CSSS 569 · Visualizing Data and Models

# PRINCIPLES FOR THE VISUAL DISPLAY OF SCIENTIFIC INFORMATION

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and

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CENTER for STATISTICS and the SOCIAL SCIENCES Turning points in the history of visual displays Tufte's principles for information design How data visualization differs from infovis Scales and scaling Making a scatterplot from scratch Sorting in tables and table-like figures

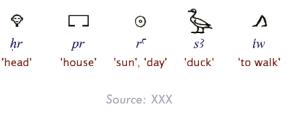


Megalaceros, a giant prehistoric deer Source: Wikipedia/public domain The visual representation of information dates back to the Lascaux cave paintings ( $\sim$ 15000 BCE)

Simplified images of a more complex physical reality

Pictographic writing followed – now simplified images could represent other ideas

These cartoons may seem primitive compared to later realistic art, but cartoons are often better communicators



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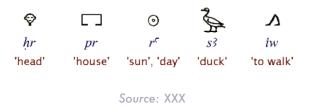
#### Where's the hand?



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Where's the hand?





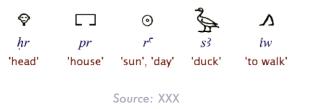


Source: Edward Tufte, VDQI

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Where's the hand? Which hand did you see first?







Source: Edward Tufte, VDQI

# The Invention of Visual Display: Three Elements

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Source: data-art.net/resources/history\_of\_vis.php

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#### Source: Tufte, VDQI



#### Source: Google Earth

Mapmakers have long known that the best maps simplify and even distort reality

Finding features in a photograph is hard – sharpening and repositioning features can help them pop out



#### Wait...Where's Giza?

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...literally unfindable without prior knowledge

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#### Even zoomed in, we can't spot the largest manmade objects on Earth

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Apparently, they're not downtown...

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#### No choice but to hunt around for a clue

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A minute of searching sandy areas later...

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Source: lexicorient.com/egypt/cairo\_m1.htm

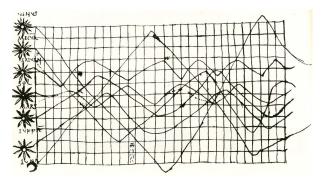
To find Waldo, use a map The richest, most beautiful

representation isn't always the most useful one

Removing lines, color, and information can help

Just like in statistical modeling: we need to (over-)simplify to learn

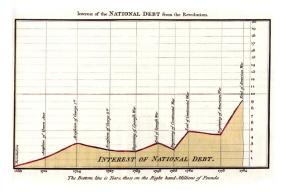
A view somewhat at odds with Tufte...



Source: Tufte, VDQI

#### Abstract visual displays are relatively new

A monk made this vague time series plot of planetary movement c. 950 CE First known use of time as a visual dimension, but unknown until much later



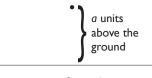
Source: Tufte, VDQI

The unknown monk's plot didn't catch on – lost in a notebook Time series plots weren't rediscovered until 1786 (!) by William Playfair Playfair's time series dealt with abstract concepts like public debt and trade deficits Playfair also invented the bar plot and pie chart The ancients knew geometry backwards and forwards

Oddly, they don't appear to have discovered graphics

Before 1637 CE, visual representations = literal depictions of physical relationships

To go beyond maps, Descartes (and perhaps Fermat) had to recognize something that seems obvious in retrospect



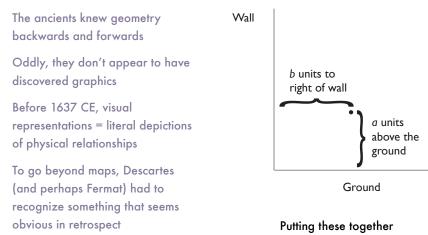
Ground

Maps show the distance between objects and a reference...

The ancients knew geometry Wall backwards and forwards Oddly, they don't appear to have b units to discovered graphics right of wall Before 1637 CE, visual representations = literal depictions of physical relationships To go beyond maps, Descartes (and perhaps Fermat) had to recognize something that seems

obvious in retrospect

...Or between one object and *multiple* references

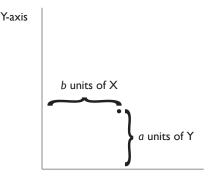


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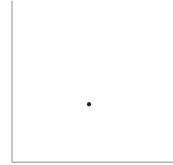
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# But what if we change the names of our references to be general?

The ancients knew geometry Y-axis backwards and forwards Oddly, they don't appear to have discovered graphics Before 1637 CE, visual representations = literal depictions of physical relationships To go beyond maps, Descartes (and perhaps Fermat) had to



X-axis

We've made something revolutionary: a relational graphic

obvious in retrospect

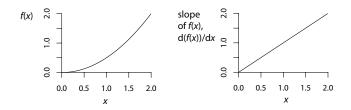
recognize something that seems

The axes of a Cartesian plane can measure anything Not just space, distance, time, or motion, but any functional relationship

The axes of a Cartesian plane can measure anything Not just space, distance, time, or motion, but any functional relationship Can you imagine learning calculus without any visual displays of functions?

$$f(\mathbf{x}) = \frac{1}{2}\mathbf{x}^2$$
 slope of  $f(\mathbf{x})$ ,  $\frac{df(\mathbf{x})}{\mathbf{x}} = \mathbf{x}$ 

versus



Cartesian plane an invaluable complement to mathematical formalism, with endless scientific applications

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Cartesian plane an invaluable complement to mathematical formalism, with endless scientific applications

On a Cartesian plane, any measurable concept can be plotted: money · attitudes · preferences · qualities · counts Still a somewhat unintuitive concept, esp. outside the social sciences Some natural scientists assume graphs always show things that physically exist (graphs are thus cartoons of things that could be photographed, or measured in meters, if only you had a ruler the right size) Most things we will display in this class could never be photographed or touched But we can still learn from visual analogies Most "types" of visual display were developed before 1900

19th century practitioners devoted enormous effort to graphics

By start of 20th century, some information designers were making very modern displays



#### From a 1911 conference on public health

By the mid-20th century, statistical graphics fell into disuse Popular use of information graphics: guick and dirty, for mass media 1970s saw reemergence of statistical graphics (e.g., John W. Tukey) Now easy to make, because of computers But computer defaults are inelegant, clunky, misleading Until 5 years ago, so were most media examples of visual display

# Today: A new golden age of data visualization

Edward Tufte wrote VDQI in the early 1980s

Responding to garish, inefficient, uninformative, misleading graphics of the time Tufte started his career as a political scientist Clearly disappointed by the quality of graphics in social science journals No one would have predicted VDQI would catch on: self-published Enormous impact: Tufte now a "guru" of information graphics; VDQI was one of Amazon.com's top 100 books of 20th century Lots of new books, conferences, and jobs in infovis followed

# Visual Display of Quantitative Information, 1983

Tufte's VDQI is several things:

- A beautiful, richly detailed, densely illustrated book
- A call for scientific integrity and seriousness in graphical display
- A polemic in favor of a particular aesthetics of information graphics



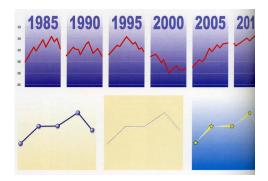
SECOND EDITION The Visual Display of Quantitative Information

My personal aesthetics are similar to (& influenced by) Tufte's But aesthetics are not a science: We can disagree over whether all of Tufte's ideas are "right"

- 1. Show viewers substance, not method or graphic design; avoid chartjunk
- 2. Maximize data, minimize ink & space; data-ink ratio
- 3. Be honest: avoid illusions and distortions; minimize the lie factor
- 4. Show the data and facilitate comparison
- 5. Use small multiples, or repetitions of a basic design

#### Tufte hates

- distracting grid lines or other scaffolding
- thick lines, overlarge plots
- gratuitous use of icons, embellishment (e.g., USA Today)
- unnecessary dimensions

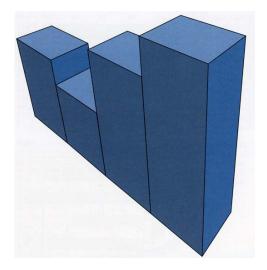


#### "If statistics is boring, then you've got the wrong numbers." Tufte

# Tufte's Principles 1. Avoid Chartjunk

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Chris Adolph (University of Washington)

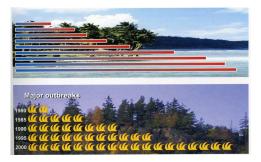
VD&M – Principles

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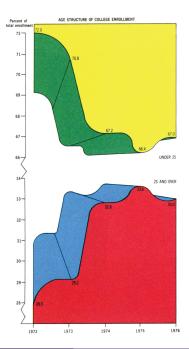
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In his first book, Tufte suggested this might be the worst graphic of all time

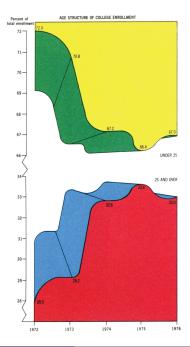
Problems?



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Problems?

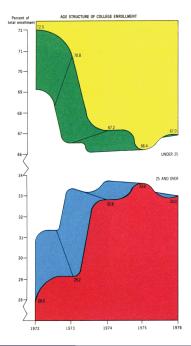
What's the scale?



In his first book, Tufte suggested this might be the worst graphic of all time

Problems?

What's the scale? Why the curves?



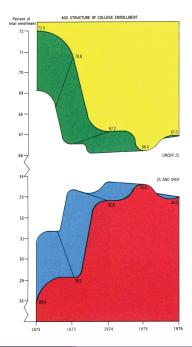
In his first book, Tufte suggested this might be the worst graphic of all time

Problems?

What's the scale?

Why the curves?

Why are there two lines?



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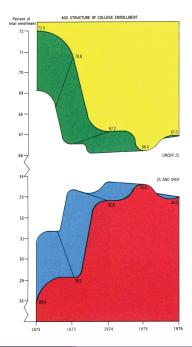
Problems?

What's the scale?

Why the curves?

Why are there two lines?

How many data points?



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#### Problems?

