

Visualizations in the Analysis Workflow

SPE

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A copy of this presentation is available on GitHub: <https://github.com/tspeidel/SPE>

Views are my own.

Agenda

1. Visualizations: Objectives and Constraints
2. Univariate Visualizations
3. Bivariate Visualizations
4. Tips & Best Practices
5. What to Look for in Visualization Tools? An Opinionated List
6. References

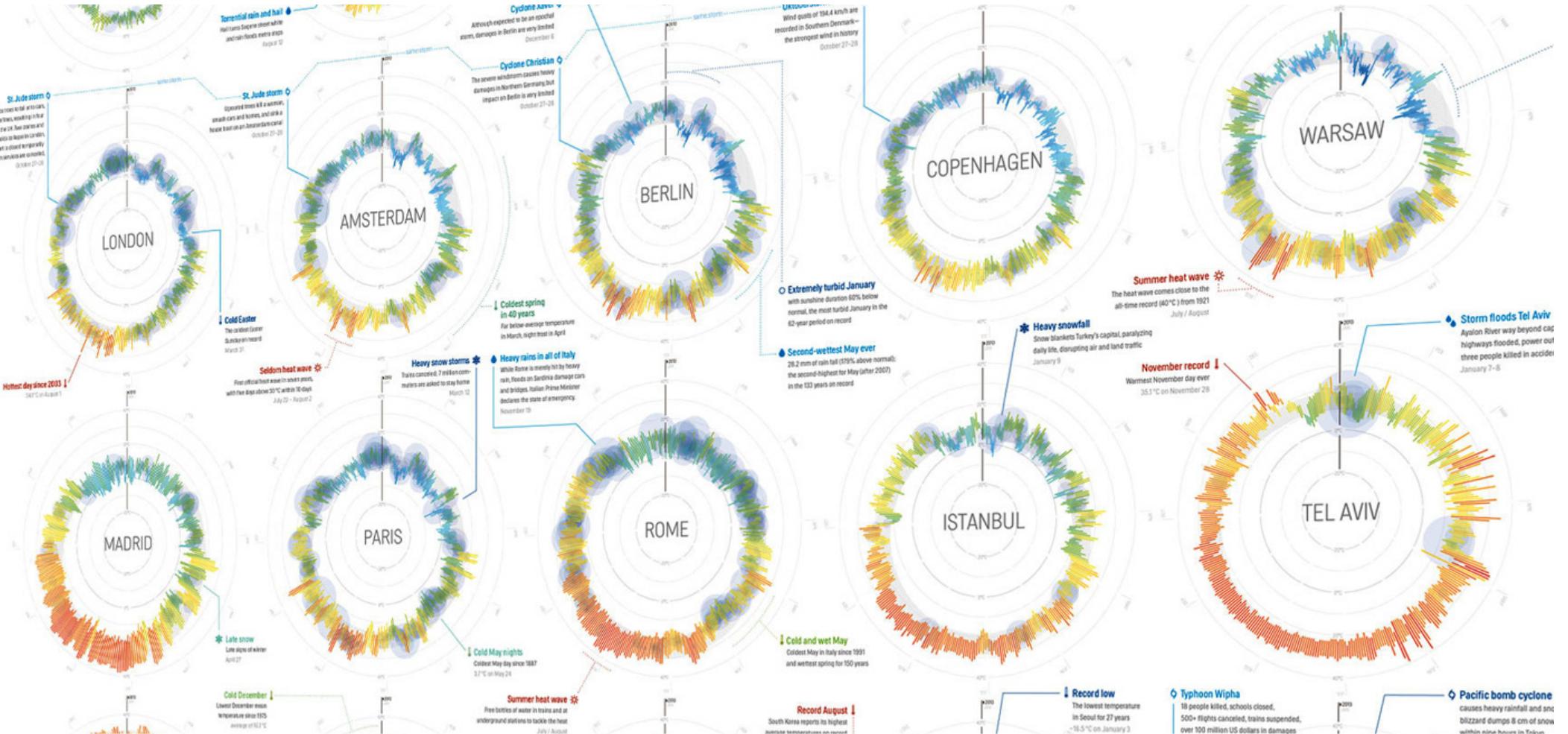
Data Manifesto

Data, in and by themselves, do not directly create knowledge. While efforts to collect and store data have increased dramatically in recent years, nearly absent is a focus on knowledge creation. In the age of Big Data, the availability of vast amounts of information can coexist with the **absence of knowledge**. **Data cannot speak for themselves**. It is in when we interpret data that knowledge is created. My focus is on **bridging the gap between data and knowledge creation**. That gap is filled by analytics and evidence based decision making.

