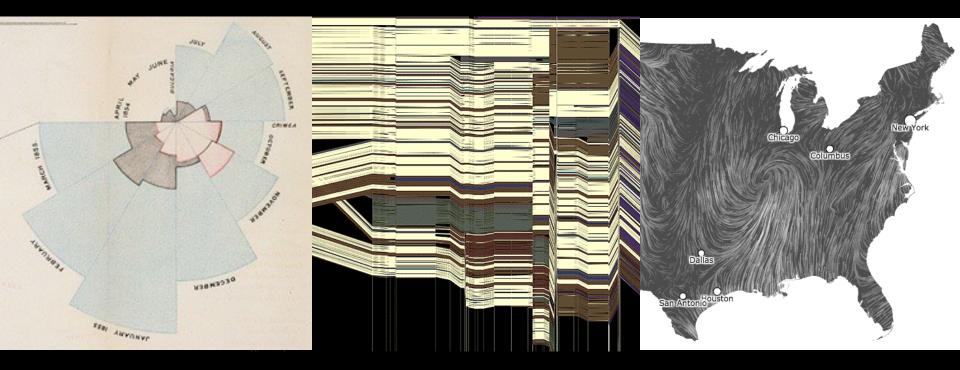
cse 442 - Data Visualization Visual Encoding Design



Jeffrey Heer University of Washington

Review: Expressiveness & Effectiveness / APT

Choosing Visual Encodings

Assume k visual encodings and n data attributes. We would like to pick the "best" encoding among a combinatorial set of possibilities of size $(n+1)^k$

Principle of Consistency

The properties of the image (visual variables) should match the properties of the data.

Principle of Importance Ordering

Encode the most important information in the most effective way.

Design Criteria [Mackinlay 86]

Expressiveness

A set of facts is *expressible* in a visual language if the sentences (i.e. the visualizations) in the language express all the facts in the set of data, and only the facts in the data.

Effectiveness

A visualization is more *effective* than another visualization if the information conveyed by one visualization is more readily perceived than the information in the other visualization.

Design Criteria Translated

Tell the truth and nothing but the truth (don't lie, and don't lie by omission)

Use encodings that people decode better (where better = faster and/or more accurate)

Effectiveness Rankings [Mackinlay 86]

QUANTITATIVE

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

ORDINAL

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

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

Effectiveness Rankings [Mackinlay 86]

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

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

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

Effectiveness Rankings [Mackinlay 86]

QUANTITATIVE

Position Length Angle Slope Area (Size) Volume Density (Value)[•] Color Sat Color Hue · Texture Connection Containment Shape

ORDINAL

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

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

Mackinlay's Design Algorithm

APT - "A Presentation Tool", 1986

User formally specifies data model and type Input: ordered list of data variables to show

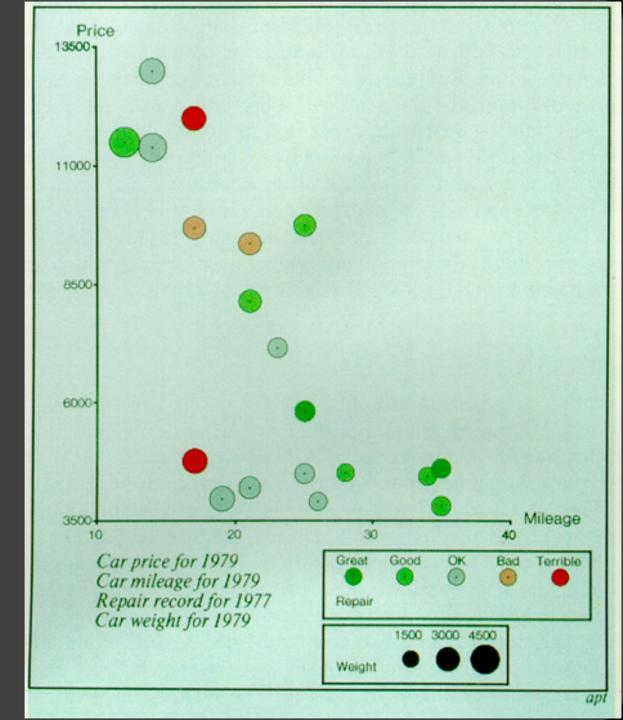
APT searches over design space Test expressiveness of each visual encoding Generate encodings that pass test Rank by perceptual effectiveness criteria