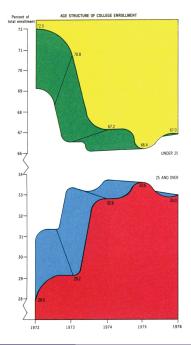
What's the scale?

Why the curves?

Why are there two lines?

How many data points?

Why such tiny text?

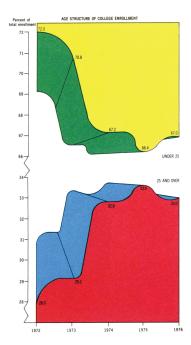


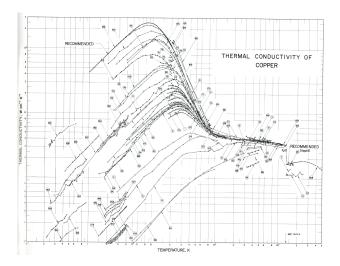
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#### Problems?

What's the scale?

- Why the curves?
- Why are there two lines?
- How many data points?
- Why such tiny text?
- Did this need four colors?

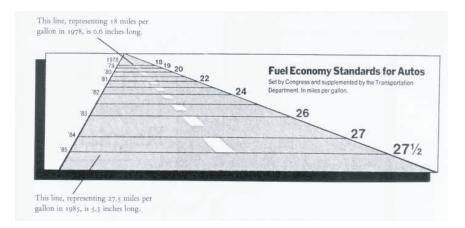




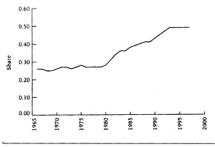
A good data/ink ratio: Literature review in a page; a model for meta-analyses Imagine this showed estimates of the effect of class size on educational performance

### **Tufte's Principles**

### 3. Avoid Distortion



#### Beware: Usually, distortions are more subtle than this...



BY THE NUMBERS: OVER 35 YEARS, CORNELL'S TUITION HAS TAKEN AN INCREASINGLY LARGER SHARE OF ITS MEDIAN STUDENT FAMILY INCOME.

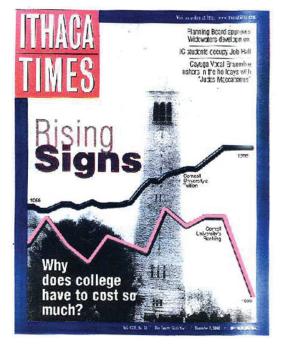


& WORLD REPORT HAS RISEN AND FALLEN ERRATICALLY.

The worst visual display I've ever seen

What is the claim?

#### Do you believe it?



An even more misleading combination of these plots on the cover

Scales are what allow us to make comparisons within and across graphics

Clearly, careful thought about scaling is essential to making good scientific visuals

## **Tufte's Principles**

### 4. Facilitate comparison

# Tufte presents this table of cancer survival rates

What's good about it?

What could be improved?

Source: Tufte, Cognitive Style of Powerpoint

	% survival rates and standard errors				
	5 year	10 year	15 year	20 year	
Prostate	98.8 0.4	95.2 0.9	87.1 I.7	81.1 3.0	
Thyroid	96.0 0.8	95.8 I.2	94.0 1.6	95.4 2.1	
Testis	94.7 1.1	94.0 1.3	91.1 1.8	88.2 2.3	
Melanomas	89.0 0.8	86.7 1.1	83.5 1.5	82.8 1.9	
Breast	86.4 0.4	78.3 0.6	71.3 0.7	65.0 1.0	
Hodgkin's disease	85.1 1.7	<b>79.8</b> 2.0	73.8 2.4	67.I 2.8	
Corpus uteri, uterus	84.3 1.0	83.2 1.3	80.8 1.7	<b>79.2</b> 2.0	
Urinary, bladder	82.1 1.0	76.2 1.4	70.3 1.9	67.9 2.4	
Cervix, uteri	70.5 1.6	64.1 1.8	62.8 2.1	60.0 2.4	
Larynx	68.8 2.1	56.7 2.5	45.8 2.8	37.8 3.1	
Rectum	62.6 1.2	55.2 1.4	51.8 1.8	<b>49.2</b> 2.3	
Kidney, renal pelvis	61.8 1.3	54.4 1.6	<b>49.8</b> 2.0	47.3 2.6	
Colon	61.7 0.8	55.4 1.0	53.9 1.2	52.3 1.6	
Non-Hodgkin's	57.8 1.0	46.3 1.2	38.3 1.4	34.3 1.7	
Oral cavity, pharynx	56.7 1.3	44.2 1.4	37.5 1.6	33.0 1.8	
Ovary	55.0 1.3	49.3 1.6	49.9 1.9	<b>49.6</b> 2.4	
Leukemia	42.5 1.2	32.4 1.3	29.7 I.5	26.2 1.7	
Brain, nervous system	32.0 1.4	29.2 1.5	27.6 1.6	26.1 1.9	
Multiple myeloma	29.5 1.6	12.7 1.5	7.0 1.3	4.8 1.5	
Stomach	23.8 1.3	19.4 1.4	19.0 1.7	14.9 1.9	
Lung and bronchus	15.0 0.4	10.6 0.4	8.1 0.4	6.5 0.4	
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There are only a few reasons to use a table instead of a graphic:

- to convey a handful of numbers
- to report precise values for lookup
- to present many different types of quantities (i.e., dimensions) for a small number of cases

Usually graphics are more effective than tables

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Simple ideas for effective tables

# 1. Minimize the use of guidelines.

Most publishers prohibit vertical lines in tables

# Boxes around the whole table are chartjunk

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Multiple myeloma	29.5 1.6	12.7 1.5	7.0 1.3	4.8 1.5
Stomach	23.8 1.3	19.4 1.4	19.0 1.7	14.9 I.9
Lung and bronchus	15.0 0.4	10.6 0.4	8.1 0.4	6.5 0.4
Esophagus	14.2 1.4	7.9 1.3	7.7 1.6	5.4 2.0
Liver, bile duct	7.5 1.1	5.8 1.2	6.3 1.5	7.6 2.0
Pancreas	4.0 0.5	3.0 1.5	2.7 0.6	2.7 0.8

Simple ideas for effective tables

#### 2. Report only a few digits.

Don't report non-significant digits

Every extra digit distracts attention from the first, most important one

	% survival rates and standard errors			
	5 year	10 year	15 year	20 year
Prostate	<b>98.8</b> 0.4	95.2 0.9	87.1 I.7	81.1 3.0
Thyroid	96.0 0.8	95.8 1.2	94.0 1.6	<b>95.4</b> 2.1
Testis	94.7 1.1	94.0 1.3	91.1 1.8	88.2 2.3
Melanomas	89.0 0.8	86.7 1.1	83.5 1.5	82.8 1.9
Breast	86.4 0.4	78.3 0.6	71.3 0.7	65.0 I.0
Hodgkin's disease	85.1 1.7	<b>79.8</b> 2.0	73.8 2.4	67.I 2.8
Corpus uteri, uterus	84.3 1.0	83.2 1.3	80.8 1.7	<b>79.2</b> 2.0
Urinary, bladder	82.1 1.0	76.2 1.4	70.3 1.9	67.9 2.4
Cervix, uteri	70.5 1.6	64.1 1.8	62.8 2.1	60.0 2.4
Larynx	68.8 2.1	56.7 2.5	45.8 2.8	37.8 3.1
Rectum	62.6 1.2	55.2 1.4	51.8 1.8	49.2 2.3
Kidney, renal pelvis	61.8 1.3	54.4 1.6	<b>49.8</b> 2.0	47.3 2.6
Colon	61.7 0.8	55.4 1.0	53.9 1.2	52.3 1.6
Non-Hodgkin's	57.8 1.0	46.3 1.2	38.3 1.4	34.3 1.7
Oral cavity, pharynx	56.7 1.3	44.2 1.4	37.5 1.6	33.0 1.8
Ovary	55.0 1.3	49.3 I.6	49.9 I.9	49.6 2.4
Leukemia	42.5 1.2	32.4 1.3	29.7 1.5	26.2 1.7
Brain, nervous system	32.0 1.4	29.2 I.5	27.6 1.6	26.1 1.9
Multiple myeloma	29.5 1.6	12.7 1.5	7.0 1.3	4.8 1.5
Stomach	23.8 1.3	19.4 1.4	19.0 I.7	14.9 1.9
Lung and bronchus	15.0 0.4	10.6 0.4	8.1 0.4	6.5 0.4
Esophagus	14.2 1.4	7.9 1.3	7.7 1.6	5.4 2.0
Liver, bile duct	7.5 1.1	5.8 1.2	6.3 1.5	7.6 2.0
Pancreas	4.0 0.5	3.0 1.5	2.7 0.6	2.7 0.8

Simple ideas for effective tables

#### 3. Order the table intelligently.

In a 2 dimensional table, order the rows and columns to highlight relationships

You can either

**diagonalize** – sort based on order, or

**cluster** – group based on similarity

More on this later...

	% survival rates and standard errors			
	5 year	10 year	15 year	20 year
Prostate	<b>98.8</b> 0.4	95.2 0.9	87.1 I.7	81.1 3.0
Thyroid	96.0 0.8	95.8 1.2	94.0 1.6	95.4 2.1
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Melanomas	89.0 0.8	86.7 1.1	83.5 1.5	82.8 1.9
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Larynx	68.8 2.1	<b>56.7</b> 2.5	45.8 2.8	37.8 3.1
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Non-Hodgkin's	57.8 I.0	46.3 1.2	38.3 1.4	34.3 1.7
Oral cavity, pharynx	56.7 1.3	44.2 1.4	37.5 1.6	33.0 1.8
Ovary	55.0 1.3	49.3 1.6	49.9 1.9	49.6 2.4
Leukemia	42.5 1.2	32.4 1.3	29.7 1.5	26.2 1.7
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Stomach	23.8 1.3	19.4 1.4	19.0 1.7	14.9 1.9
Lung and bronchus	15.0 0.4	10.6 0.4	8.1 0.4	6.5 0.4
Esophagus	14.2 1.4	7.9 I.3	7.7 1.6	5.4 2.0
Liver, bile duct	7.5 1.1	5.8 1.2	6.3 1.5	7.6 2.0
Pancreas	4.0 0.5	3.0 1.5	2.7 0.6	2.7 0.8

Simple ideas for effective tables

#### 3. Order the table intelligently.

In a 3+ dimensional table, nest the dimensions intelligently.

