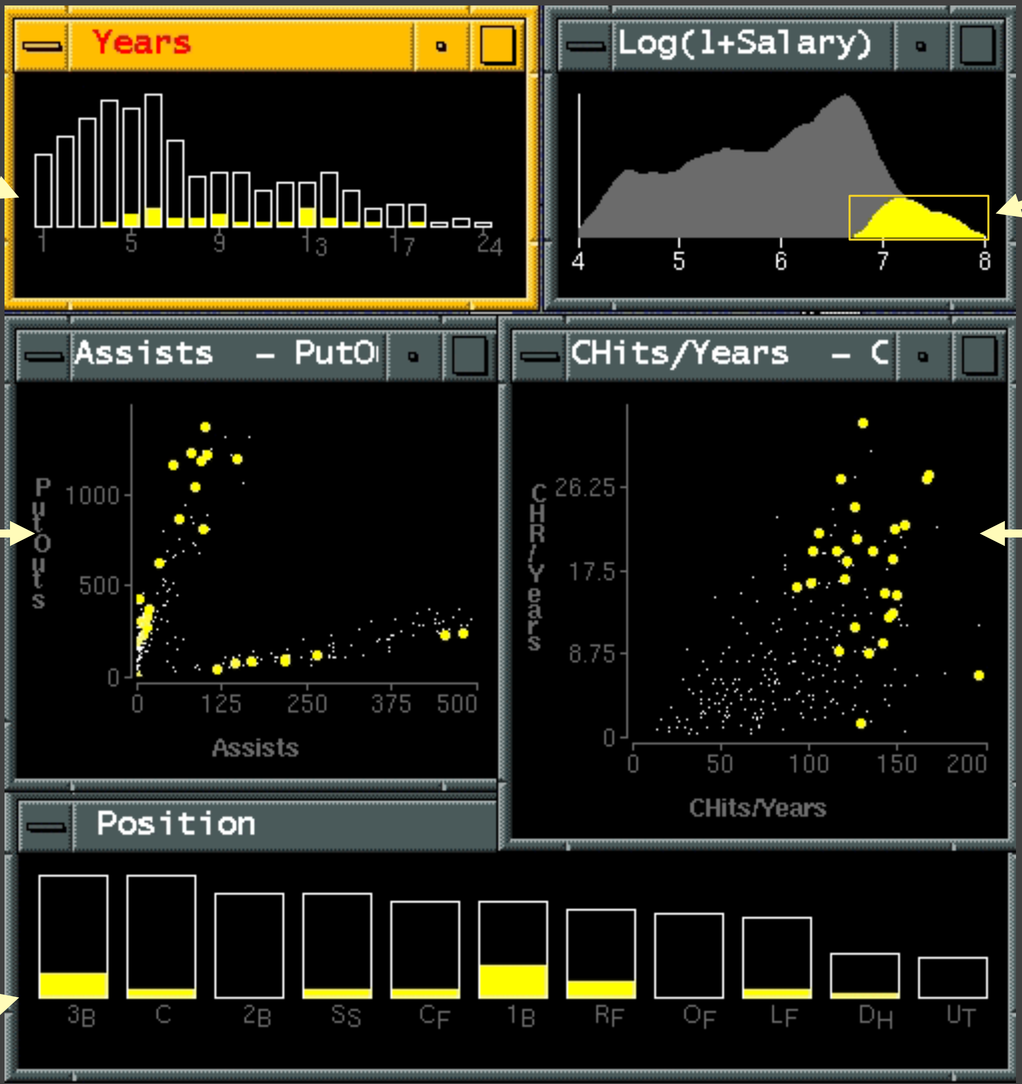
how long in majors

select high salaries

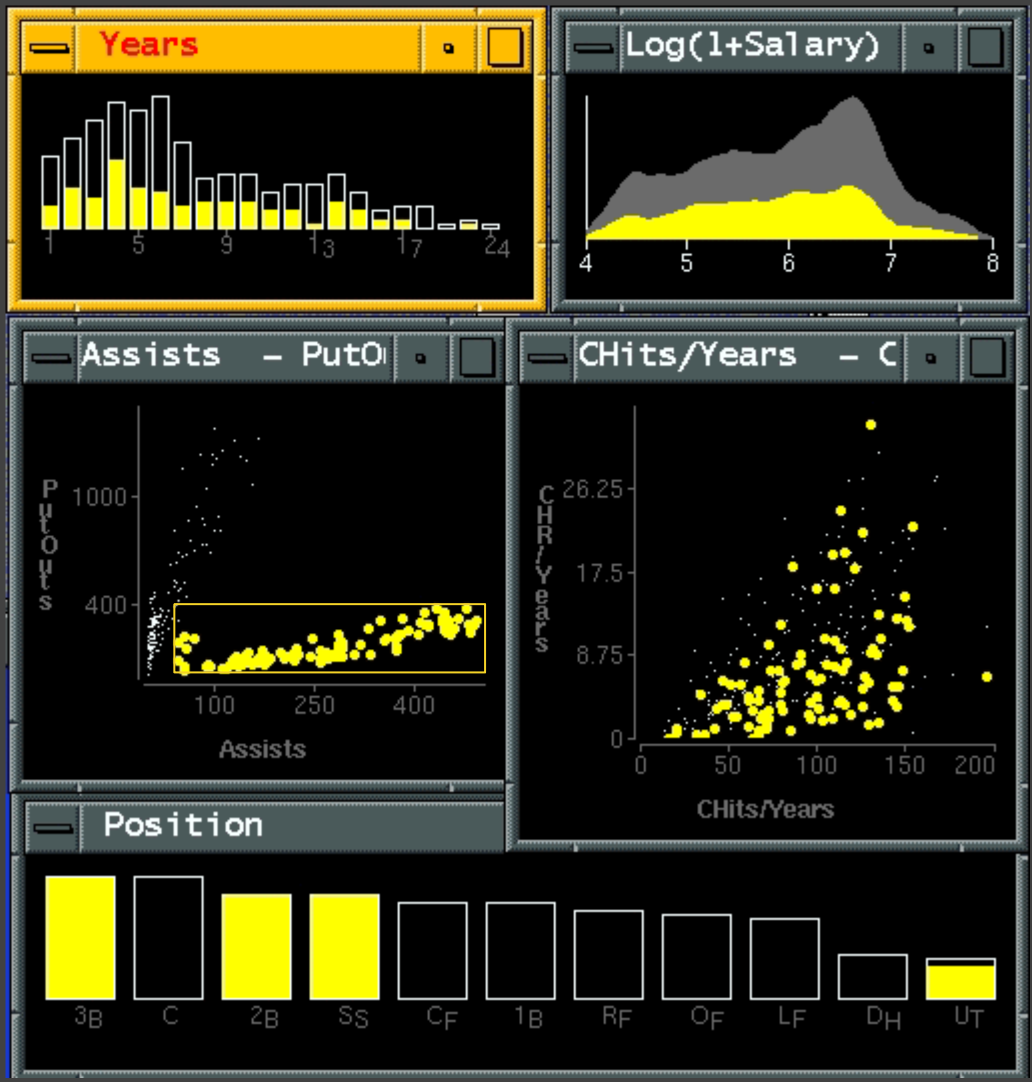
avg assists vs avg putouts (fielding ability)

avg career HRs vs avg career hits (batting ability)