Output the "most effective" visualization

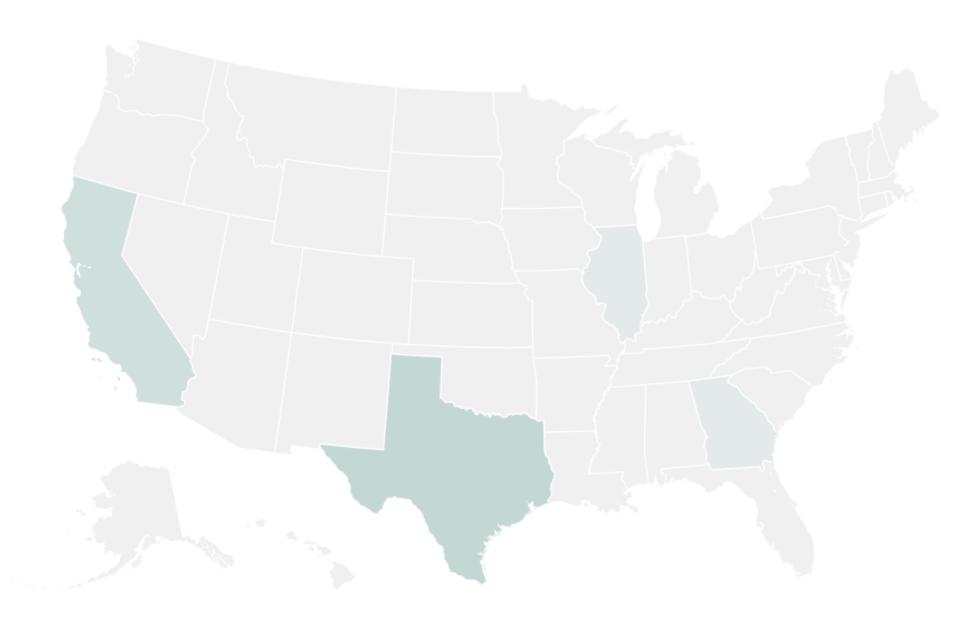
APT

Automatically generate chart for car data

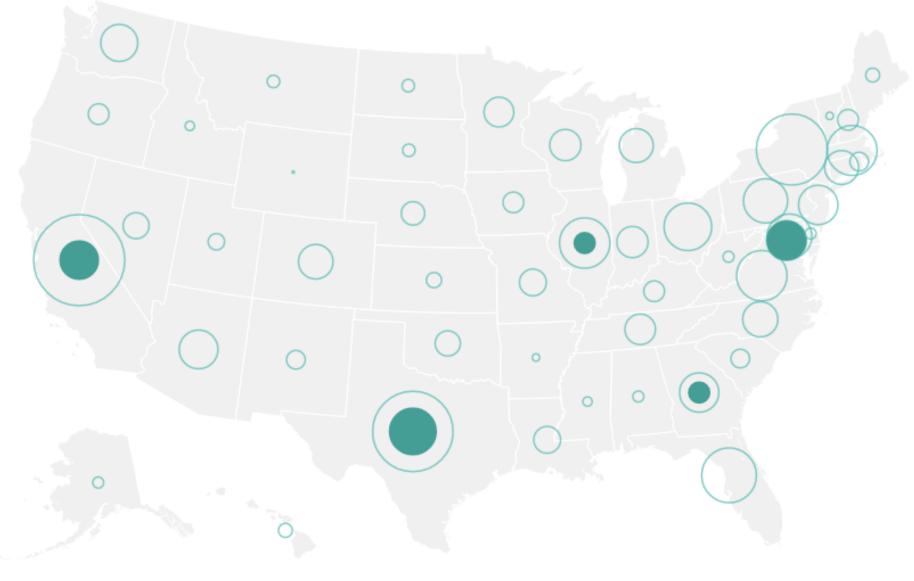
Input variables:1. Price2. Mileage3. Repair4. Weight



Design Examples



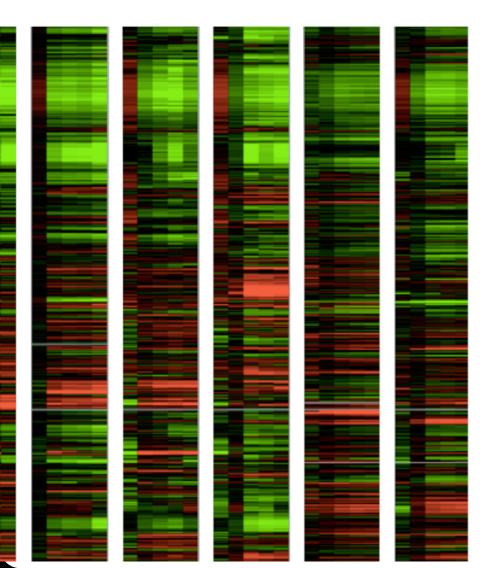
Color Encoding



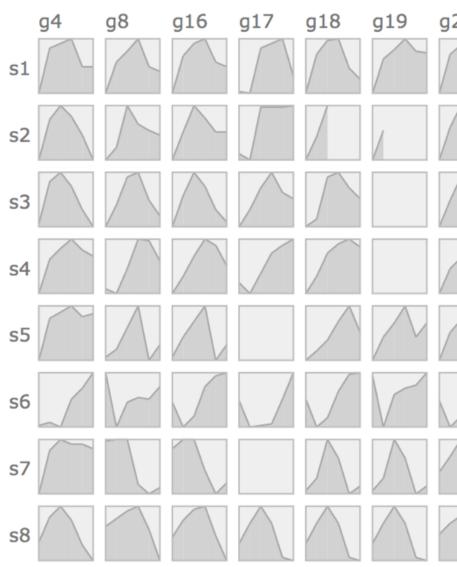
Area Encoding

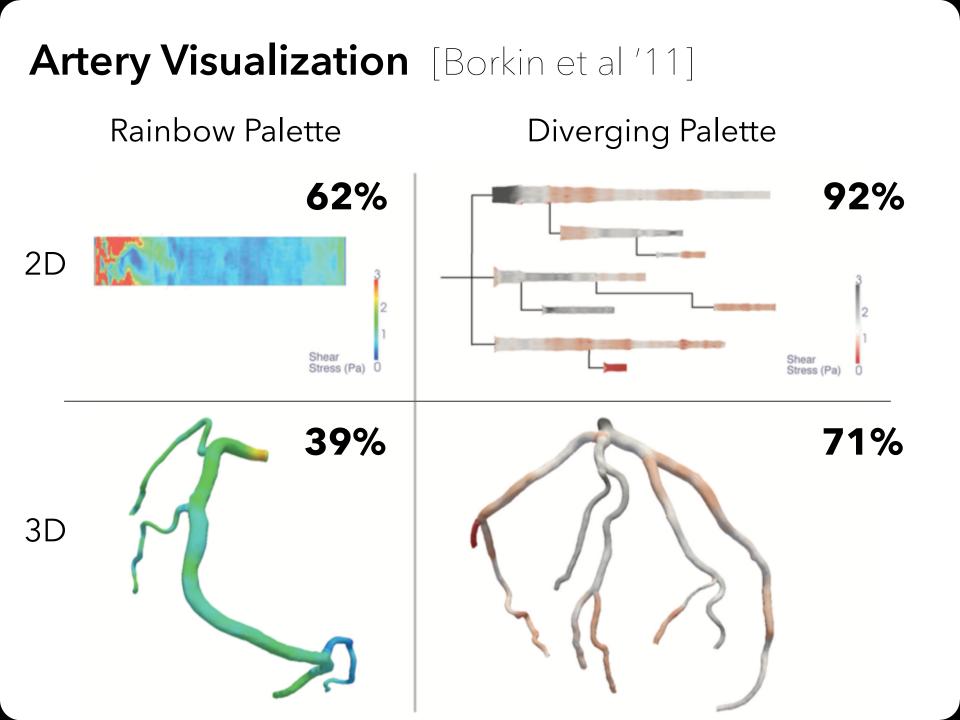
Gene Expression Time-Series [Meyer et al '11]

Color Encoding



Position Encoding





Other Visual Encoding Channels?

wind map

April 1, 2015 11:35 pm EST (time of forecast download)