#### Note:

Table order applies to 1-dimensional plots, like dot plots...

and to super tables of plots where rows or columns are categories

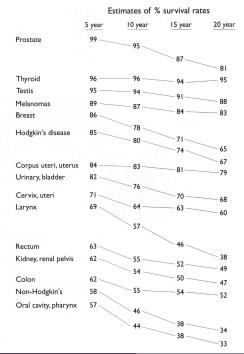
	% survival rates and standard errors			
	5 year	10 year	15 year	20 year
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Thyroid	96.0 0.8	95.8 1.2	94.0 1.6	95.4 2.1
Testis	94.7 1.1	94.0 1.3	91.1 1.8	88.2 2.3
Melanomas	89.0 0.8	86.7 1.1	83.5 1.5	82.8 1.9
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Corpus uteri, uterus	84.3 1.0	83.2 1.3	80.8 1.7	<b>79.2</b> 2.0
Urinary, bladder	82.1 1.0	76.2 1.4	70.3 1.9	67.9 2.4
Cervix, uteri	70.5 1.6	64.1 1.8	62.8 2.1	60.0 2.4
Larynx	68.8 2.1	56.7 2.5	45.8 2.8	37.8 3.1
Rectum	62.6 1.2	55.2 1.4	51.8 1.8	<b>49.2</b> 2.3
Kidney, renal pelvis	61.8 1.3	54.4 1.6	<b>49.8</b> 2.0	47.3 2.6
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Non-Hodgkin's	57.8 1.0	46.3 1.2	38.3 1.4	34.3 1.7
Oral cavity, pharynx	56.7 1.3	44.2 1.4	37.5 1.6	33.0 1.8
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Brain, nervous system	32.0 1.4	29.2 1.5	27.6 1.6	26.1 1.9
Multiple myeloma	29.5 1.6	12.7 1.5	7.0 1.3	4.8 1.5
Stomach	23.8 1.3	19.4 1.4	19.0 1.7	14.9 1.9
Lung and bronchus	15.0 0.4	10.6 0.4	8.1 0.4	6.5 0.4
Esophagus	14.2 1.4	7.9 1.3	7.7 1.6	5.4 2.0
Liver, bile duct	7.5 1.1	5.8 1.2	6.3 1.5	7.6 2.0
Pancreas	4.0 0.5	3.0 1.5	2.7 0.6	2.7 0.8

The table at left (from Tufte) is effectively designed

It is diagonalized, uses few digits, and facilitates lookup

But tables always limit comparison

The brain is slower to grasp numerals than graphical representations of numbers

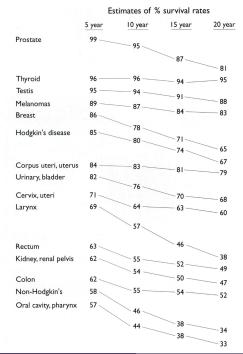


This figure (also from Tufte) may be an improvement

It keeps (almost) all the virtues of the table, but also makes comparison easier

Instead of digging information out of the table, it now hits the reader "between the eyes"

What's the scale?

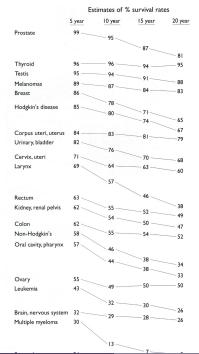


This figure (also from Tufte) may be an improvement

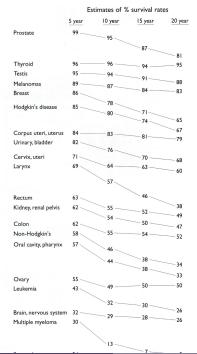
It keeps (almost) all the virtues of the table, but also makes comparison easier

Instead of digging information out of the table, it now hits the reader "between the eyes"

What's the scale? There isn't one!



# What's missing from the figure that was in the table?



What's missing from the figure that was in the table?

Measures of uncertainty.

The table had standard errors

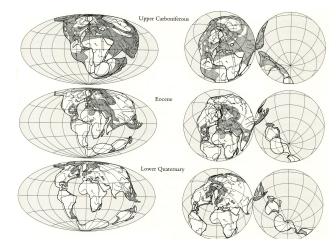
A major focus of this course is including uncertainty in plots like this one

### **Tufte's Principles**

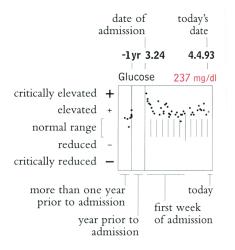
### 5. Small Multiples

Small Multiples: Repetition of a display concept

Tufte's most useful concept



Source: Tufte, Visual Explanations



Tufte proposes medical charts follow the format at left

This chart is annotated for pedagogical purposes

Lots of information; little distracting scaffolding

But the real pay off of this model plot is that it can be repeated once learned...

### **Tufte's Principles**

Surname, Forename M.

### 5. Small Multiples

Right lower lobe pneumonia, hallucinations, new onset diabetes, history of manic depressive illness -1yr 3.24 -1vr 3.24 4.4.93 -1vr 3.24 4.4.93 -1yr 3.24 4.4.93 4.4.93 WBC 11100 c/ul Psychosis Glucose Mood + · . . . . . ٠... 98.8° F Haloperidol 6.0 mg Reg Insulin Li 0.56 mmol/I 1 1 - 5

admitted 3.24.93

4.4.93 7-South, Bed 5

Discharge. PB MD 1200 4.4.93

No delirium. JT MD 900 4.4.93

Enema given. PAC RN 1100 4.3.93

Will treat for probable constipation. MBM 2245 4.2.93

Vomited three times. RW RN 2230 4.2.93

Left lower lobe infiltrate or atelectasis. AL MD 1500 4.2.93

Alert and oriented. No complaints. PAC RN 1100 4.1.93

Attending to activities of daily living. PAC RN 1100 3.31.93

A complete layout using small multiples to convey hundreds of pieces of information

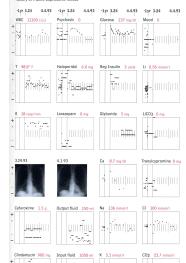
Elegant, information-rich, hard to make ...Goal: tools to make this easier

How to Make Small Multiples

 Start with a detailed, multifunctional plot

2. Then tile these plots to incorporate extra variables & dimensions Surname, Forename M. admitted 3.24.93

Right lower lobe pneumonia, hallucinations, new onset diabetes, history of manic depressive illness



4.4.93 7-South, Bed 5

Discharge. PB MD 1200 4.4.93 No delirium. JT MD 900 4.4.93

o deminant. of his 500 4.4.55

Enema given. PAC RN 1100 4.3.93

Will treat for probable constipation. MBM 2245 4.2.93

Vomited three times. RW RN 2230 4.2.93

Left lower lobe infiltrate or atelectasis. AL MD 1500 4.2.93

Alert and oriented. No complaints. PAC RN 1100 4.1.93

Attending to activities of daily living. PAC RN 1100 3.31.93

Ambulates with assistance. Weak. PAC RN 1400 3.30.93

Still coughing. Breath sounds diminished at right base. PB MD 1000 3.30.93

Discontinued sitters. MM RN 1500 3.29.93

Follows directions. DB RN 1500 3.28.93

More relaxed. CM RN 700 3.28.93

Drowsy and sleeping. MT RN 2130 3.27.93

Out of restraints. JMT MD 1330 3.27.93

Left conjunctivitis; treat with garamycin drops. DJS MD 1230 3.27.93

4-point restraints and sitter needed. PM RN 1500 3.26.93

4-point restraints required. Delirious. Switching to half normal saline for hydration. Parathyroid hormone test results pending. LMG MD 930 3.26.93

Pulled out IV twice. Hallucinating. Attempted to drink call light. CM RN 700 3.26.93

Next screen

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P hundañ

-1yr 3.24 4.4.93 -1yr 3.24 4.4.93

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-1yr 3.24 4.4.93 -1yr 3.24

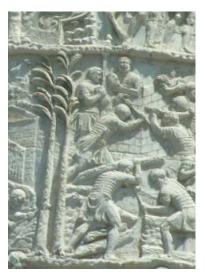
### **Tufte's Principles**

1. Start with a detailed, multifunctional plot

2. Then tile these plots to incorporate extra variables & dimensions

The principles of small multiples extend to virtually any VDSI

Were the inscriptions on Trajan's column cut individually, or pressed from a single mold?



### 5. Small Multiples

Were the inscriptions on Trajan's column cut individually, or pressed from a single mold?

Small multiples – tiled & overlapped – offer an elegant solution



Source: Tufte, Visual Explanations

### **Tufte's Principles**

### 5. Small Multiples



Karen Cheng (UW-Art) uses the same technique in Designing Type (2006, Yale Univ Press) to explain differences across fonts Big data and cheap computing created demand and opportunity for better data visuals in the media

Graphic designers, computer scientists, and journalists have responded: Information Visualization, or InfoVis

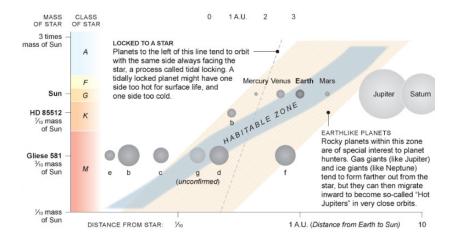
Beautiful, data-rich graphics for exploring public data

Different goals from scientific visulization of data

InfoVis: emphasis on fun, exploration, beauty, and "wow"

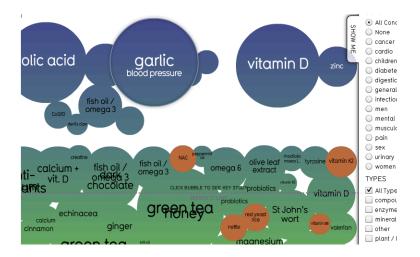
Scientific Visuals: structured comparison, precision, and inference

### InfoVis Tackles...Extrasolar Planets



Source: Jonathan Corum, New York Times, "Habitable Zones," www.nytimes.com/interactive/2011/12/03/science/space/1202-planet.html

## ...Snake Oil For a good reason, break the rules



Source: David McCandless and collaborators, "Snake Oil," informationisbeautiful.net/

visualizations/snake-oil-scientific-evidence-for-nutritional-supplements-vizsweet/

### But the rules exist for a reason

In Comparison How does natural gas compare with other fossil fuels? OIL NATURAL GAS COAL 46 years left 63 years left 119 years left TWEAK YEARLY PRODUCTION INCREASE TWEAK YEARLY PRODUCTION INCREASE TWEAK VEARLY PRODUCTION INCREASE -296 average increase: 1% average increase: 2% average increase: 4%

# Source: David McCandless for General Electric, visualization.geblogs.com/visualization/gas

VD&M - Principles

### ...Inequality

### Different rules for user interaction?



Source: David McCandless and others, www.informationisbeautiful.net/ visualizations/what-are-wallst-protestors-angry-about

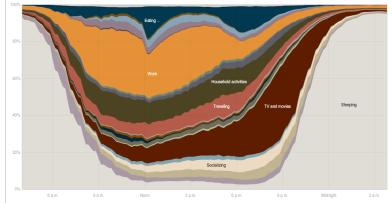
### ...Time Use

### **DataVis Approach**

#### Everyone

Sleeping, eating, working and watching television take up about two-thirds of the average day.