distribution of positions played

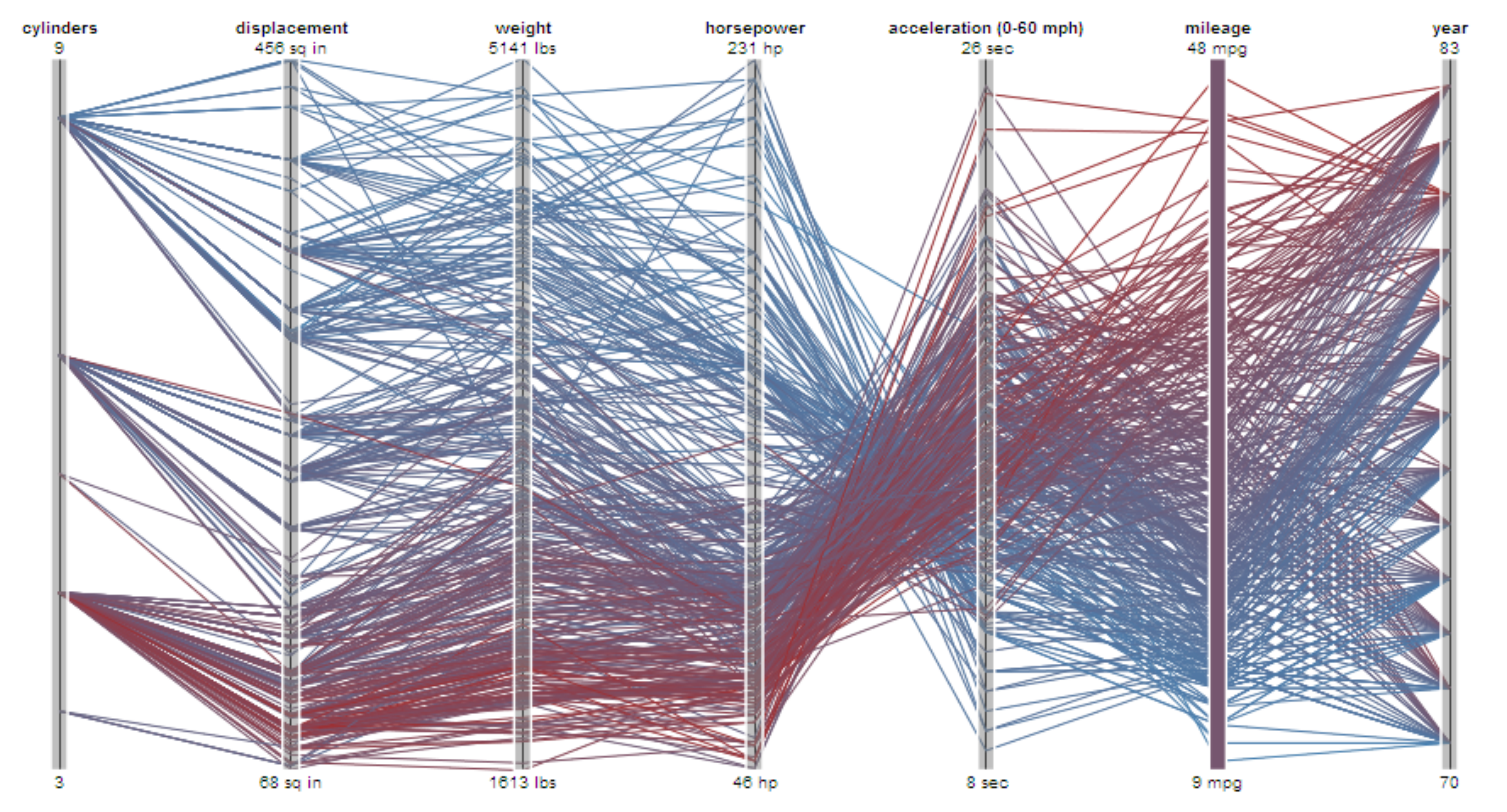


Linking Assists to Position



Parallel Coordinates

Parallel Coordinates [Inselberg]



Parallel Coordinates [Inselberg]

Visualize up to ~two dozen dimensions at once

1. Draw parallel axes for each variable
2. For each tuple, connect points on each axis

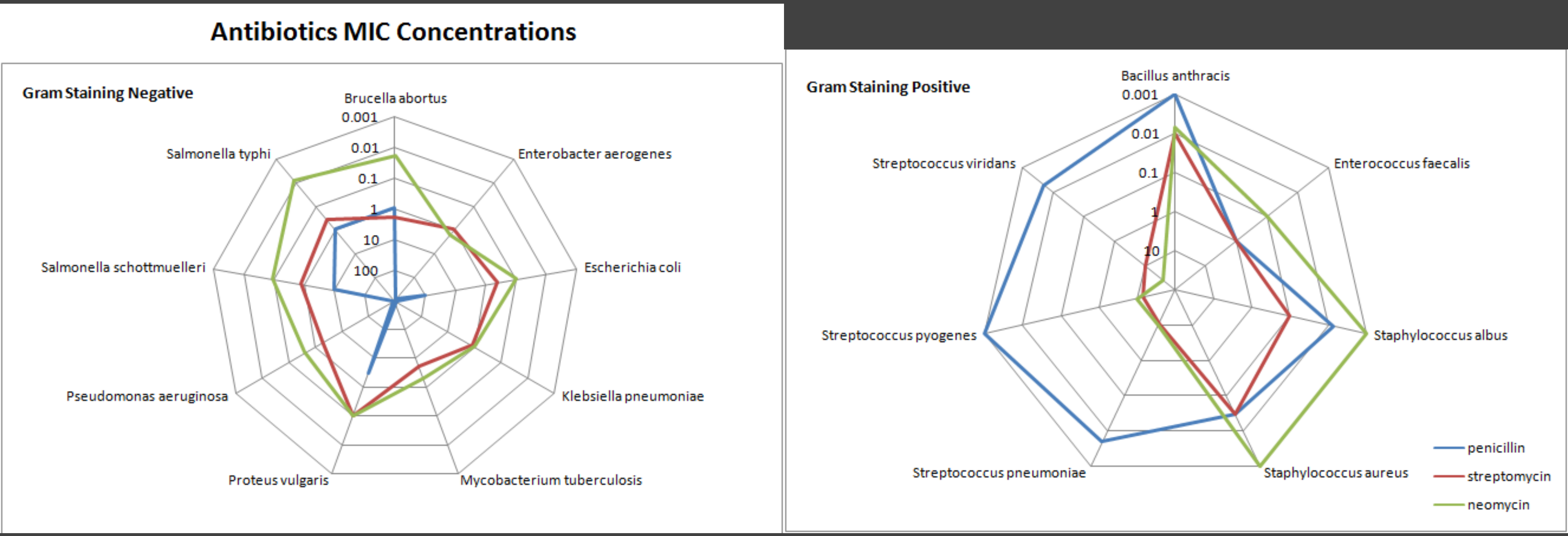
Between adjacent axes: line crossings imply neg. correlation, shared slopes imply pos. correlation.