1. Visualizations: Objectives and Constraints

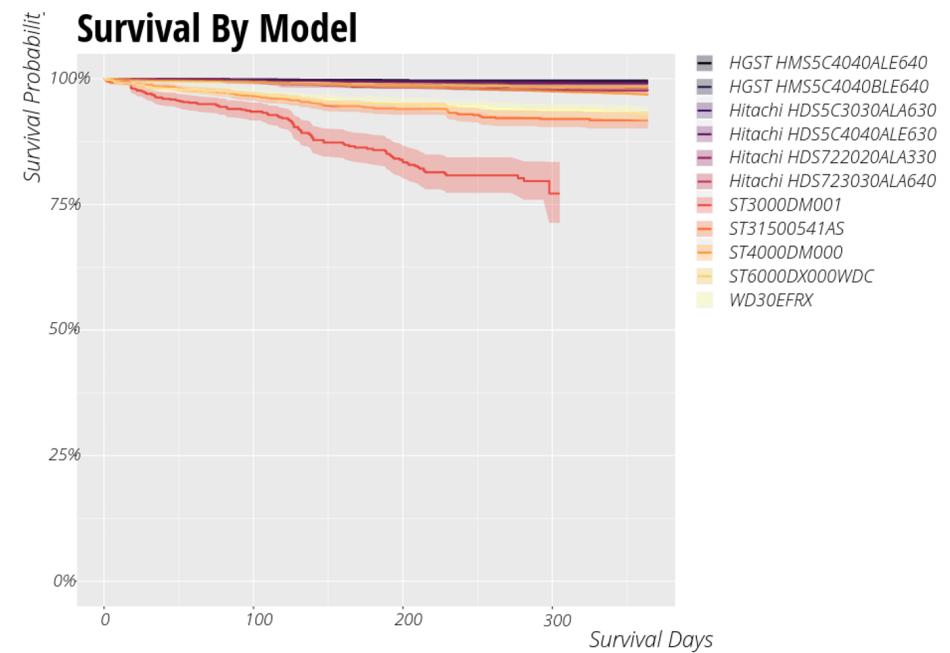
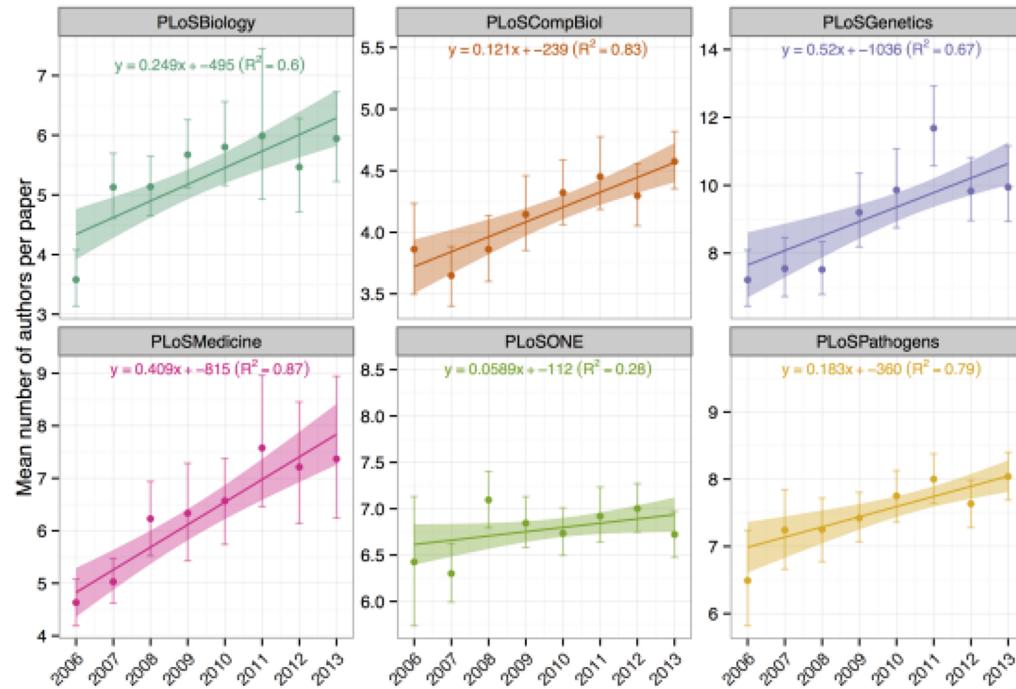
First Goal of Visualizations

To summarize, communicate and engage (telling a story)



Second Goal of Visualizations

To identify, understand, highlight features or relationships (helping the readers make up their mind)



Kaplan-Meier survival curves of time to failure for each hard drive model. Steeper curves indicate faster failure rates. By 300 days, only 77% of ST3000DM001 were still running, compared to >94% for all other drives. Could this be caused by the age of the drives?

[1] Gelman, Unwin. 2013 ↗

To Persuade or to Inform?

We **cannot** achieve both effectiveliy at the same time!