top speed: 30.5 mph average: 10.2 mph



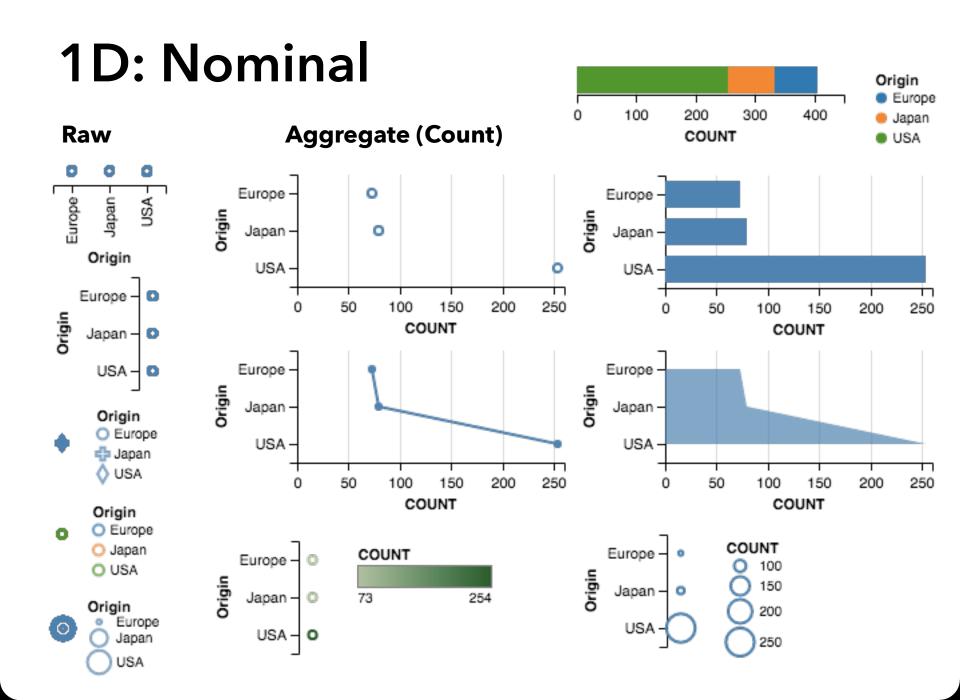
A Design Space of Visual Encodings

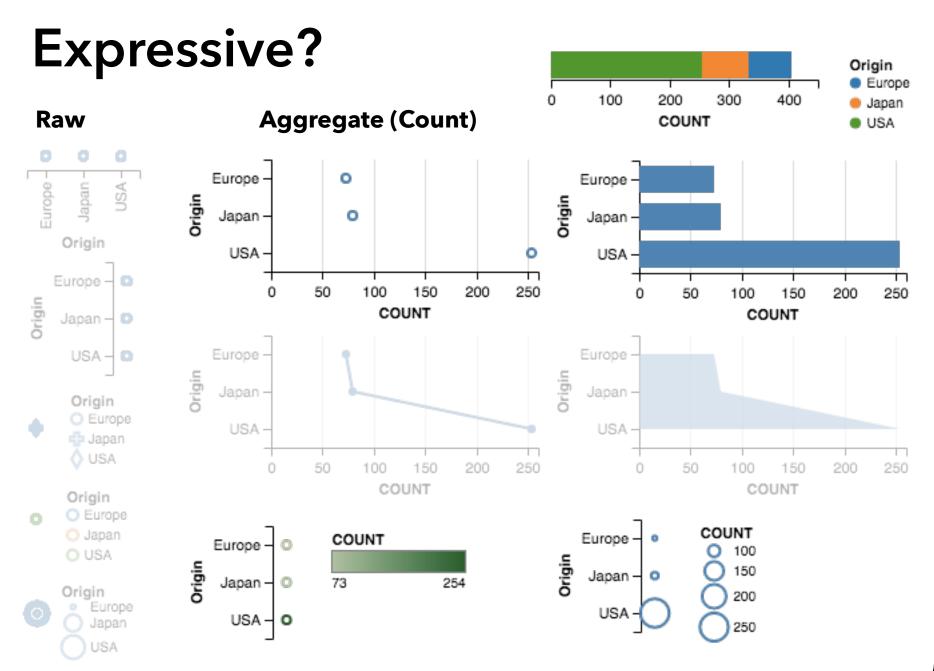
Mapping Data to Visual Variables

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,* ...).

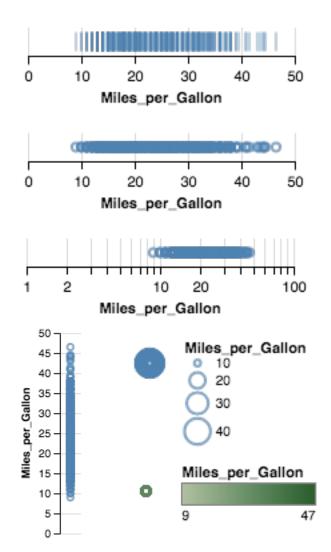
These options define a large combinatorial space, containing both useful and questionable charts!



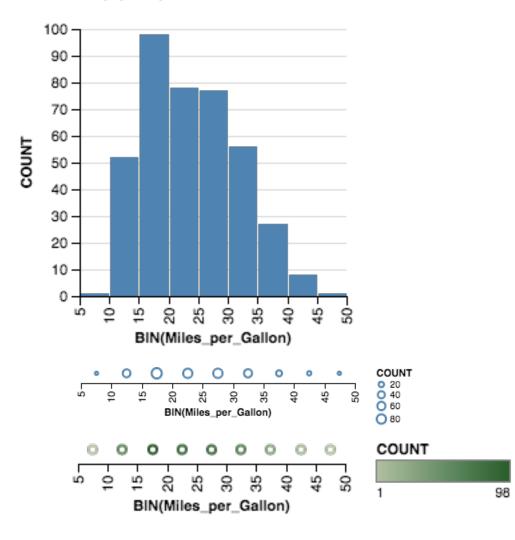


1D: Quantitative

Raw

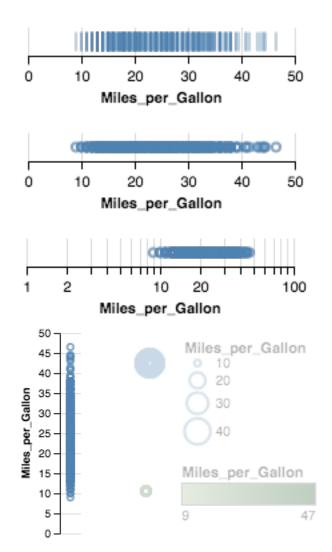


Aggregate (Count)

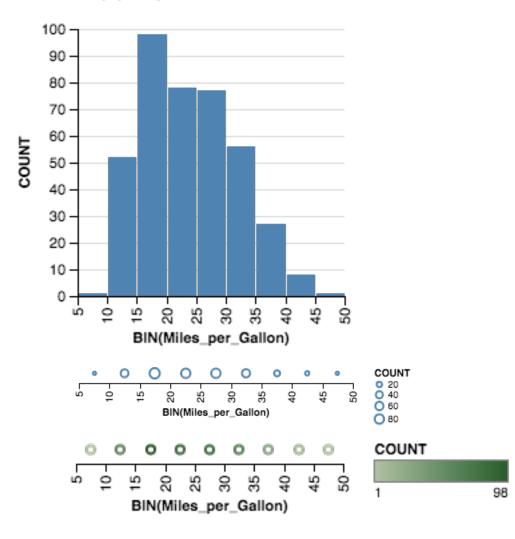


Expressive?