Full plot can be cluttered. **Interactive selection** can be used to assess multivariate relationships.

Highly sensitive to axis **scale** and **ordering**.

Expertise required to use effectively!

Radar Plot / Star Graph

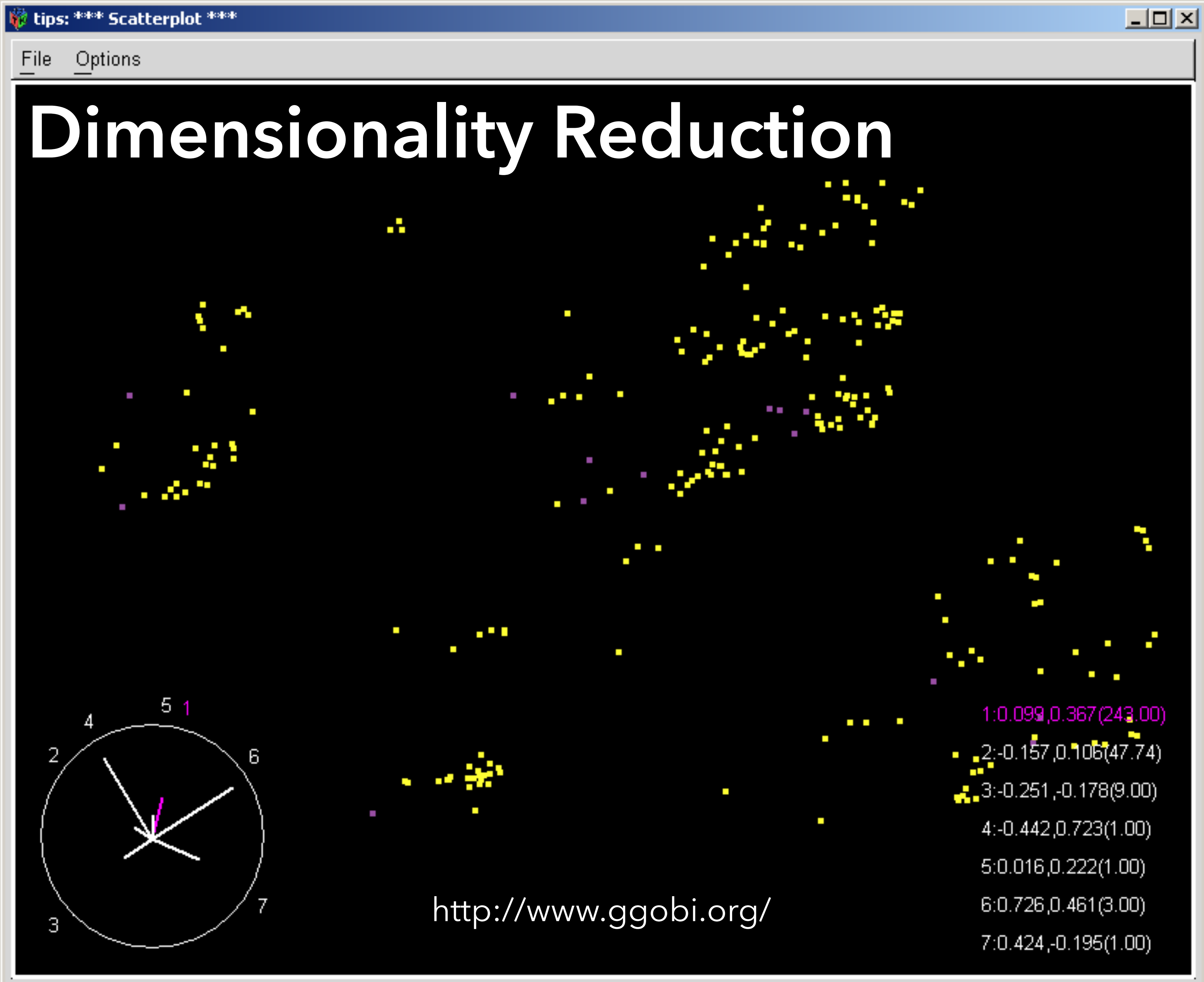


“Parallel” dimensions in polar coordinate space

Best if same units apply to each axis

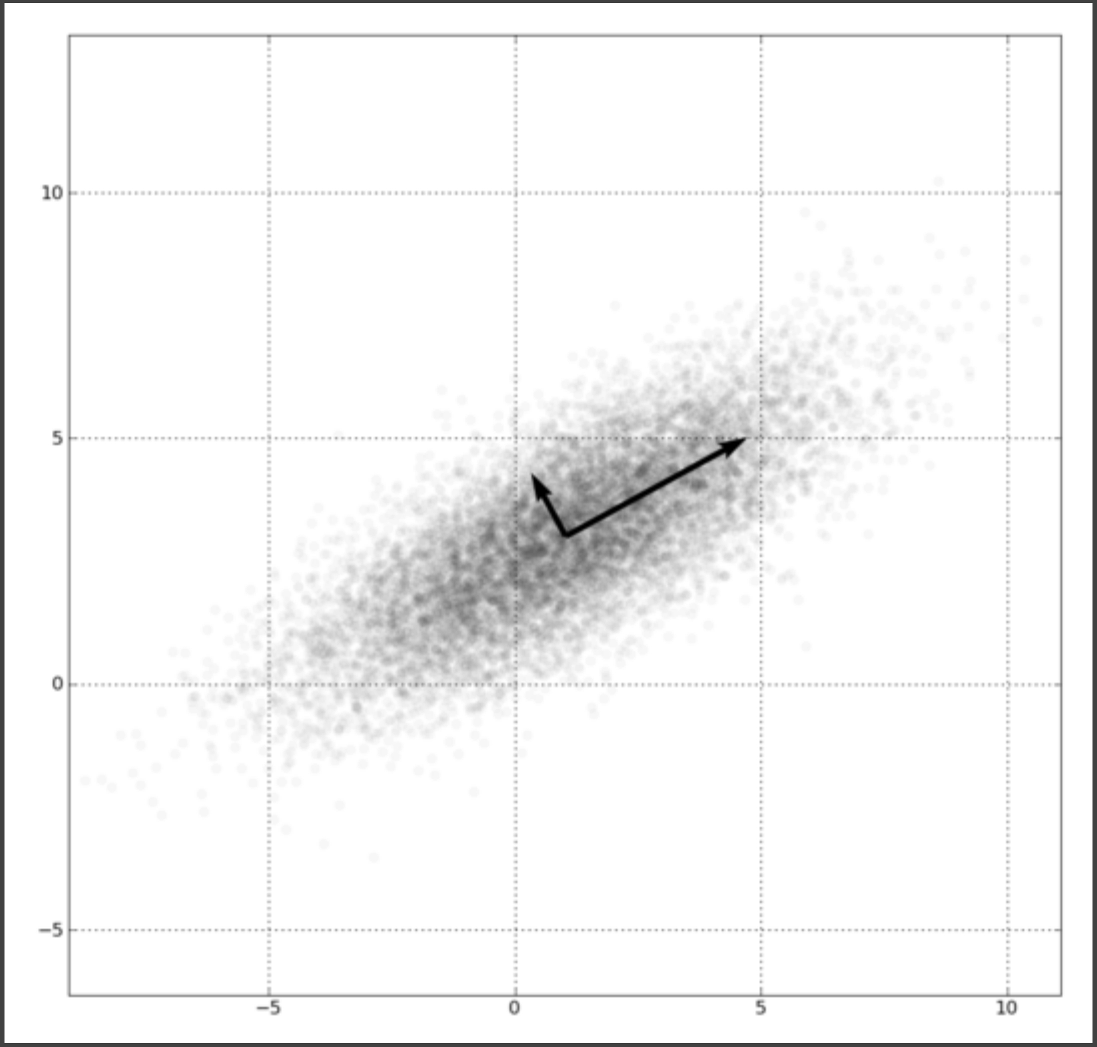
Dimensionality Reduction

Dimensionality Reduction



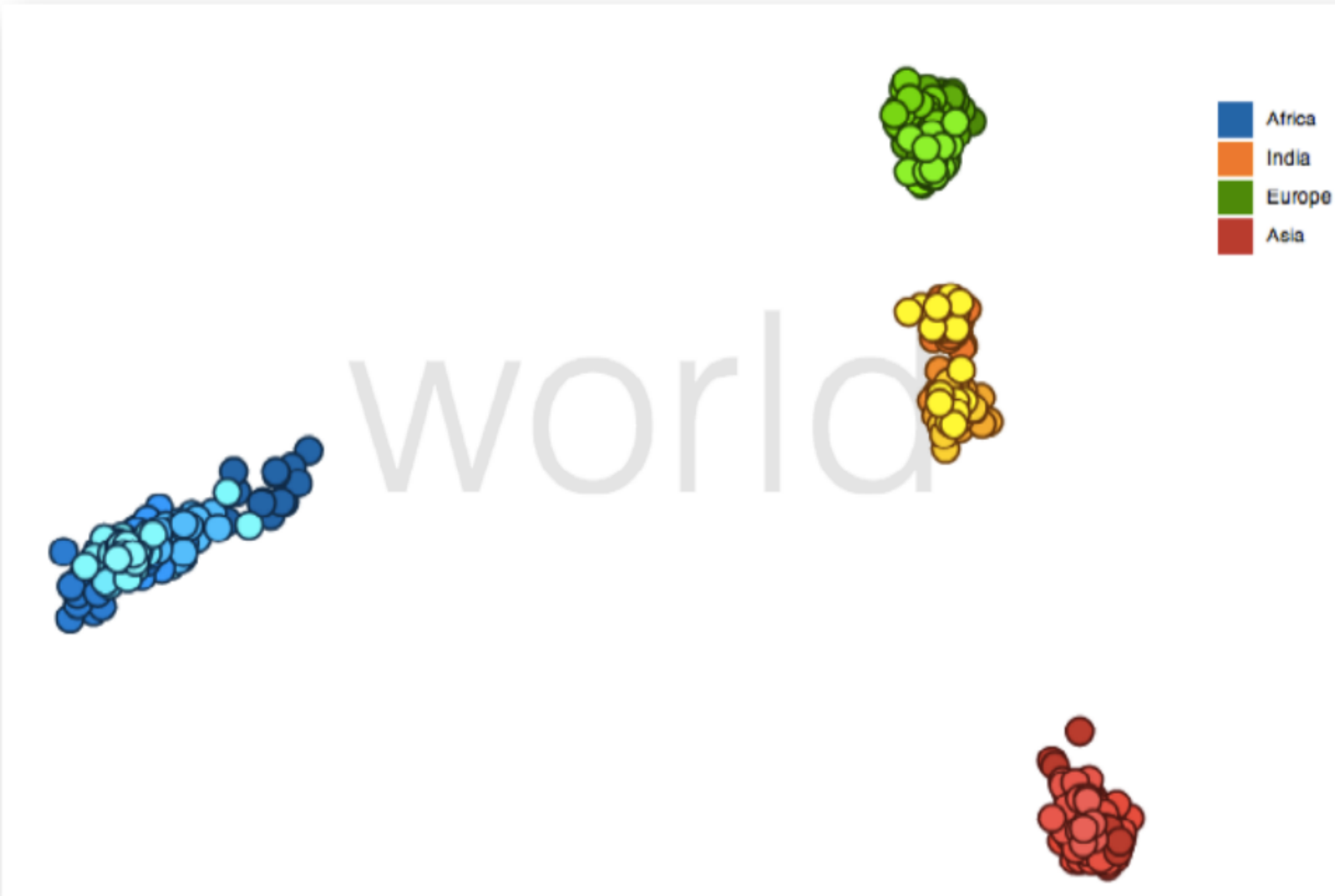