Everyone	Employed	White	Age 15-24	H.S. grads	No children
Men	Unemployed	Black	Age 25-64	Bachelor's	One child
Women	Not in lab	Hispanic	Age 65+	Advanced	Two+ children



Source: Amanda Cox (CSSS grad) et al, "How different groups spend their day," New York Times, 8/2/2009, http://www.nytimes.com//interactive/2009/07/31/

Chris Adolph (University of Washington)

VD&M – Principles

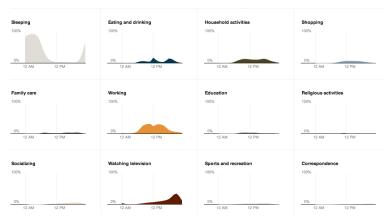
### ...Time Use

# VDSI approach

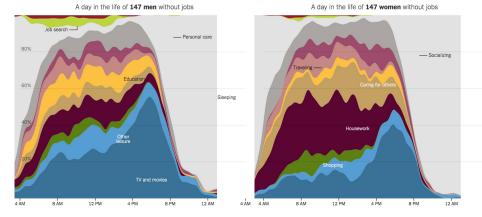
#### Everyone

The essentials — sleeping, eating, and working — take up the better part of the day, often ended with watching television.

Everyone	Age 15 to 19	With children
Men	18 and over	Children under 3
Women	75 and over	No children



Source: Nathan Yau, "How Americans spend their day", projects.flowingdata.com/timeuse



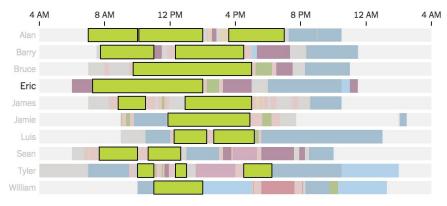
A beautiful synthesis is possible (note the example now focuses on the unemployed) NYT's Upshot group revisited this problem in January 2015 using a blend of data visualization techniques and InfoVis polish

Josh Katz, "How nonemployed Americans spend their weekdays: Men vs. Women," New York Times,

http://www.nytimes.com/interactive/2015/01/06/upshot/

how-nonemployed-americans-spend-their-weekdays-men-vs-women.html Chris Adolph (University of Washington) VD&M - Principles

#### 10 men



The Upshot's new approach follows Tufte's principles:

1. Show as much data as possible

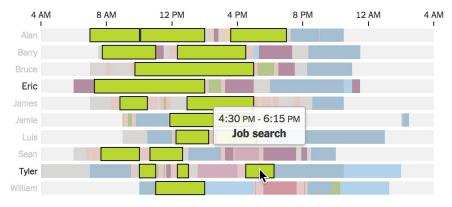
here, down to lowest level of individual by time by use

Josh Katz, "How nonemployed Americans spend their weekdays: Men vs. Women," New York Times,

http://www.nytimes.com/interactive/2015/01/06/upshot/

how-nonemployed-americans-spend-their-weekdays-men-vs-women.html

#### 10 men



The Upshot's approach follows Tufte's principles:

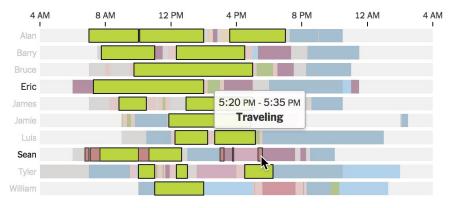
 Establish the logic of the graphic with a detailed example here, through an interactive display that allows user to select each use

Josh Katz, "How nonemployed Americans spend their weekdays: Men vs. Women," New York Times,

http://www.nytimes.com/interactive/2015/01/06/upshot/

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http://www.nytimes.com/interactive/2015/01/06/upshot/

how-nonemployed-americans-spend-their-weekdays-men-vs-women.html

#### TV and movies

Watching television and movies is a significantly more common activity for the nonemployed than looking for work. For every one person whose main activity was job searching, there were almost six whose main activity was television and movie watching.

The gender breakdown is striking. Of the 65 people who devoted more of their daytime to watching TV and movies than any other activity, 46 are men versus 19 who are women.



With the design established, the Upshot used a series of small multiples to show differences across sexes

Here, they show all respondents whose largest time use was television

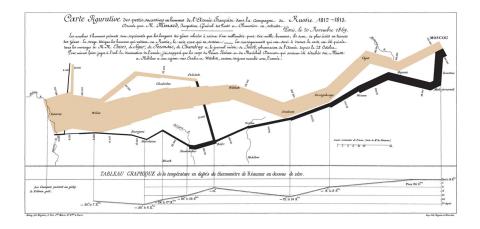
Recommendation: sort rows so similar individuals are stacked together (cluster analysis)



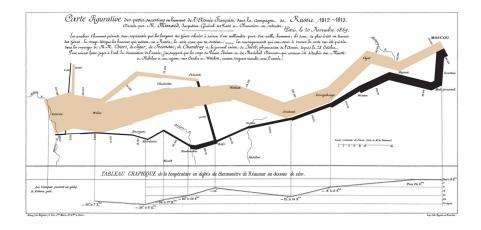
Finally, an ambitious graphic shows all data at once

This can only work by grouping individuals first by sex (columns of plots),

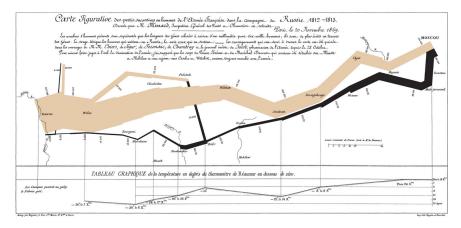
and then by similarity of time usage (rows of data, sorted via cluster analysis) Turning points in the history of visual displays Tufte's principles for information design How data visualization differs from infovis Scales and scaling Making a scatterplot from scratch Sorting in tables and table-like figures

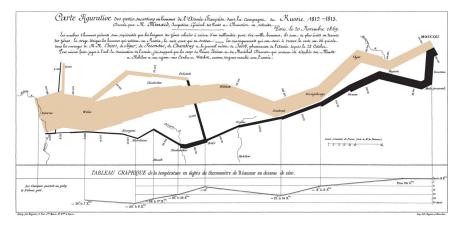


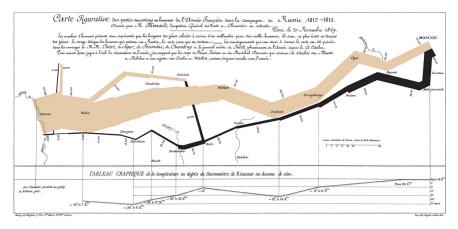
#### Perhaps the best plot ever: Minard's display of Napoleon's March on Moscow



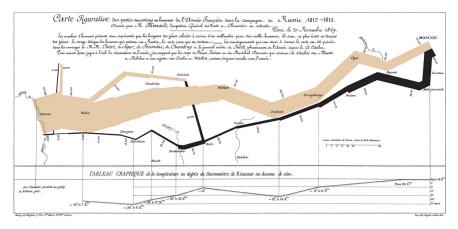
Some plots combine multiple elements into a single super-plot or **confection** Good confections are better than the sum of their components because they facilitate connection or comparison across elements







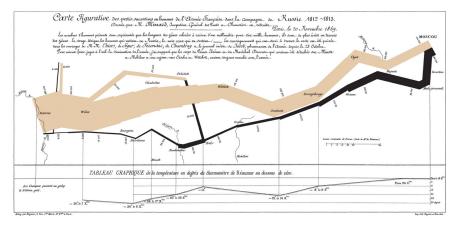
 Latitude of army & features Y-coordinate



1. Latitude of army & features

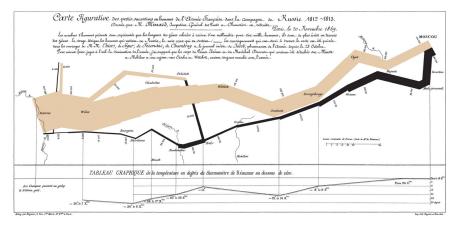
Y-coordinate

2. Longitude of army & features X-coordinate



- 3. Size of army
- 1. Latitude of army & features Y-coordinate
- 2. Longitude of army & features X-coordinate

#### width of line, numerals

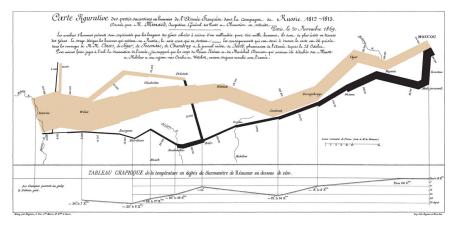


- Latitude of army & features Y-coordinate
- 2. Longitude of army & features X-coordinate