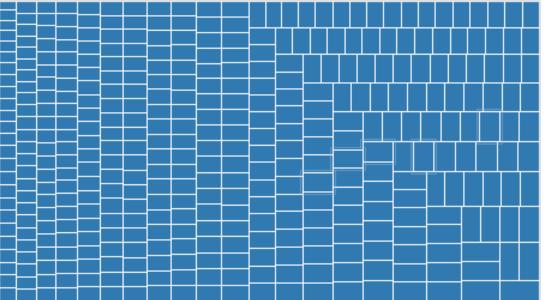
Raw

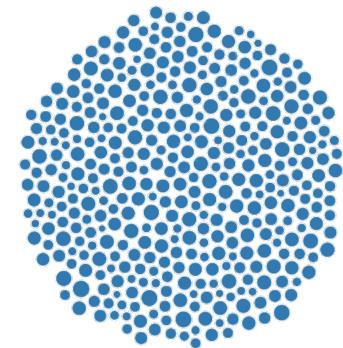


Aggregate (Count)



Raw (with Layout Algorithm)

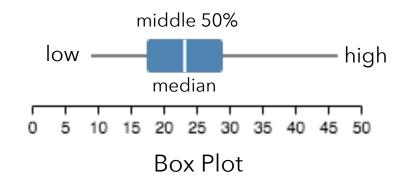


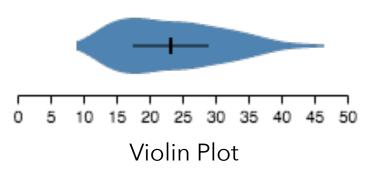


Treemap

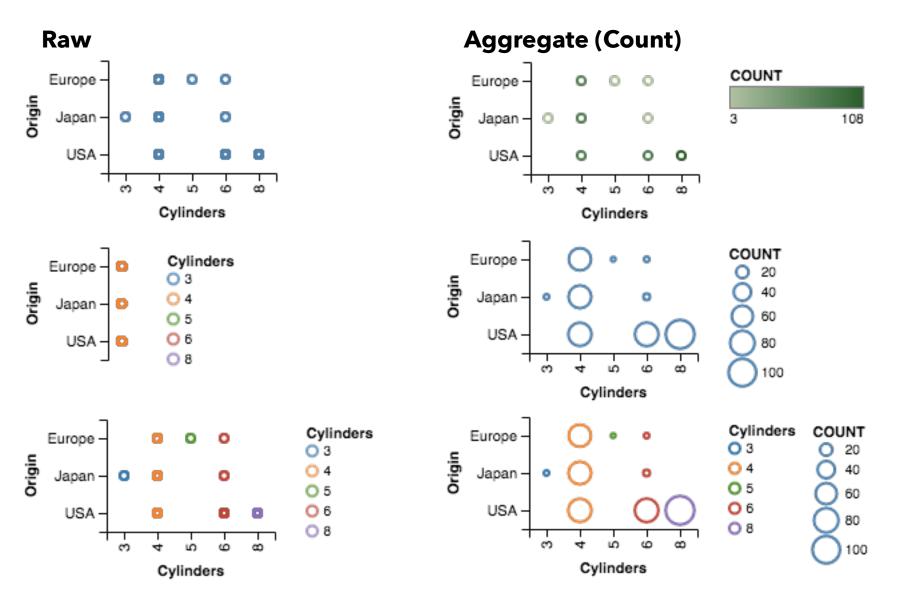
Bubble Chart

Aggregate (Distributions)



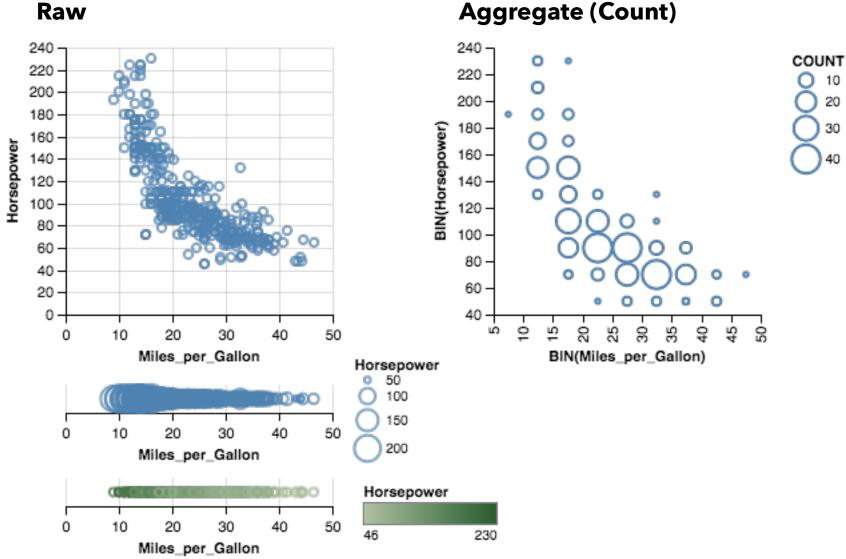


2D: Nominal x Nominal



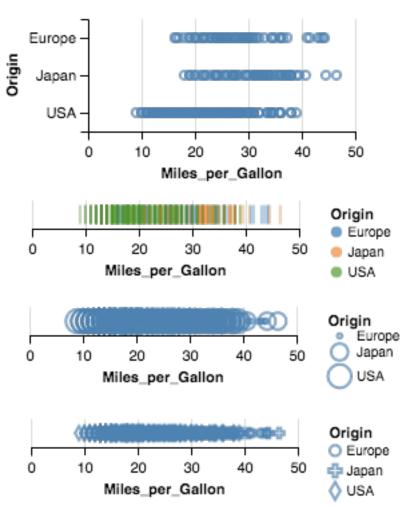
2D: Quantitative x Quantitative

Raw

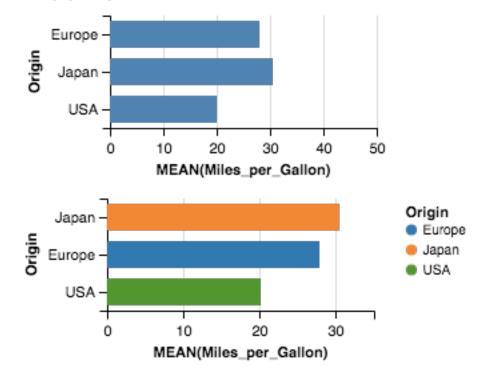


2D: Nominal x Quantitative

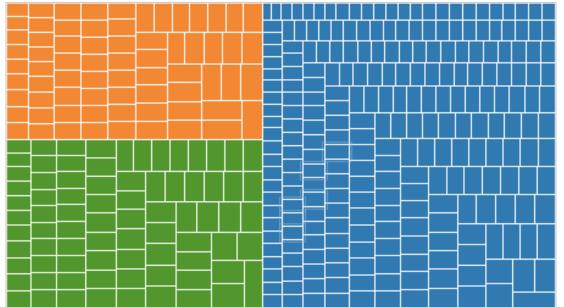
Raw

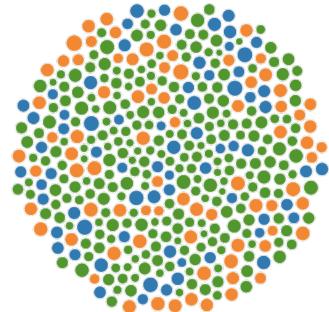


Aggregate (Mean)