http://www.ggobi.org/

Principal Components Analysis

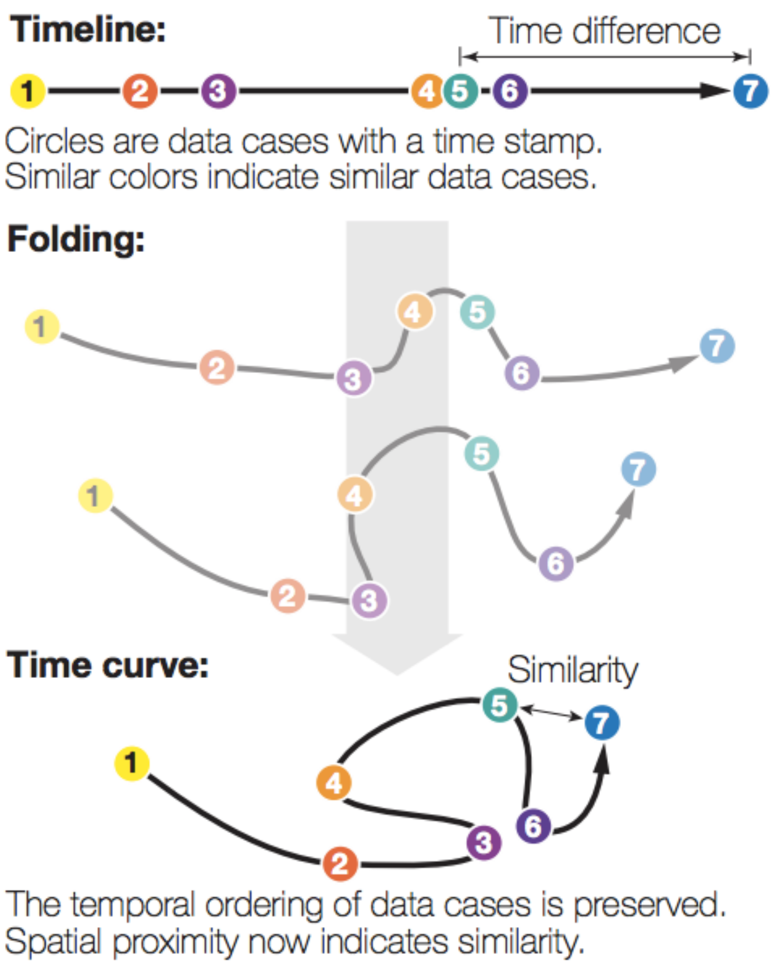


1. Mean-center the data.
2. Find ⊥ basis vectors that maximize the data variance.
3. Plot the data using the top vectors.