To Persuade



To Inform

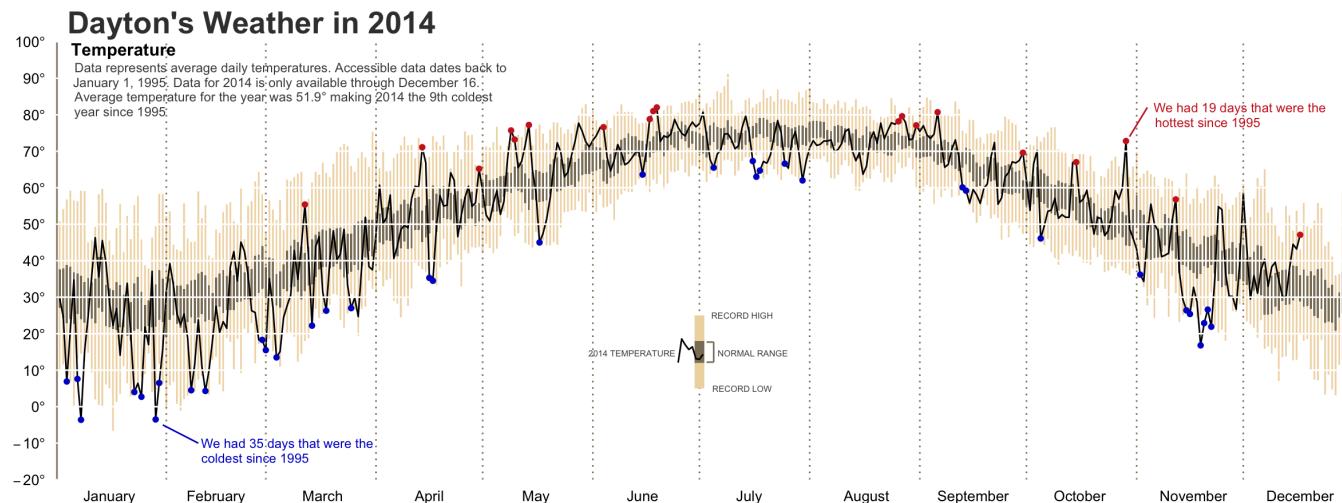
Nutrition Facts		
Serving Size 1 cup (228g)		
Servings Per Container 2		
Amount Per Serving		
Calories	250	Calories from Fat 110
% Daily Value*		
Total Fat	12g	18%
Saturated Fat	3g	15%
Trans Fat	3g	
Cholesterol	30mg	10%
Sodium	470mg	20%
Total Carbohydrate	31g	10%
Dietary Fiber	0g	0%
Sugars	5g	
Protein	5g	
Vitamin A		4%
Vitamin C		2%
Calcium		20%
Iron		4%
* Percent Daily Values are based on a 2,000 calorie diet. Your Daily Values may be higher or lower depending on your calorie needs.		
Calories	2,000	2,500
Total Fat	Less than 65g	80g
Sat Fat	Less than 20g	25g
Cholesterol	Less than 300mg	300mg
Sodium	Less than 2,400mg	2,400mg
Total Carbohydrate	300g	375g
Dietary Fiber	25g	30g

[1] Spiegelhalter, Pearson, Short. 2011 ↗

To Remember or to Understand?