Raw (with Layout Algorithm)

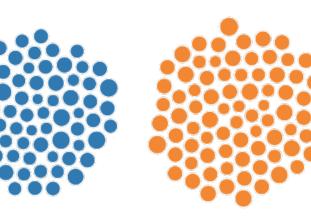




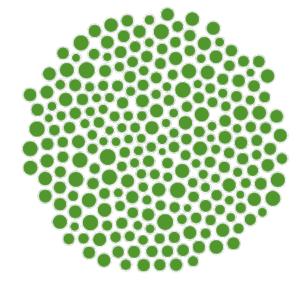
Bubble Chart

Origin Europe Japan USA

Treemap







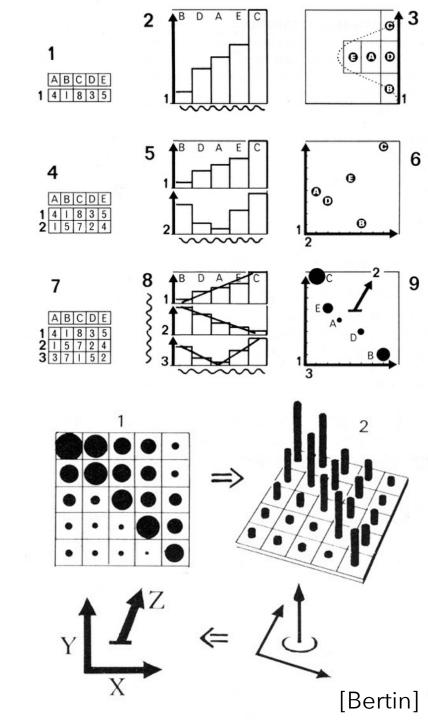
3D and Higher

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?



Administrivia

A2: Exploratory Data Analysis

Use visualization software to form & answer questions

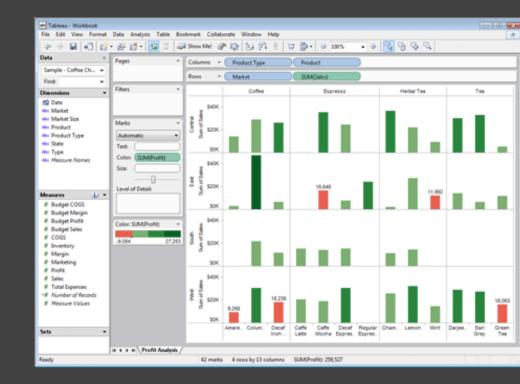
First steps:

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



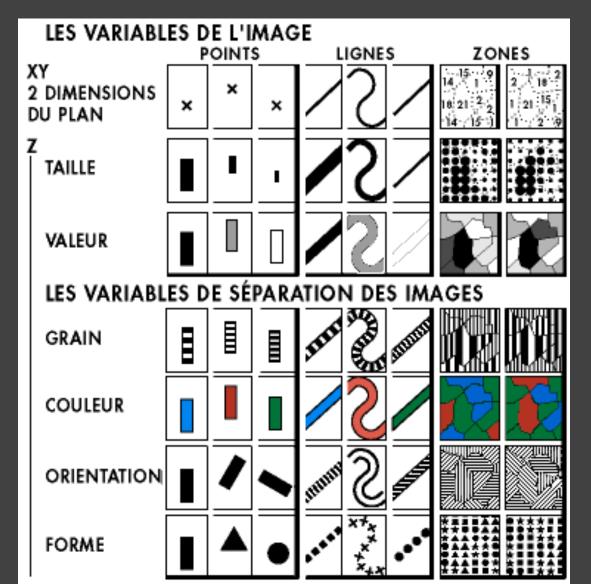
Screenshots of most insightful views (10+) Include titles and captions for each view Due by 11:59pm Monday, Oct 16

Multidimensional Data

Visual Encoding Variables

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

~8 dimensions?