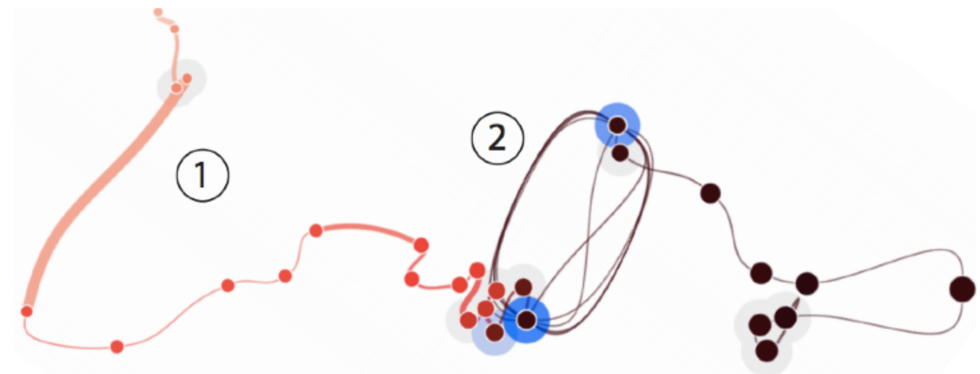
PCA of Genomes [Demiralp et al. '13]



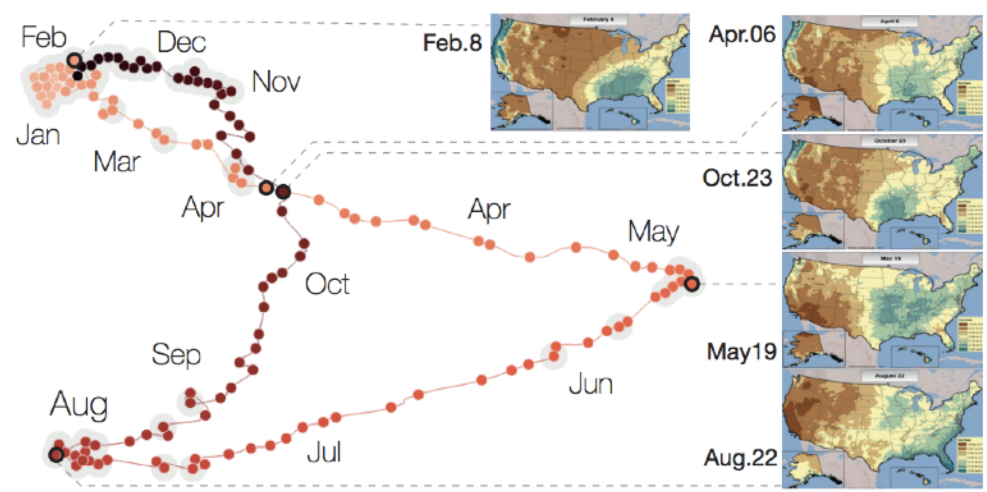
Time Curves [Bach et al. '16]



(a) Folding time



Wikipedia "Chocolate" Article



U.S. Precipitation over 1 Year

Many Reduction Techniques!

Principal Components Analysis (PCA)

Multidimensional Scaling (MDS)

Locally Linear Embedding (LLE)

t-Dist. Stochastic Neighbor Embedding (t-SNE)

Isomap

Auto-Encoder Neural Networks

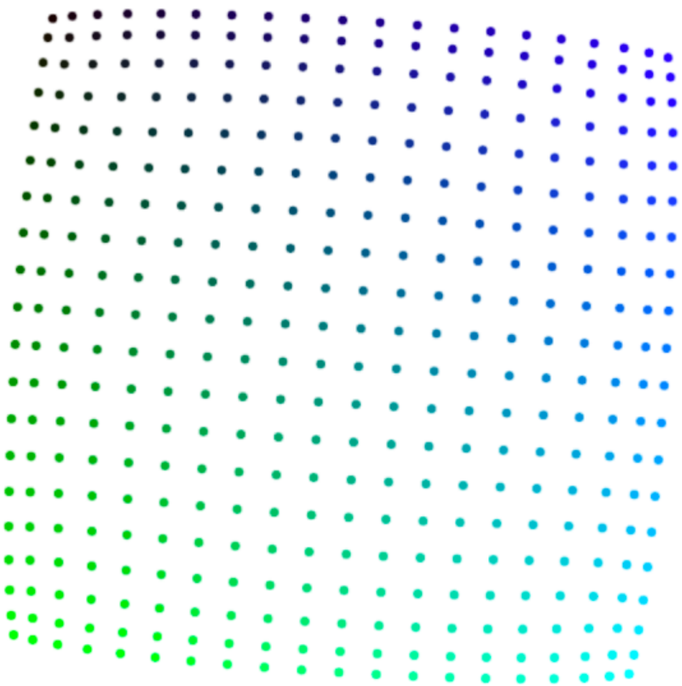
Topological Methods

…

Distill ABOUT PRIZE SUBMIT

How to Use t-SNE Effectively

Although extremely useful for visualizing high-dimensional data, t-SNE plots can sometimes be mysterious or misleading. By exploring how it behaves in simple cases, we can learn to use it more effectively.