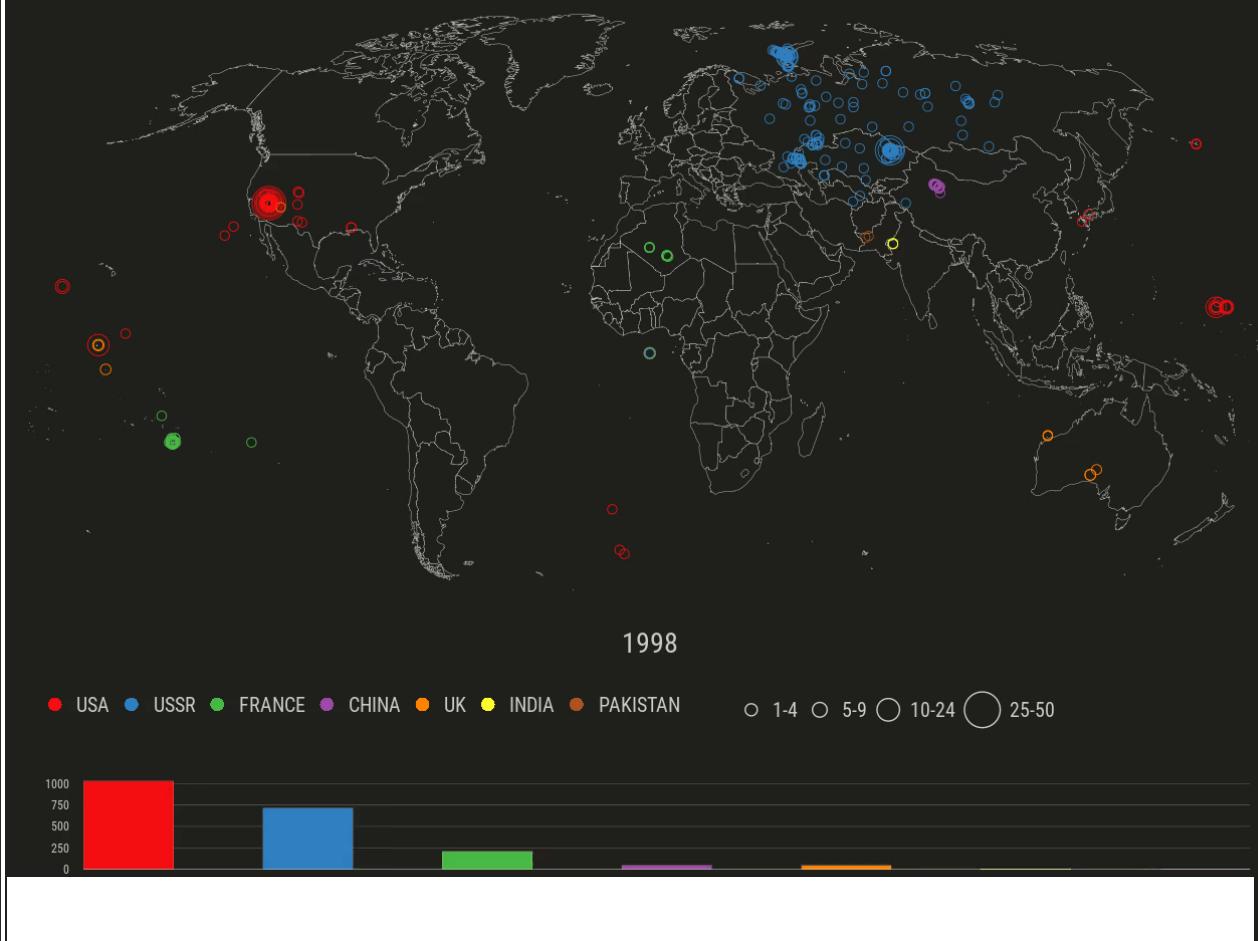
It is possible to achieve both if: (1):

1. Titles and supporting text should convey the message of a visualization
2. If used appropriately, **pictograms** do not interfere with understanding and can improve recognition
3. Redundancy helps effectively communicate the message



Nuclear Explosions, 1945–1998

Stockholm International Peace Research Institute (SIPRI) and Sweden's Defence Research Establishment