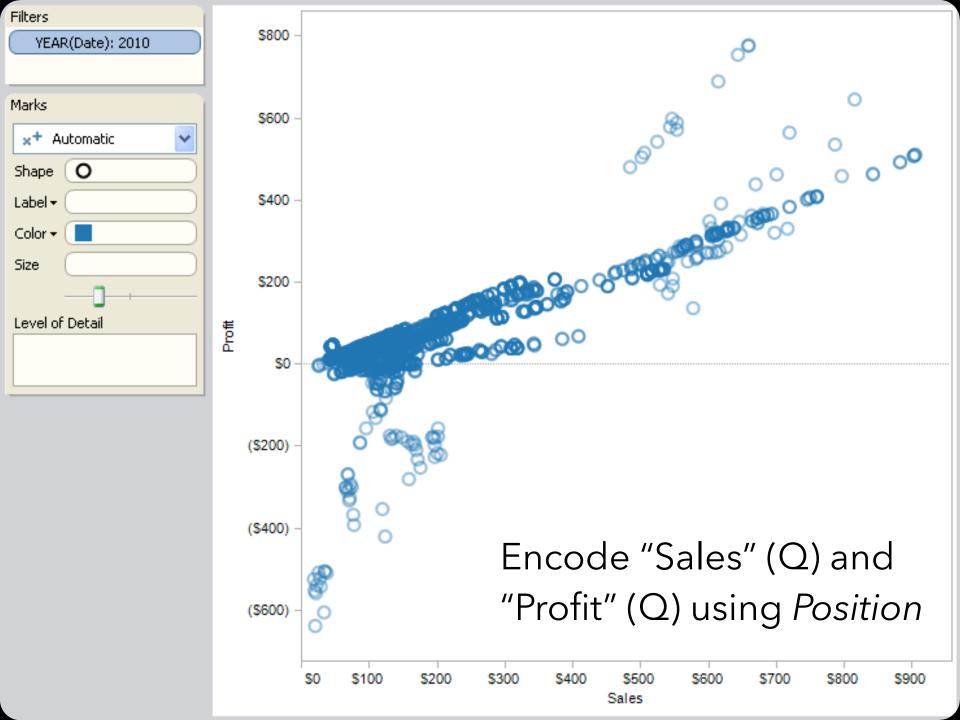


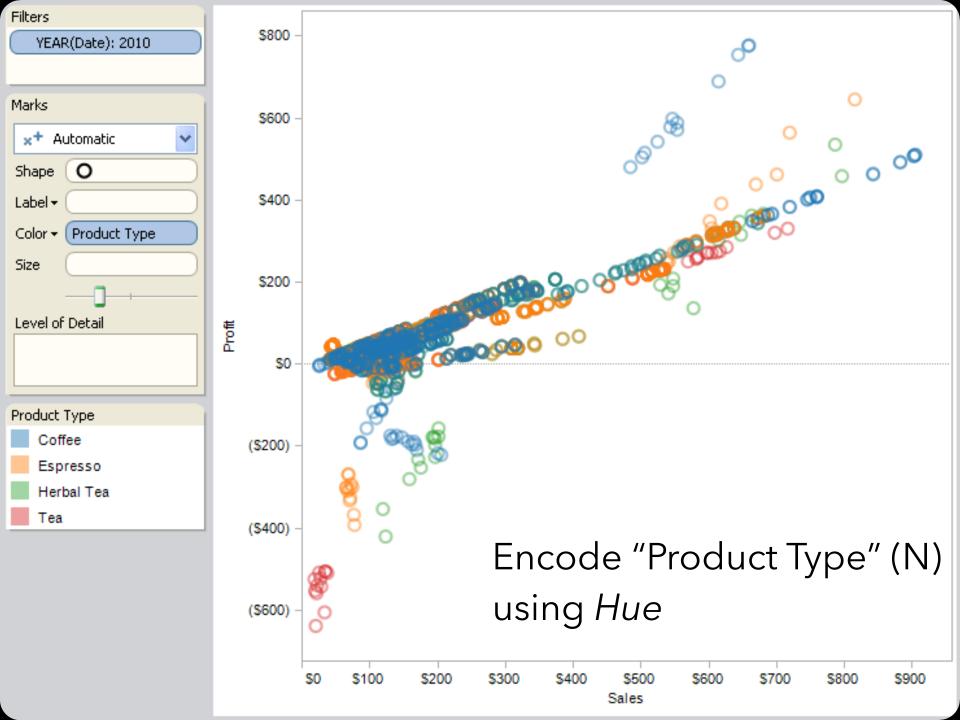
Example: Coffee Sales

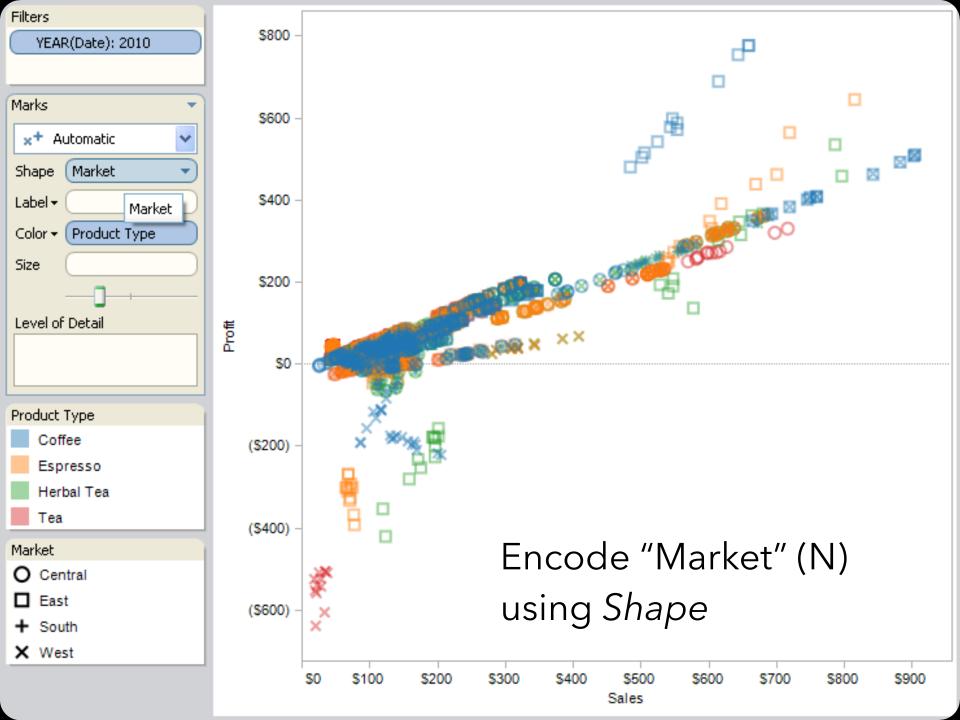
Sales figures for a fictional coffee chain

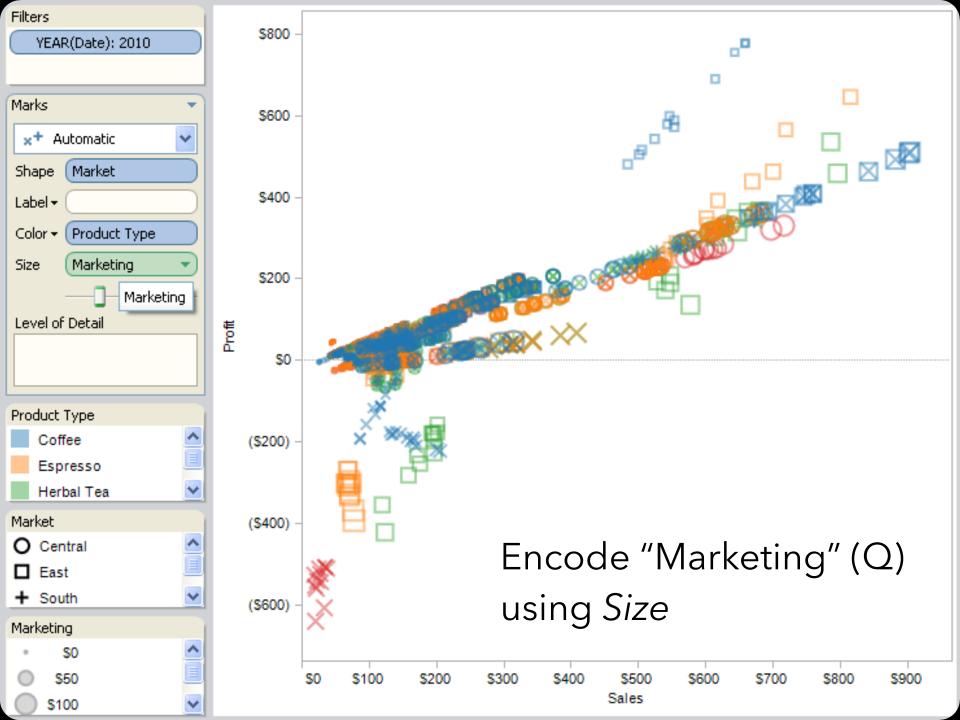
SalesQ-RatioProfitQ-RatioMarketingQ-RatioProduct TypeN {CoffeeMarketN {Central

Q-Ratio Q-Ratio Q-Ratio N {Coffee, Espresso, Herbal Tea, Tea} N {Central, East, South, West}