3. Size of army

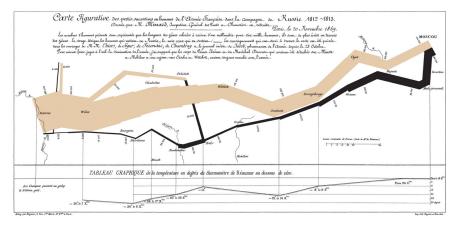
width of line, numerals

- 4. Advance vs. Retreat
  - color of line



- Latitude of army & features Y-coordinate
- 2. Longitude of army & features X-coordinate

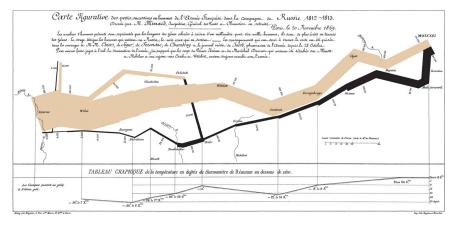
- 3. Size of army
  - width of line, numerals
- 4. Advance vs. Retreat
  - color of line
- 5. Division of army
  - splitting of line



- Latitude of army & features Y-coordinate
- 2. Longitude of army & features X-coordinate

- 3. Size of army
  - width of line, numerals
- 4. Advance vs. Retreat
  - color of line
- 5. Division of army
  - splitting of line

6. Temperature linked lineplot

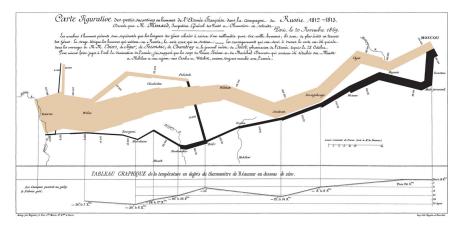


- Latitude of army & features Y-coordinate
- Longitude of army & features X-coordinate

- 3. Size of army
  - width of line, numerals
- 4. Advance vs. Retreat
  - color of line
- 5. Division of army
  - splitting of line

- 6. Temperature linked lineplot
- 7. Time

#### linked lineplot



Combines narrative & analysis: a technique mostly lost until this century

May be a spurious relationship here: time and temperature Note the deaths at river crossings – usually, these rivers would be frozen Did Napoleon choose too warm a winter to invade Russia? Tufte is best known, but many other people work on VDSIs

Jacques Bertin, J. W. Tukey are foundational figures, as is...

William Cleveland (statistician), who emphasizes:

- Avoiding cognitive pitfalls
- Transforming data to highlight relationships
- Combining data and model fits: unique ability of graphics

Later weeks of 569 focus on Cleveland's contributions (Cognition, EDA)

Let's turn from general principles to specific **Scaling** is an issue for most scientific graphics Good scaling incorporates many concerns of Tufte & Cleveland:

Graphical integrity Highlighting relationships Facilitating comparison Maximixing data ink

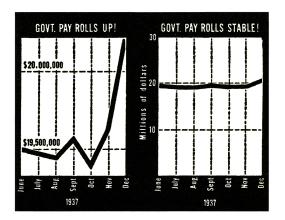
Two parts to scaling:

anchoring and stretching

Some people assert as a "rule-of-thumb" that graphical axes must always include zero

Hoff's example at the right is the likely origin of this misleading advice

(To be sure, Hoff never offers it as a rule)



#### Choose scales carefully!

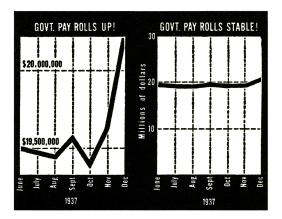
Start point

End point

Units (usual choices: linear or log)

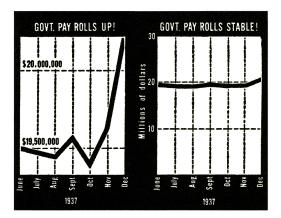
Parallel scales (optional)

You choices depend on what you want to show and compare, not a general rule



Even in Hoff's example, the left plot is *better* than the right plot

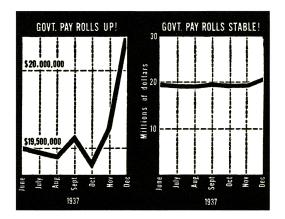
Public budgets are usually very sticky, and 3% changes can be a big deal

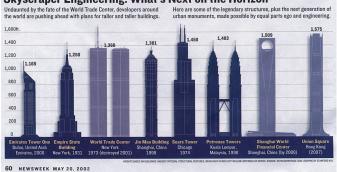


Neither plot is ideal – instead, a scale that corresponds to the "usual range" in which budgets might vary would be a better choice

But that suggests the plot is incomplete until compared with another set of data

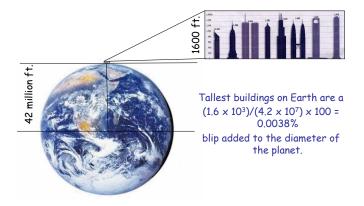
...leading back to Tufte's recommendation to plot small multiples





#### **Skyscraper Engineering: What's Next on the Horizon**

#### What's "zero," exactly, in plots like this one? The ground?



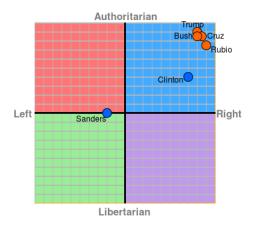
#### Source: Alyssa Goodman, Harvard-Smithsonian Center for Astrophysics

#### The center of the planet?

Sometimes, there is no meaningful baseline at all

Is there a defensible "zero point" on ideology?

#### 2016 US Presidential Primaries



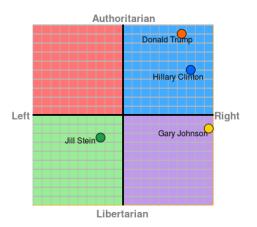
Source: www.politicalcompass.org

Sometimes, there is no meaningful baseline at all

Is there a defensible "zero point" on ideology?

Can you guess Political Compass's ideological preference?

#### 2016 US Presidential General



#### Source: www.politicalcompass.org

### Stretching the scale

The most natural scaling for axes is linear

Each inch on the page = k units on the scale.

Linear scales are just one option, and not helpful for skewed data

Logarthmic scaling is often better:

- doesn't hide data in the corner
- allows linear fits to log data

Remember to label on the original scale

If you do print exponents, indicate the base of the log (e, 10, etc.)

Choose carefully between linear, log-linear, and log-log plots to facilitate useful comparison of data points Systems of political parties differ across democracies

In some countries (like the US), two major parties vie to win elections by turning out their base plus middle class swing voters

In other countries (most European countries) there are many parties, including large parties dominated by the working class

Some political scientists claim having more parties – including worker parties – produces more redistribution

Source: Torben Iversen & David Soskice, 2002, "Why do some democracies redistribute more than others?" Harvard University.

### Making a scatterplot from scratch

### Concepts for this example

#### Effective number of parties:

- Number of parties varies across countries
- Electoral rules largely determine potential number parties
  - Winner take all (US) ightarrow pprox 2 parties
  - Proportional representation  $\rightarrow$  more parties
- To see this, discount trivial parties and use effective number of parties

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Poverty reduction:

### Making a scatterplot from scratch

### Concepts for this example

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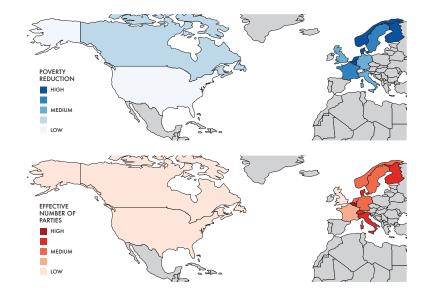
#### Poverty reduction:

- Percent lifted out of poverty by taxes and transfers
- Poverty = an income below 50% of mean income

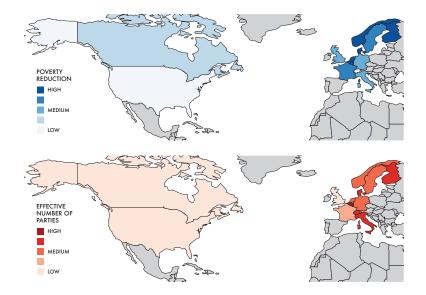
### What if we mapped the data?



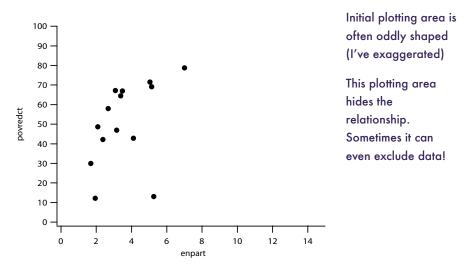
This map of poverty reduction is colorful, but how to relate it to the number of parties?



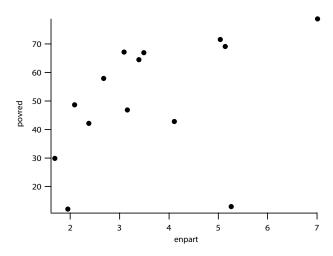
This map of poverty reduction is colorful, but how to relate it to the number of parties? A pair of maps?



Multiple maps relate variables to geography, not to each other Geography is incidental to our example: we need a scatterplot to focus on variables



Aside: Filled symbols are good for a little data, but open symbols are better when data overlap

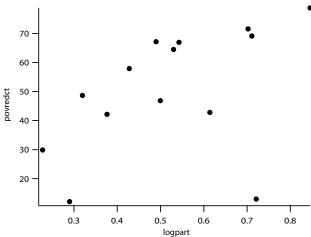


Critical user decision: Impose sensible, data based plot limits

Even more important with small multiples: unreadable without consistent, substantively-driven limits across plots

Don't just leave this to your package to decide

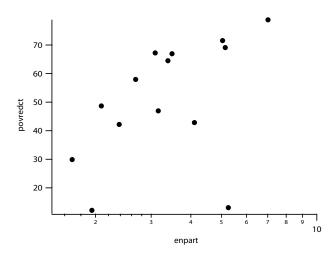
There appears to be a curvilinear relationship. We can bring that out with...



Log scaling.

But why print the exponents?