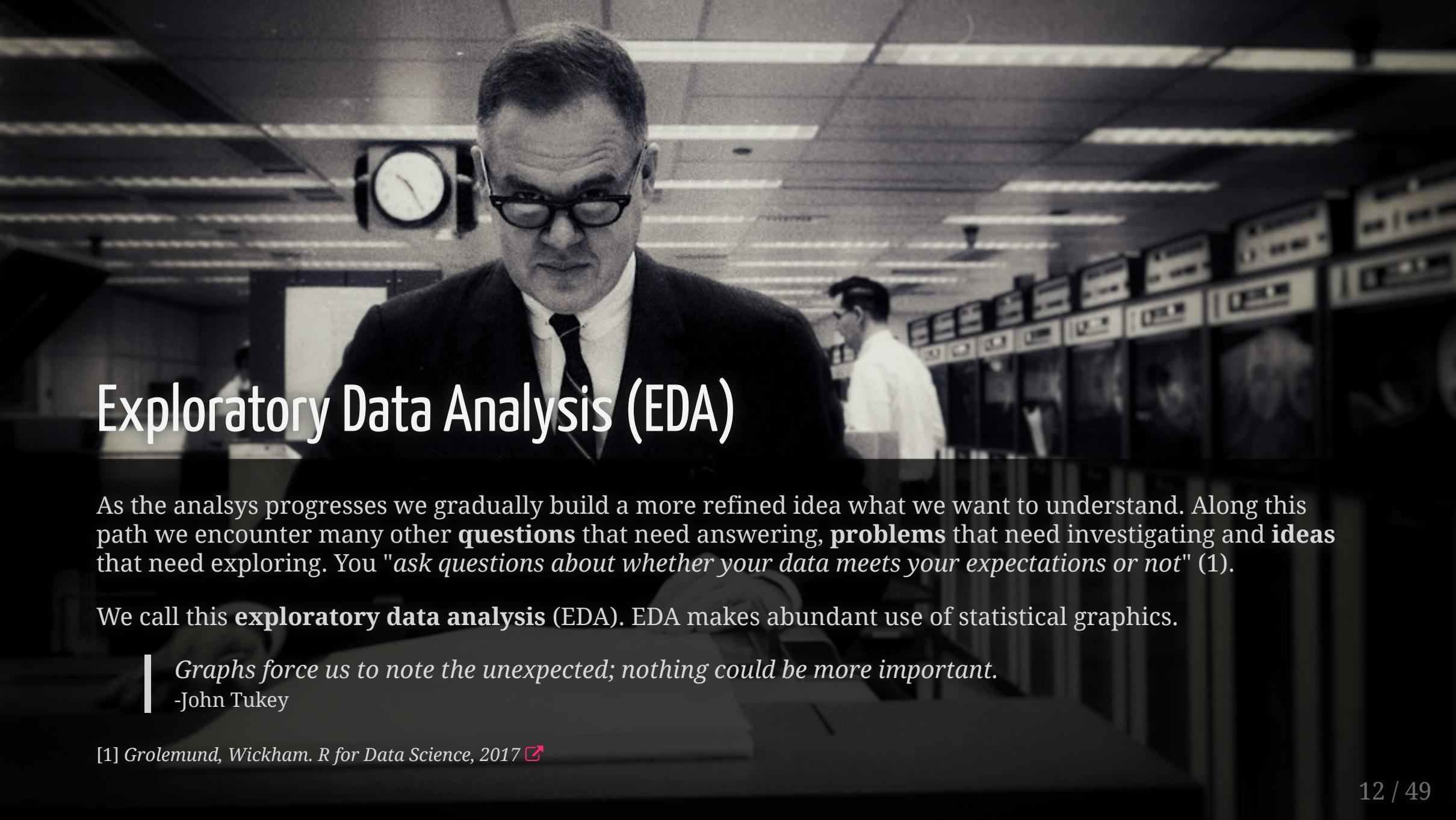
2. Univariate Visualizations

Data

The dataset originates from Doublet (2001).

well	depth	program	helium.porosity	gdens	kmax	k90	rtype	gr	rhob	pe	nphils	lld	lls
1509	6354.5	10-acre	8.6	2.84	6.57	1.52	1	26.81	2.720	3.411	0.0865	456.78	167.17
1509	6355.5	10-acre	5.2	2.85	0.09	0.07	1	22.83	2.745	3.326	0.0648	634.94	257.95
1509	7078.5	10-acre	1.7	2.83	0.40	0.12	1	21.09	2.758	3.146	0.0658	634.60	525.03
1509	7079.5	10-acre	1.9	2.82	0.25	0.17	1	24.99	2.761	3.237	0.0693	1003.90	811.04
1509	7080.5	10-acre	2.3	2.86	0.75	0.37	1	24.39	2.776	3.268	0.0648	1349.71	1204.42

- [1] Doublet, L.E. (2001) An Integrated Geologic and Engineering Characterization of the North Robertson (Clear Fork) Unit, Gaines County, Texas. Petroleum Engineering PhD thesis, Texas A&M University.
[2] Thanks to D. Kaviani for pointing me to the data and for the preparatory work.



Exploratory Data Analysis (EDA)

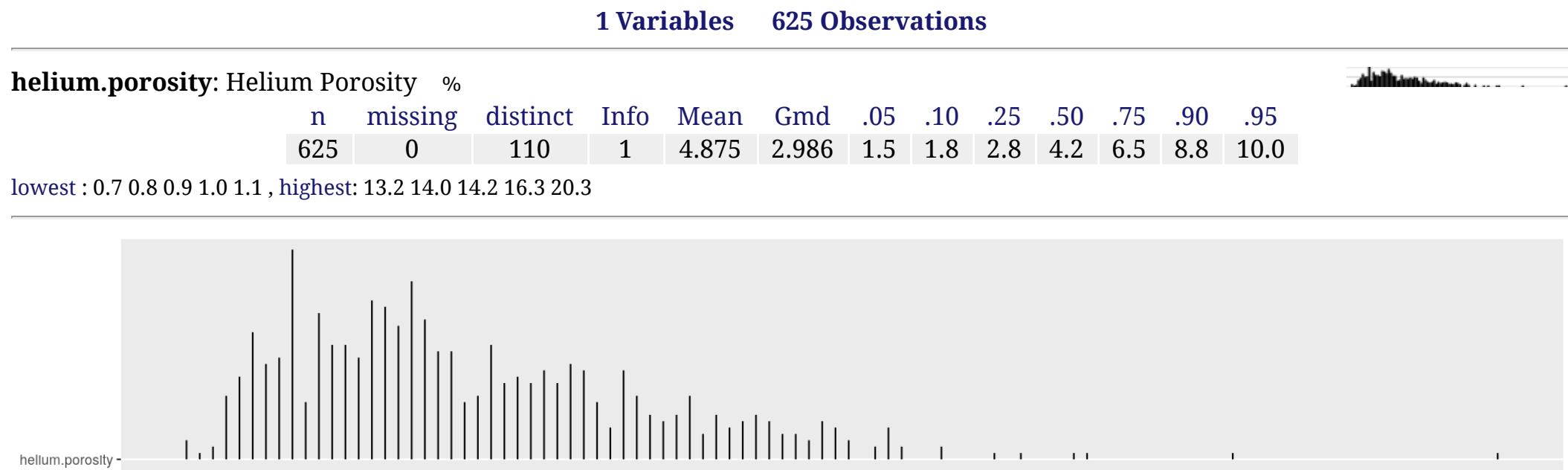
As the analysis progresses we gradually build a more refined idea what we want to understand. Along this path we encounter many other **questions** that need answering, **problems** that need investigating and **ideas** that need exploring. You "ask questions about whether your data meets your expectations or not" (1).