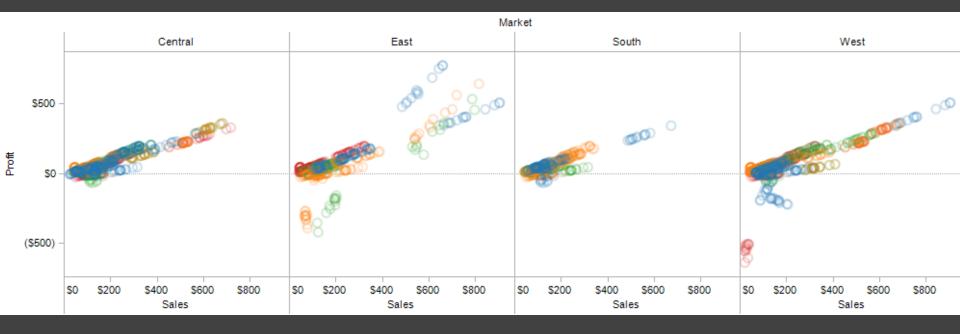






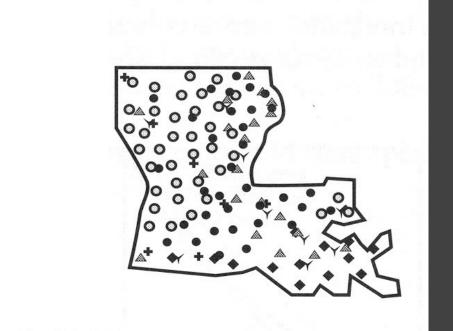


Trellis Plots



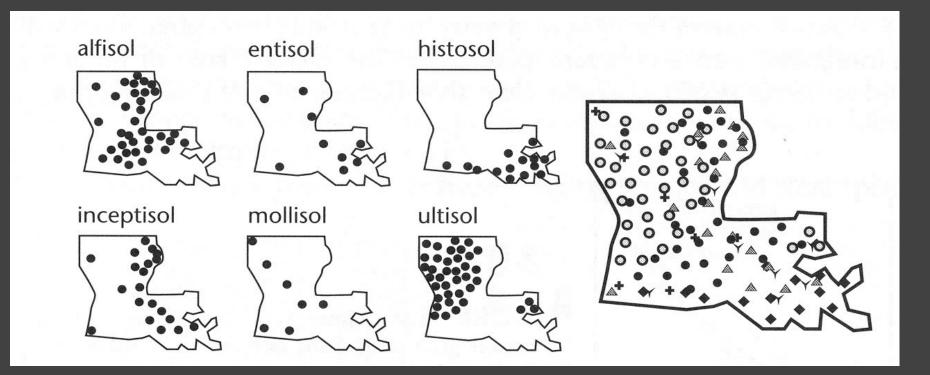
A *trellis plot* subdivides space to enable comparison across multiple plots. Typically nominal or ordinal variables are used as dimensions for subdivision.

Small Multiples



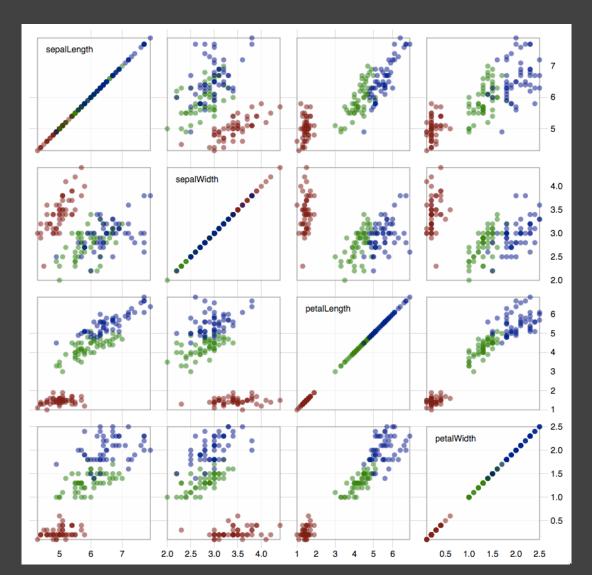
[MacEachren '95, Figure 2.11, p. 38]

Small Multiples



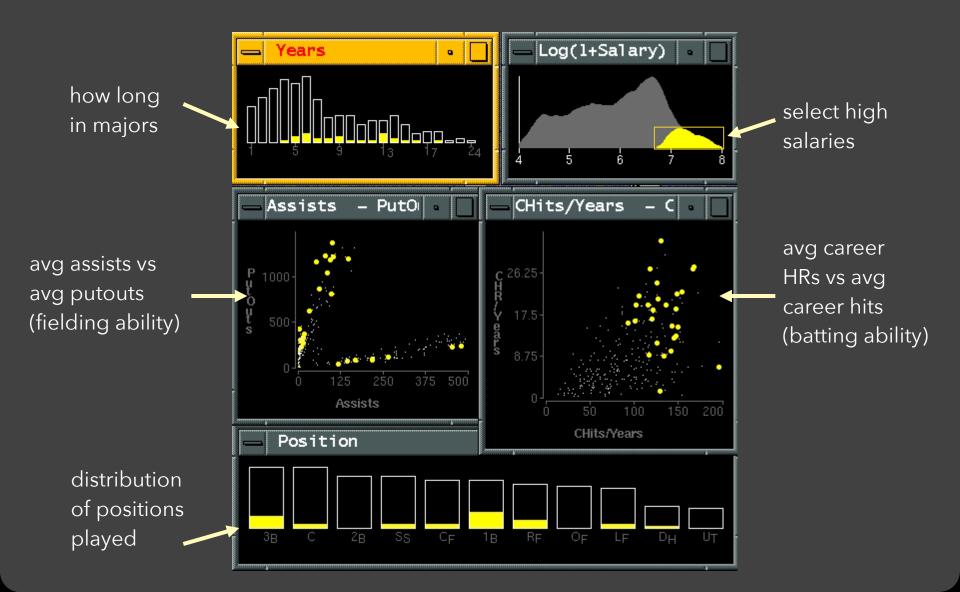
[MacEachren '95, Figure 2.11, p. 38]

Scatterplot Matrix (SPLOM)

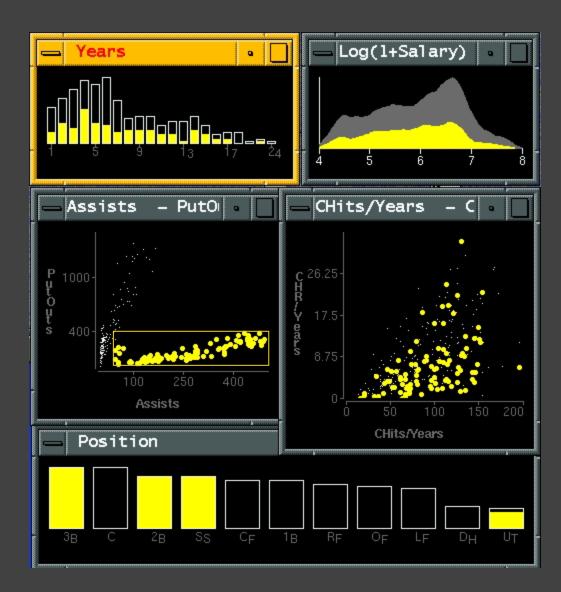


Scatter plots for pairwise comparison of each data dimension.