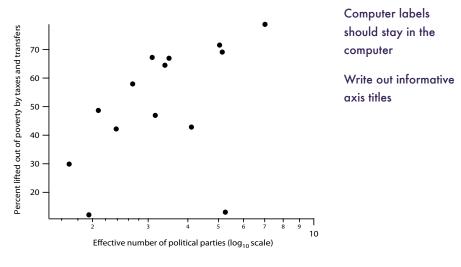
Logs aren't intuitive for many readers, but they don't need to even know we are using them in a graphic...



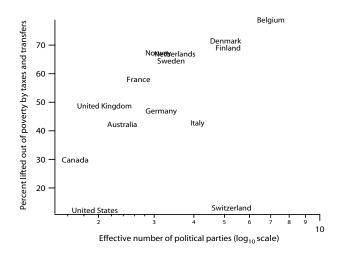
To make log scales easier for everyone to read, use a log scale but supply linear labels...

That is, plot the tick markets at the log values (exponents), but label them with the original linear scale numbers corresponding to those tick marks

Next problem: Why use abbreviated computer labels for our variables?



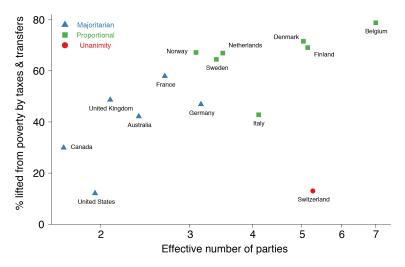
Next question: What are those outliers?



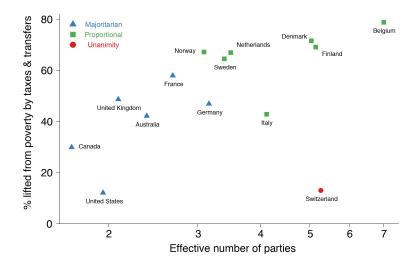
Next, we can try to figure out what makes the US and Switzerland so different With only a little data & some big outliers, we should show the name of each case as a label

Sometimes we can just replace our plotted points with these labels

Here, let's combine the glyph (symbol) and text label for each point, so that we can use our glyphs to encode a third variable

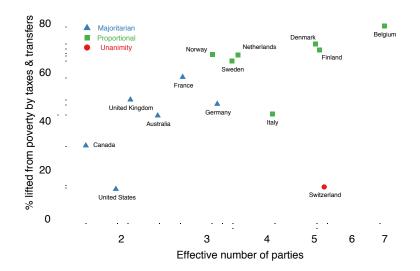


This plot and following plots are made using scatter (tile package in R)



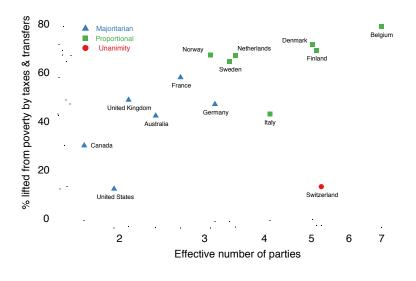
Scatterplots relate two distributions.

Why not make those marginal distributions explicit?

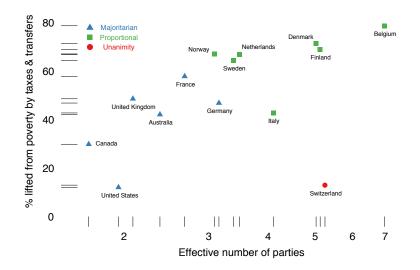


Rugs accomplish this by replacing the axis lines with the plots

We could choose any plotting style: from the histogram-like dots...

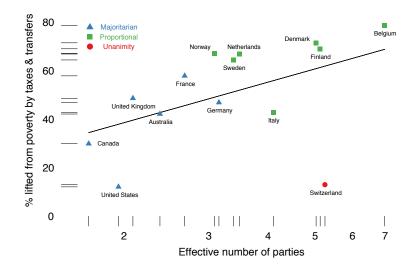


... to a strip of jittered data...

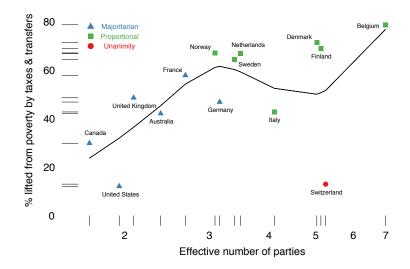


...to a set of very thin lines marking each observation

Because we have so few cases, thin lines work best for this example

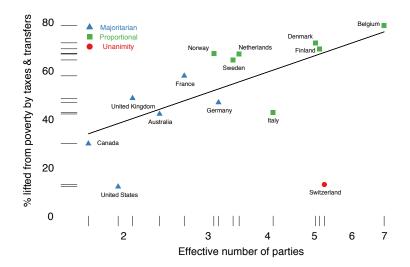


Let's add a parametric model of the data: a least squares fit line tile can do this for us

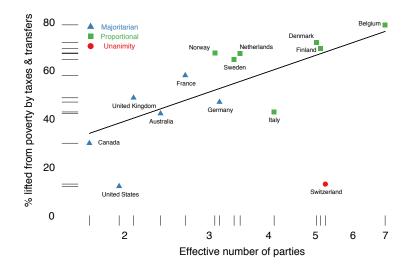


But we don't have to be parametric

A local smoother, like loess, often helps show non-linear relationships

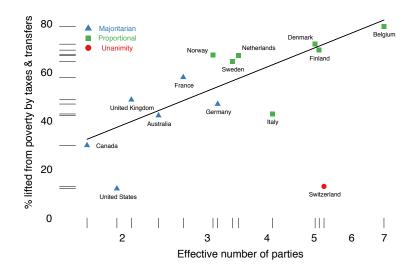


M-estimators weight observations by an influence function to minimize the influence of outliers

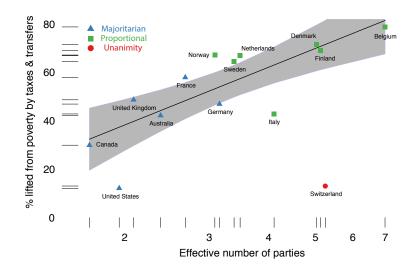


Even with an M-estimator, every outlier has some influence

Thus any one distant outlier can bias the result



A robust and resistant MM-estimator, shown above, largely avoids this problem Only a (non-outlying) fraction of the data influence this fit. rlm(method="MM")



In our final plot, we add 95 percent confidence intervals for the MM-estimator A measure of uncertainty is essential to reader confidence in the result

1. Decide on dimensions: aspect ratio, axis limits

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- 2. Add axis labels, plot titles

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The tile package for R can help with all of the above: sensible defaults and powerful options

ARMS RACE HANDOUT

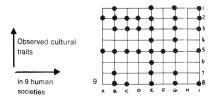
#### ARMS RACE HANDOUT

Just as we scale continuous dimensions in plots, we sort categorical dimensions in tables or table-like graphs

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In Semiologie Graphique (1967), Jacques Bertin suggested sorting to diagonalize



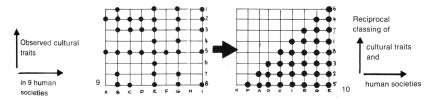
Sorting on the alphabet or a numerical ID is arbitrary, random, and pattern-hiding

Summarize the relationship in this figure

#### ARMS RACE HANDOUT

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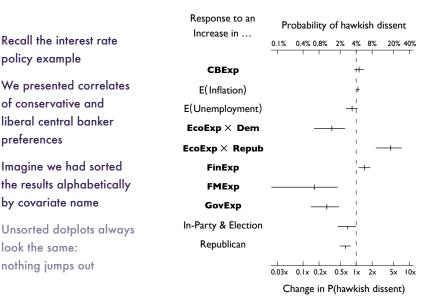
In Semiologie Graphique (1967), Jacques Bertin suggested sorting to diagonalize



Sorting on the alphabet or a numerical ID is arbitrary, random, and pattern-hiding Did you see the Likert-scaling of cultural traits? Obvious when sorted to produce a "diagonal" arrangement

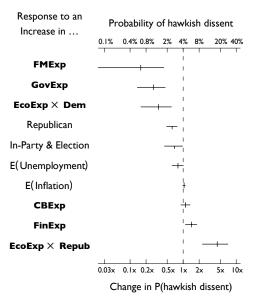
Recall the interest rate policy example

We presented correlates of conservative and liberal central banker preferences



# Sorting in Tables and Table-like Graphs

In the final graphic, I sorted by size of effect Immediately tells a story, especially when I **bold** the career covariates An arbitrary ordering in a figure is always a missed opportunity: seize it to highly covariation



John Gotti, a New York mob boss, was famously acquitted in a series of trials in the 1980s

Following a 1987 acquittal, the New York Times suggested the jury was swayed by a defense chart summarizing the crimes of prosecution witnesses

# GOTTI IS ACQUITTED BY A FEDERAL JURY IN CONSPIRACY CASE

## NEW CHARGES ARE LIKELY

Verdict is the First Setback in Recent Government Drive Against Mafia Leaders

### By LEONARD BUDER

John Gotti was acquitted of Federal racketeering and conspiracy charges yesterday in the Government's first major setback in its recent assault on organized crime.

Mr. Gotti, who the Government says is the leader of the nation's most powerful Mafia family, and six co-defendants were found not guilty of charges they took part in a criminal enterprise. They were accused of carrying out illegal gambling and loansharking operations, armed hijackings and at least two murders over an 18year period.

Despite yesterday's verdict, Federal investigators said the 46-year-old Mr. Gotti might face indictment on new charges as head of the Gambino crime family. "I can't comment but I won't deny it," said Thomas L. Sheer, head of the Federal Bureau of Investigation in New York, when asked if the F.B.I. was building up another case against Mr. Cotti

#### 'We'll Be Starting Again'

"They'll be ready to frame us again in two weeks," Mr. Gotti told a reporter before leaving the Brooklyn courthouse in a gray Cadillac that was waiting for him. "In three weeks we'll be starting again, just watch."

Until vesterday, Federal prosecutors 1 in the Southern and Eastern Districts of New York had recorded a string of successes in major organized-crime cases.