We call this **exploratory data analysis** (EDA). EDA makes abundant use of statistical graphics.

Graphs force us to note the unexpected; nothing could be more important.

-John Tukey

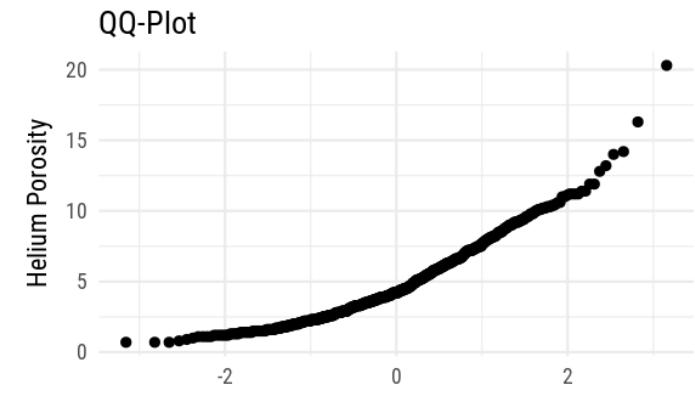
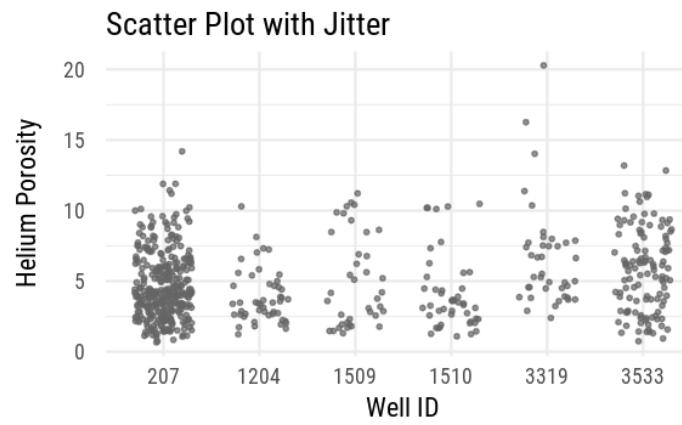
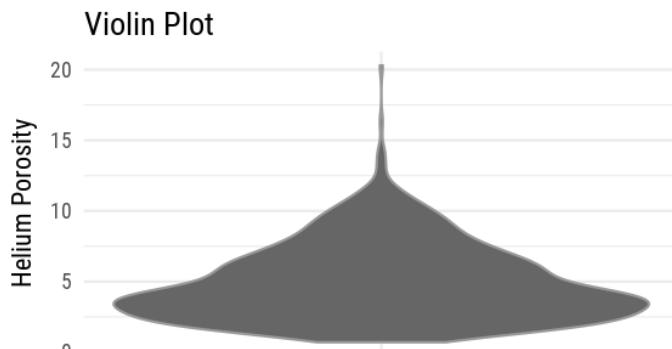
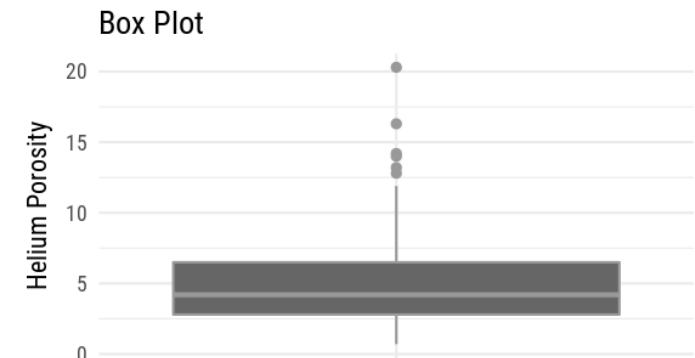
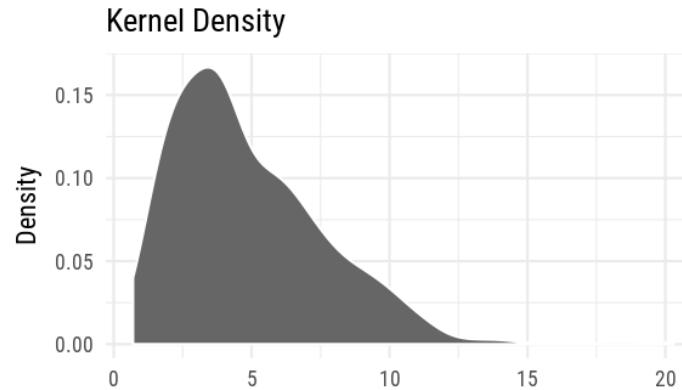
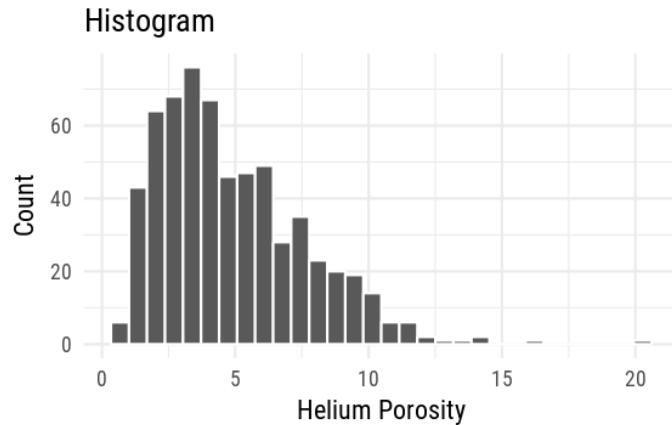
Summary Statistics