Multiple Coordinated Views

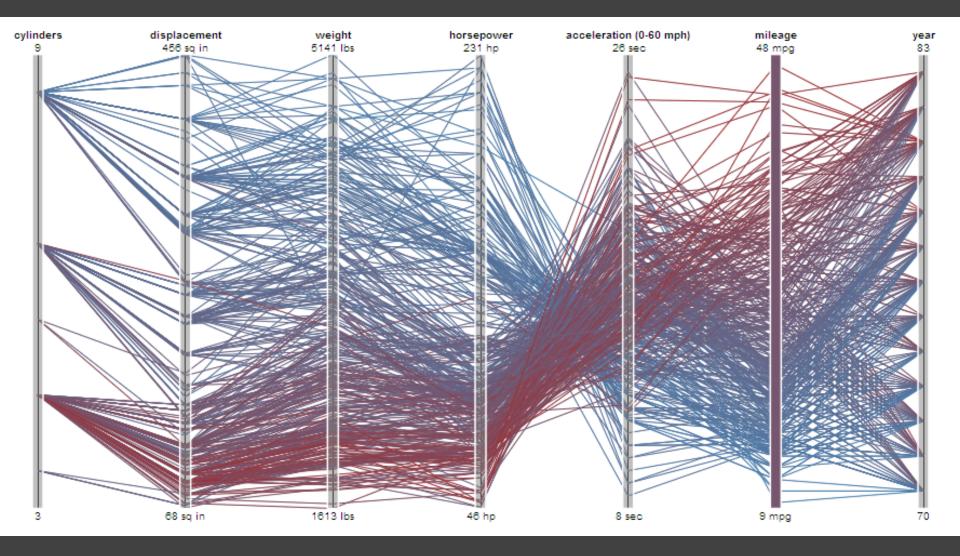


Linking Assists to Position



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

Antibiotics MIC Concentrations Bacillus anthracis Gram Staining Positive **Gram Staining Negative** 0.001 Brucella abortus 0.001 0.01 0.01 Salmonella typhi Enterobacter aerogenes Streptococcus viridans Enterococcus faecalis 0.1 0.1 10 Salmonella schottmuelleri 100 Escherichia coli Streptococcus pyogenes Staphylococcus albus Klebsiella pneumoniae Pseudomonas aeruginosa penicillin Streptococcus pneumoniae Staphylococcus aureus streptomycin Proteus vulgaris Mycobacterium tuberculosis neomvcin

"Parallel" dimensions in polar coordinate space Best if same units apply to each axis

Dimensionality Reduction

5 1

6

7

2

З

File Options

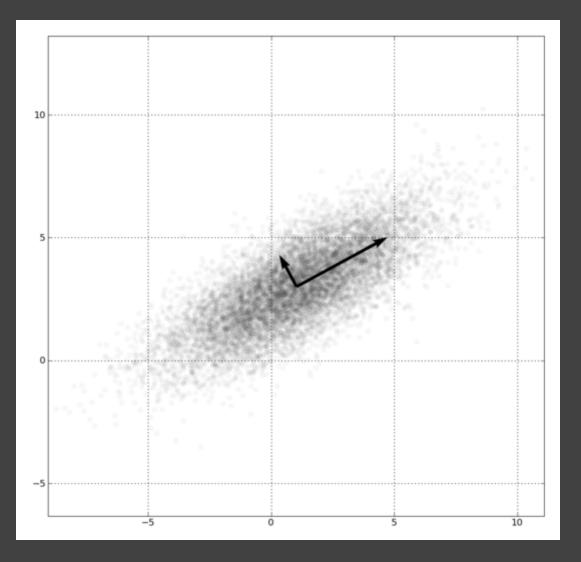
Dimensionality Reduction

http://www.ggobi.org/

1:0.099,0.367(243.00) 2:-0.157,0.106(47.74) 3:-0.251,-0.178(9.00) 4:-0.442,0.723(1.00) 5:0.016,0.222(1.00) 6:0.726,0.461(3.00) 7:0.424,-0.195(1.00)

<u> – – ×</u>

Principal Components Analysis

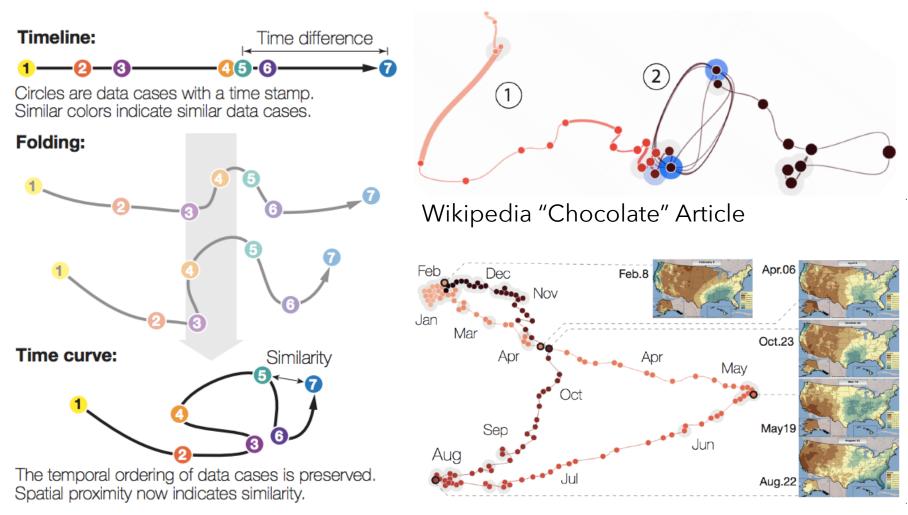


1. Mean-center the data. 2. Find \perp basis vectors that maximize the data variance. 3. Plot the data using the top vectors.

PCA of Genomes [Demiralp et al. '13]



Time Curves [Bach et al. '16]



(a) Folding time

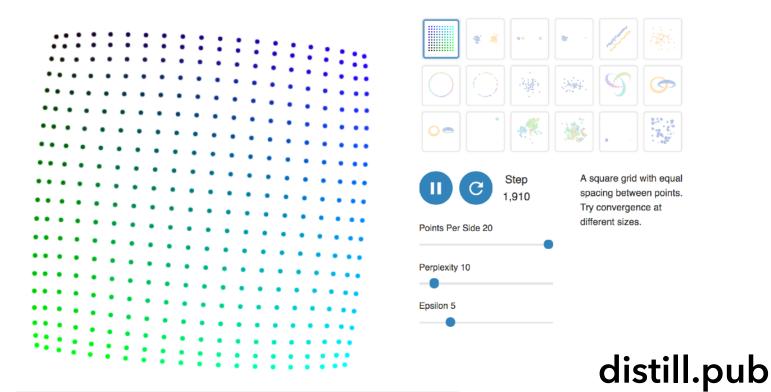
U.S. Precipitation over 1 Year

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**

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.



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!