Within the last six months, the heads of the city's four other Mafia families have been convicted after trials in Manhattan and Brooklyn. They, like Mr. Gotti and his co-defendants, had been charged under the Federal Racketeer Influenced and Corrupt Organizations Act, or RICO.

#### Key Witnesses Were Criminals

"Obviously they perceived there was something wrong with the evidence," said Andrew J. Maloney, the United States Attorney in Brooklyn, referring to the jury.

Many of the Government's key witnesses were criminals who testified for the prosecution under grants of immunity or in return for payments and other benefits.

The last piece of evidence requested by the jury for re-examination was a chart introduced by the defense that showed the criminal backgrounds of seven prosecution witnesses. It listed 69 crimes, including murder, drug possession and sales and kidnapping.

Mr. Gotti's lawyer, Bruce Cutler, said the jury showed "courage" because "it's not easy to say no to a Federal prosecutor." He said the jury had not been impressed with the testimony of "paid Government informants who lie, who use drugs, who kill people."

The verdict, which came on the seventh day of jury deliberations after a trial that lasted almost seven months, surprised many in the nacked courtroom. Friends of the defendants cheered and applauded; the Government prosecutors, Diane F. Giacalone and John Gleeson, looked glum.

Mr. Gotti, who has been dubbed 'Dapper Don'' because of his expensive attire and impeccable grooming, and his co-defendants hugged and kissed each other and their lawyers.

Then they stood and applauded as the 12 members of the jury - whose identities had been kept secret to preroom escorted by Federal marshals .... mony against Mr. Gotti ....



The New York Times

# A Weakness In Gotti Case

John Gotti

Major U.S. Witnesses Viewed as Unreliable

#### By SELWYN RAAB

Many lawyers and prosecutors who followed events in the seven-month trial of John Gotti said the underlying weakness of the prosecution's case was its apparent reliance on turncoat career criminals as key wit-

nesses against Mr. Gotti Nows and six co-defendants. Analysis

A signal that the credibility of the prosecution's

principal witnesses was in doubt came yesterday morning when the jury, in its final request before acquitting the defendants of all charges, reviewed an exhibit introduced by the defense.

It was a chart listing the lengthy criminal records of seven prosecution witnesses who had obtained promises of leniency and other favors from the vent possible tampering - left the Government in return for their testi-

## Source: NYT reproduced in Tufte, Envisioning Information

John Gotti, a New York mob boss, was famously acquitted in a series of trials in the 1980s

Following a 1987 acquittal, the New York Times suggested the jury was swayed by a defense chart summarizing the crimes of prosecution witnesses

## **Key Witnesses Were Criminals**

"Obviously they perceived there was something wrong with the evidence," said Andrew J. Maloney, the United States Attorney in Brooklyn, referring to the jury.

Many of the Government's key witnesses were criminals who testified for the prosecution under grants of immunity or in return for payments and other benefits

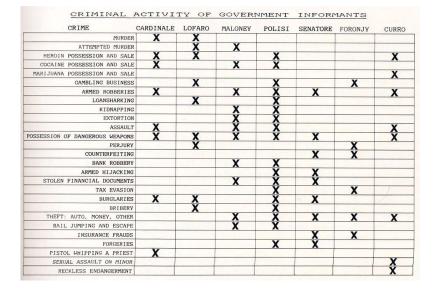
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Analysis

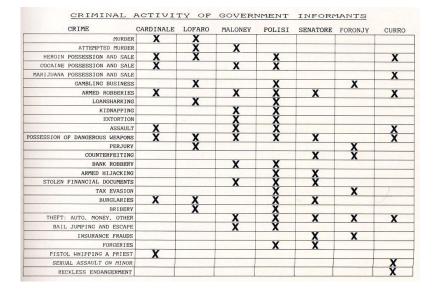
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It was a chart listing the lengthy criminal records of seven prosecution witnesses who had obtained promises of leniency and other favors from the Government in return for their testimony against Mr. Gotti ....

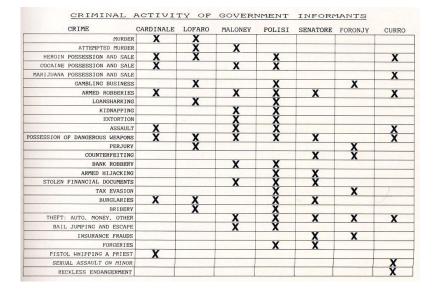
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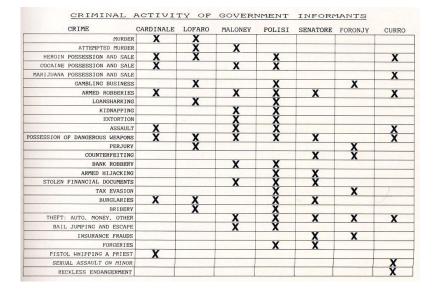
Not a scientific chart – pure advocacy. Breaks the rules on purpose:



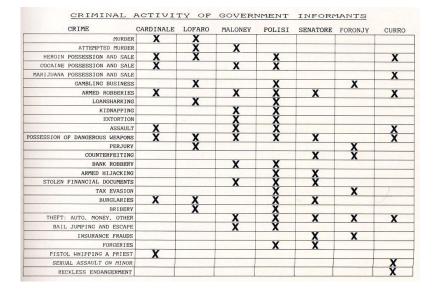
Not a scientific chart – pure advocacy. Breaks the rules on purpose: 1. Unbundles categories to produce more ink



Not a scientific chart – pure advocacy. Breaks the rules on purpose: 2. Unsorts the rows to spread the X's everywhere



Not a scientific chart - pure advocacy. Breaks the rules on purpose: 3. Mixes legal terms with lurid descriptions to titilate & overwhelm



Not a scientific chart – pure advocacy. Breaks the rules on purpose: 4. Centers the worst offender's column for maximum impact

# Suppose you're the prosecutor. Can you turn these tricks around on Gotti?

C	riminal Activ	ity of (	Gover	nmen	t Infor	mants			
		CARINALE						CURRO	TYPE
	Reckless Endangerment							3	Violent
	Sexual Assult on a Minor							1	
	Pistol Whipping a Priest	1							
	Armed Hijacking				1		2		
	Bank Robbery					1	3		
oss	ession of Dangerous Weapons	1		3	3	4	2	5	
	Assault	2				6	1	5	
	Extortion					3	4		
	Kidnapping					1	2		
	Armed Robberies	2			3	3	2	6	
	Attempted Murder			2		2			
	Murder	1		1					
	Theft: Auto, Money, Other		5		4	6	2	8	Theft
	Burglaries	2		3	1		2		
	Marijuana Possession and Sale							5	Narcotic
	Cocaine Posession and Sale	2				3	1		
	Heroin Possession and Sale	1		3			1	5	
	Bail Jumping and Escape		2			1	2		Judicia
2	Perjury		1	1					
lenx	Forgeries				3		2		Financia
i i	Insurace Frauds		1		1				
S	Bribary			1			2		
Violations of Confidence	Tax Evasion		1				1		
tion	Stolen Financial Documents				1	1	2		
io/a	Counterfiting		1		2				
2	Loansharking			2			1		
	Gambling Business		2	1			2		
	Different Types of Crimes	8	7	g	9	9	17	8	
	Total Number of Crimes		13	17		31	34	35	
	Violations of Confidence	0	8	5	7	2	12	0	
	Falsehood Index	0.00%	61.54%	29.41%	36.84%	6.45%	35.29%	0.00%	Average 2
	Key to Cell Shades	1	2	3	4	5	6	≥7	

Source: Toby Braun, http://www.tbid.com/toybox/pg/tufte.html

## Suppose you're the prosecutor. Can you turn these tricks around on Gotti?

	Falsehood Index	0.00%	01.54%	29.41%	30.84%	6.45%	35.29%	0.00%	Average 2
		0.00%	61.54%	29.41%	36.84%		35.29%		4
	Total Number of Crimes Violations of Confidence	12	13	17	19	31	34	35	
	Different Types of Crimes	8	7	9	9	9	17	8	
	Gambling Business		2	1			2		
2	Loansharking			2			1		
1016	Counterfiting		1		2				
tion	Stolen Financial Documents				1	1	2		
0 5	Tax Evasion		1				1		
3	Bribary			1			2		
Violations of Confidence	Insurace Frauds		1		1				
len	Forgeries				3		2		Financia
2	Perjury		1	1					
	Bail Jumping and Escape		2			1	2		Judicia
	Heroin Possession and Sale	1		3	_		1	5	
	Cocaine Posession and Sale	2				3	1		
	Marijuana Possession and Sale							5	Narcotic
	Burglaries	2		3	1		2		
	Theft: Auto, Money, Other		5		4	6	2	8	Theft
	Murder	1		1					
	Attempted Murder			2		2			
	Armed Robberies	2			3	3	2	6	
	Kidnapping					1	2		
	Extortion					3	4		
	Assault	2				6	1		
os	session of Dangerous Weapons	1		3	3	4	2	5	
	Bank Robbery					1	3		
	Armed Hijacking				1		2		
	Pistol Whipping a Priest	1							
	Sexual Assult on a Minor							1	
	Reckless Endangerment	÷						3	Violen
		CARINALE					POLISI	CURRO	TYPE

# Classify crimes as violent or dishonest, count them & classify witnesses into "types." Would this work?

	raisenood muex	0.00%	01.04%	20.41/6	30.04 /6	0.40 %	30.2576	0.00%	meraya zi
_	Falsehood Index	0.00%	61.54%	29.41%	36.84%	6.45%	35.29%	-	Average 2
	Total Number of Crimes Violations of Confidence	12	13	17	19	31	34	35	
	Different Types of Crimes	8	7	9	9	9	17	8	
	Gambling Business		2	1			2		
-	Loansharking			2			1		
101	Counterfiting		1		2				
1002	Stolen Financial Documents				1	1	2		
20	Tax Evasion		1				1		
3	Bribary			1			2		
LUC	Insurace Frauds		1		1				
Violations of Confidence	Forgeries			_	3		2		Financia
8	Perjury		1	1					
	Bail Jumping and Escape		2			1	2		Judicia
	Heroin Possession and Sale	1		3			1	5	
	Cocaine Posession and Sale	2				3	1		
	Marijuana Possession and Sale							5	Narcotic
	Burglaries	2		3	1		2		
	Theft: Auto, Money, Other		5		4	6	2	8	Theft
	Murder	1		1					
	Attempted Murder			2		2			
	Armed Robberies	2		_	3	3	2	6	
	Kidnapping				_	1	2		
	Extortion				_	3	4		
	Assault	2			_	6	1	5	
oss	ession of Dangerous Weapons	1		3	3	4	2	5	
	Bank Robbery					1	3		
	Armed Hijacking				1		2		
	Pistol Whipping a Priest	1							
	Sexual Assult on a Minor							1	
	Reckless Endangerment							3	Violen
		CARINALE	OHONJI	LOFANO 13	ENATONE	ALONET	POLISI	CURRO	TYPE

Classify crimes as violent or dishonest, count them & classify witnesses into "types." Would this work? No.