Step 1,910

A square grid with equal spacing between points. Try convergence at different sizes.

Points Per Side 20

Perplexity 10

Epsilon 5

MARTIN WATTENBERG Google Brain

FERNANDA VIÉGAS Google Brain

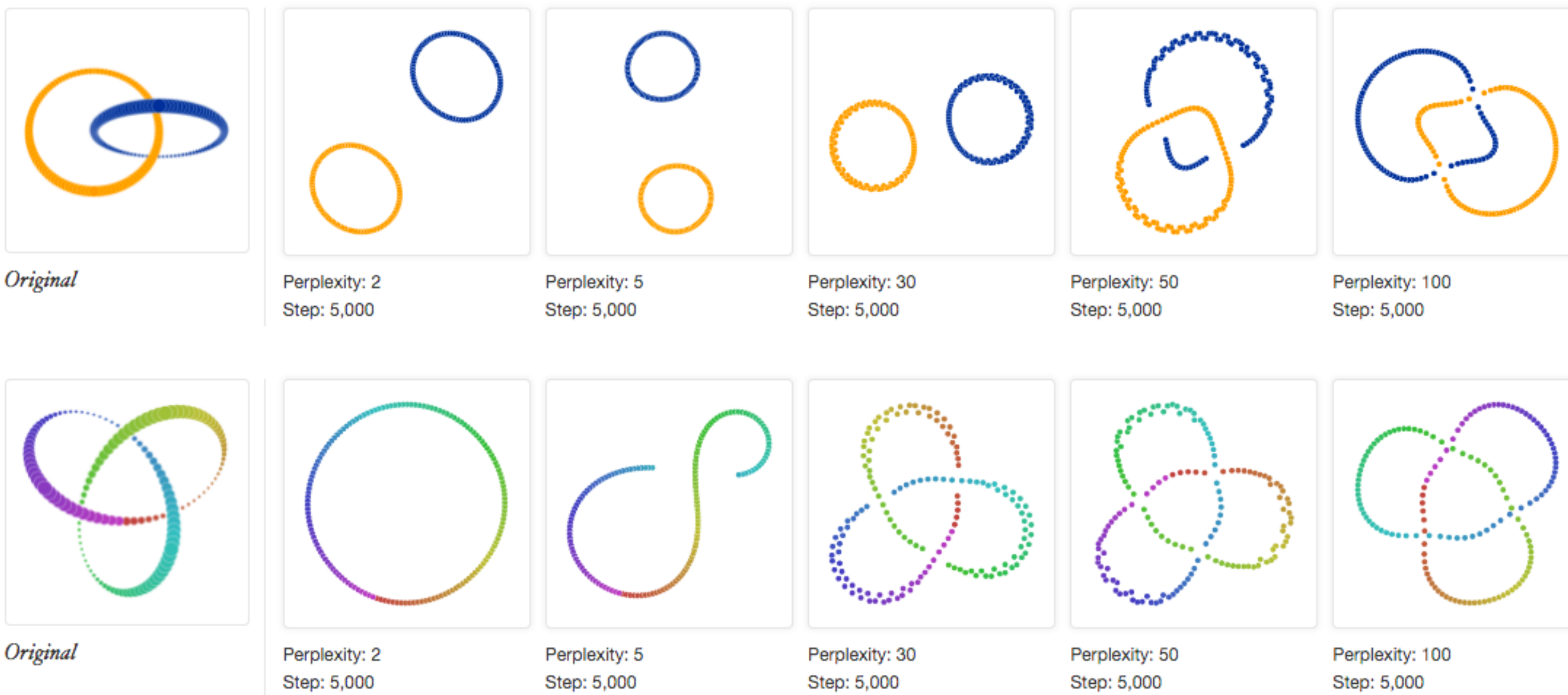
IAN JOHNSON Google Cloud

Oct. 13 2016

Citation: Wattenberg, et al., 2016

distill.pub

Visualizing t-SNE [Wattenberg et al. '16]



Visual Encoding Design

Use **expressive** and **effective** encodings
Avoid **over-encoding**
Reduce the problem space
Use **space** and **small multiples** intelligently
Use **interaction** to generate *relevant* views

Rarely does a single visualization answer all questions. Instead, the ability to generate appropriate visualizations quickly is critical!