*Gmd stands for **Gini mean difference**, a scale independent measure of dispersion (it is the mean absolute difference between any pairs of observations).*

Info is a measure of how continuous the variable is.

Alternative Univariate Visualizations



Bivariate

Numbers become evidence by being in relation to.

-Edward R. Tufte, Visual Explanations: Images & Quantities, Evidence & Narrative (1997)

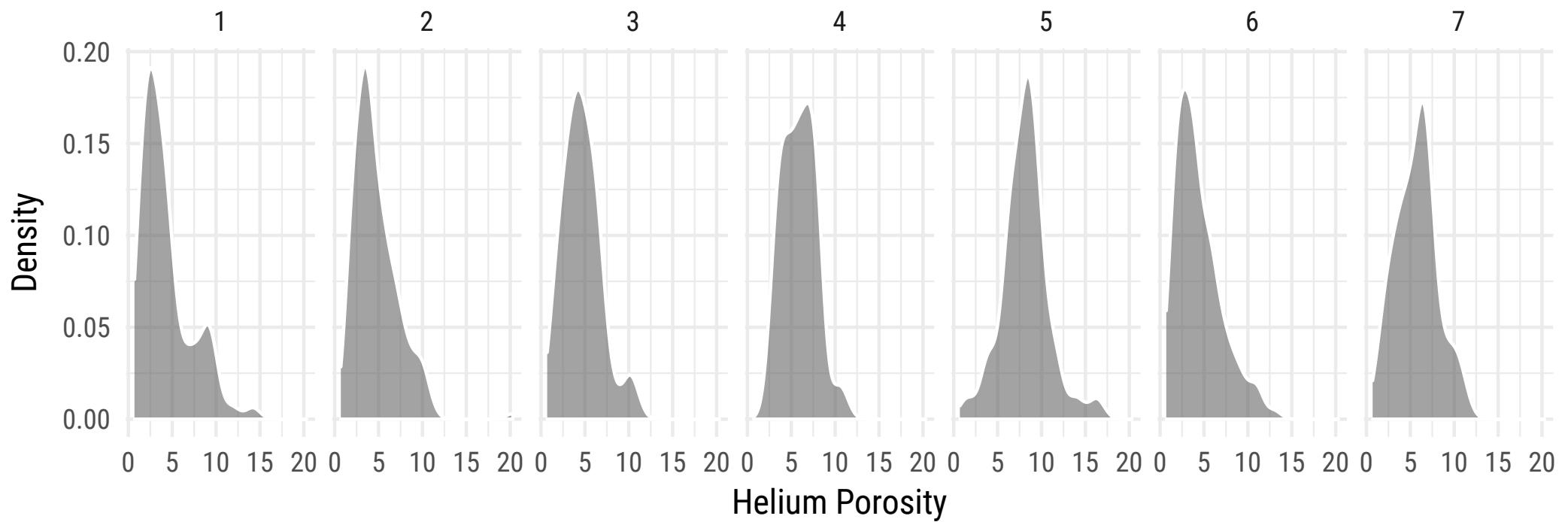
Tables

Baseline characteristics by rock type.										
		1 N=80	2 N=180	3 N=37	4 N=26	5 N=42	6 N=229	7 N=31	Combined N=625	Test Statistic
Depth	ft	7008 7063 7128 6945 ± 308	6812 7008 7153 6916 ± 277	6858 7016 7092 6939 ± 246	6949 7151 7157 7002 ± 274	7225 7233 7244 7234 ± 14	6532 6880 7098 6823 ± 316	6791 6958 7159 6871 ± 296	6800 7042 7152 6910 ± 303	$F_{6\ 618}=29$, P<0.001
Helium Porosity	%	2.3 3.5 5.2 4.3 ± 2.9	3.0 4.2 6.0 4.7 ± 2.6	3.1 4.5 6.1 4.7 ± 2.1	4.3 5.8 7.5 5.9 ± 1.9	6.6 8.2 9.4 8.2 ± 2.7	2.5 3.8 5.8 4.4 ± 2.6	4.0 6.1 7.0 5.7 ± 2.3	2.8 4.2 6.5 4.9 ± 2.7	$F_{6\ 618}=15$, P<0.001