		CARINALE I	ORONJY	LOFARO	SENATORE	MALONEY	POLISI	CURRO	TYPE
	Reckless Endangerment							3	Violent
	Sexual Assult on a Minor							1	
	Pistol Whipping a Priest	1							
	Armed Hijacking				1		2		
	Bank Robbery					1	3		
oss	ession of Dangerous Weapons	1		3	3	4	2	5	
	Assault	2				6	1	5	
	Extortion					3	4		
	Kidnapping					1	2		
	Armed Robberies	2			3	3	2	6	
	Attempted Murder			2		2			
	Murder	1		1					
	Theft: Auto, Money, Other		5		4	6	2	8	Theft
	Burglaries	2		3	1		2		
	Marijuana Possession and Sale							5	Narcotic
	Cocaine Posession and Sale	2				3	1		
	Heroin Possession and Sale	1		3			1	5	
	Bail Jumping and Escape		2			1	2		Judicia
8	Perjury		1	1					
Jel N	Forgeries				3		2		Financia
JIII	Insurace Frauds		1		1				
3	Bribary			1			2		
5	Tax Evasion		1				1		
2	Stolen Financial Documents				1	1	2		
VIDIBIDITS OF COTTIGENCE	Counterfiting		1		2				
2	Loansharking			2			1		
	Gambling Business		2	1			2		
	Different Types of Crimes	8	7	9		9	17	8	
	Total Number of Crimes	12	13	17	19	31	34	35	
	Violations of Confidence	0	8	5	7	2	12	0	
	Falsehood Index	0.00%	61.54%	29.41%	36.84%	6.45%	35.29%	0.00%	Average 2

Classify crimes as violent or dishonest, count them & classify witnesses into "types." 1. Index is meaningless: why divide by total crimes?

		CARINALE I	ORONJY	LOFARO	SENATORE	MALONEY	POLISI	CURRO	TYPE
	Reckless Endangerment							3	Violent
	Sexual Assult on a Minor							1	
	Pistol Whipping a Priest	1							
	Armed Hijacking				1		2		
	Bank Robbery					1	3		
oss	ession of Dangerous Weapons	1		3	3	4	2	5	
	Assault	2				6	1	5	
	Extortion					3	4		
	Kidnapping					1	2		
	Armed Robberies	2			3	3	2	6	
	Attempted Murder			2		2			
	Murder	1		1					
	Theft: Auto, Money, Other		5		4	6	2	8	Theft
	Burglaries	2		3	1		2		
	Marijuana Possession and Sale							5	Narcotic
	Cocaine Posession and Sale	2				3	1		
	Heroin Possession and Sale	1		3			1	5	
	Bail Jumping and Escape		2			1	2		Judicia
8	Perjury		1	1					
Jel N	Forgeries				3		2		Financia
JIII	Insurace Frauds		1		1				
3	Bribary			1			2		
5	Tax Evasion		1				1		
2	Stolen Financial Documents				1	1	2		
VIDIBIDITS OF COTTIGENCE	Counterfiting		1		2				
2	Loansharking			2			1		
	Gambling Business		2	1			2		
	Different Types of Crimes	8	7	9		9	17	8	
	Total Number of Crimes	12	13	17	19	31	34	35	
	Violations of Confidence	0	8	5	7	2	12	0	
	Falsehood Index	0.00%	61.54%	29.41%	36.84%	6.45%	35.29%	0.00%	Average 2

Classify crimes as violent or dishonest, count them & classify witnesses into "types." 2. Average of index is doubly meaningless

VD&M – Principles

Violations of Confidence	Perjury		2	1		1	2		Judicial
	Bail Jumping and Escape		2			1	2		Judicial
	Heroin Possession and Sale	1		3		-	1	5	
	Cocaine Posession and Sale	2				3	1		
	arijuana Possession and Sale							5	Narcotic
	Burglaries	2		3	1		2		
			5			6		8	Theft
	Theft: Auto, Money, Other		5		4	6	2	8	Theft
	Murder	1		1					
						2			
	Attempted Murder	-		2		2	-		
	Armed Robberies	2			3	3	2	6	
	Kidnapping					1	2		
					_				
	Extortion					3	4		
		2			_			5	
00000	Assault	2	_	0		6	- 1	5	
osses	sion of Dangerous Weapons	1		3	3	4	2	5	
	Bank Robbery				_	1	3		
	Armed Hijacking				1		2		
	Pistol Whipping a Priest	1							
	Sexual Assult on a Minor							1	
	Reckless Endangerment							3	Violen
		CARINALE	ORONJY	LOFARO	SENATORE	ALONEY	POLISI	CURRO	TYPE

Classify crimes as violent or dishonest, count them & classify witnesses into "types." 3. Cell shading suggests a few crimes  $\approx$  no crimes

	riminal Activ	CARINALE					POLISI	CURRO	TYPE
	Reckless Endangerment			20174110				3	Violent
	Sexual Assult on a Minor							1	
	Pistol Whipping a Priest	1							
	Armed Hijacking				1		2		
	Bank Robbery					1	3		
oss	ession of Dangerous Weapons	1		3	3	4	2	5	
	Assault	2				6	1	5	
	Extortion					3	4		
	Kidnapping					1	2		
	Armed Robberies	2			3	3	2	6	
	Attempted Murder			2		2			
	Murder	1		1					
	Theft: Auto, Money, Other		5		- 4	6	2	8	Theft
	Burglaries	2		3	1		2		
	Marijuana Possession and Sale					2		5	Narcotic
	Cocaine Posession and Sale					3	1		
	Heroin Possession and Sale			3			1	5	
	Bail Jumping and Escape		2			1	2		Judicia
8	Perjury		1	1					
	Forgeries				3		2		Financia
	Insurace Frauds		1		1				
5	Bribary			1			2		
	Tax Evasion		1				1		
ŝ	Stolen Financial Documents				1	1	2		
100	Counterfiting		1		2				
-	Loansharking			2			1		
	Gambling Business		2	1			2		
	Different Types of Crimes		7	9	9	9	17	8	
	Total Number of Crimes		13	17	19	31	34	35	
	Violations of Confidence		8	5	7	2	12	0	
	Falsehood Index	0.00%	61.54%	29.41%	36.84%	6.45%	35.29%	0.00%	Average 2

Classify crimes as violent or dishonest, count them & classify witnesses into "types." 4. Unbundled categories now makes cells fainter

	Violations of Confidence Falsehood Index	0.00%	61.54%	29.41%		6,45%	35,29%	0	Average 2
	Total Number of Crimes		13	17		31	34	35	
	Different Types of Crimes		7	9		9	17	8	
	Gambling Business		2	2			2		
2	Loansharking		1	2			1		
2	Counterfiting		1		2	1	2		
2	Stolen Financial Documents		1		1	1	2		
5	Tax Evasion		1	1			2		
	Insurace Frauds Bribary		1	1	1		2		
5	Insurace Frauds		1		3		2		rinanci
	Perjury Forgeries		1	1	3		2		Financi
	Bail Jumping and Escape		2			1	2		Judicia
_		1		3			1	5	
	Cocaine Posession and Sale Heroin Possession and Sale	2				3	1		
	arijuana Possession and Sale Cocaine Posession and Sale							5	Narcoti
	Burglaries	2		3	1		2		himme - "
	Theft: Auto, Money, Other		5	0		6	2	8	Theft
		1		1	4				Theft
	Attempted Murder Murder			2		2			
	Armed Robberies	2			3	3	2	6	
	Kidnapping					1	2		
	Assault Extortion	2				6	1	5	
osses	sion of Dangerous Weapons	1		3	3	4	2	5	
	Bank Robbery					1	3		
	Armed Hijacking				1		2		
	Pistol Whipping a Priest	1							
	Sexual Assult on a Minor							1	
	Reckless Endangerment							3	Violer
		CARINALE	FORONJY	LOFARO	SENATORE	MALONEY	POLISI	CURRO	TYP

Classify crimes as violent or dishonest, count them & classify witnesses into "types." "Believe the honest drug dealer, and the guy who pistol whipped a priest" What if we wanted to approach the question of witness similarity as scientists?

1. Which crimes tend to cluster together?

2. Which criminals are similar to each other?

What if we wanted to approach the question of witness similarity as scientists?

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Let's order the rows and columns by similarity using cluster analysis

A diagram sorted in this fashion is called a **heatmap** 

Maloney Polisi Cardinale Lofaro Foronjy Curro Counterfeiting Insurance Frauds Theft: Auto, Money, Other Heroin Possession & Sale **Buralaries** Armed Robberies Possesion of Danaerous Weapons Tax Evasion Gamblina Business Loansharkina Bribery **Reckless Endangerment** Maurijana Possession & Sale Sexual Assault on Minor Pistol Whipping a Priest Murder Attempted Murder Periury Stolen Financial Documents Armed Hijackina **Forgeries** Cocaine Possession & Sale Assault **Bailjumping & Escape** Bank Robbery Kidnapping Extortion

Senatore

# What if we wanted to approach the question of witness similarity as scientists?

1. Which crimes tend to cluster together?

2. Which criminals are similar to each other?

Let's order the rows and columns by similarity using cluster analysis

A diagram sorted in this fashion is called a **heatmap** 

...it also helps to combine redundant categories



Substantive Focus

Initial Minimalism

Develop a Style

Write Results Around Figures

Follow Through