Density	g/cm³	2.840 2.845 2.860 2.843 ± 0.036	2.830 2.840 2.860 2.826 ± 0.193	2.830 2.840 2.850 2.843 ± 0.019	2.822 2.840 2.850 2.837 ± 0.032	2.723 2.740 2.750 2.745 ± 0.038	2.830 2.850 2.860 2.846 ± 0.020	2.830 2.840 2.850 2.837 ± 0.036	2.830 2.840 2.850 2.832 ± 0.108	$F_{6\ 618}=21$, P<0.001
Kmax Permeability	md	0.100 0.330 1.248 23.706 ± 199.208	0.070 0.250 1.088 1.983 ± 7.148	0.040 0.150 0.450 0.742 ± 1.465	0.092 0.210 0.697 1.236 ± 2.465	0.053 0.105 0.367 0.342 ± 0.532	0.090 0.280 1.120 2.018 ± 6.363	0.100 0.220 1.040 1.249 ± 2.397	0.070 0.240 1.020 4.525 ± 71.474	$F_{6\ 618}=2$, P=0.063

a b c represent the lower quartile a, the median b, and the upper quartile c for continuous variables. x ± s represents $\bar{X} \pm 1$ SD.
 Test used: Kruskal-Wallis test .

Kernel Density

Kernel density plots have the unique advantage that they are self-standardizing. This make **comparisons** across rock type easier.

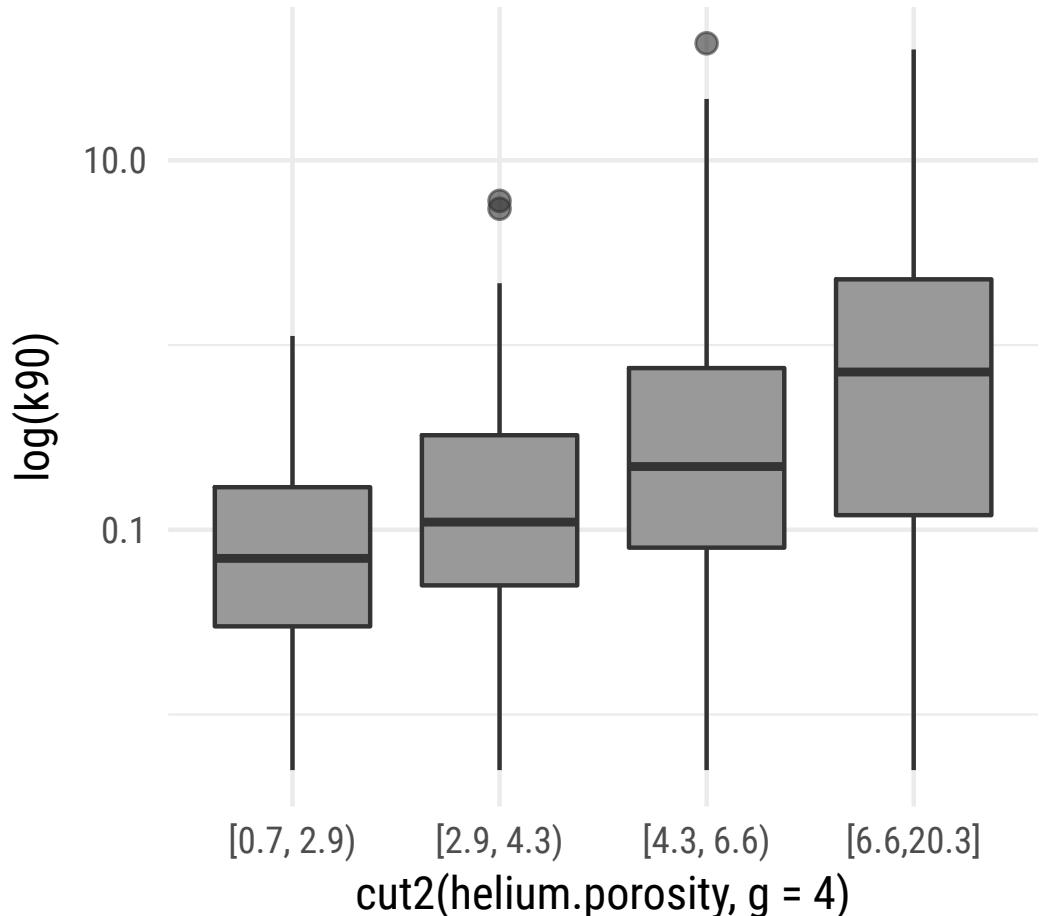
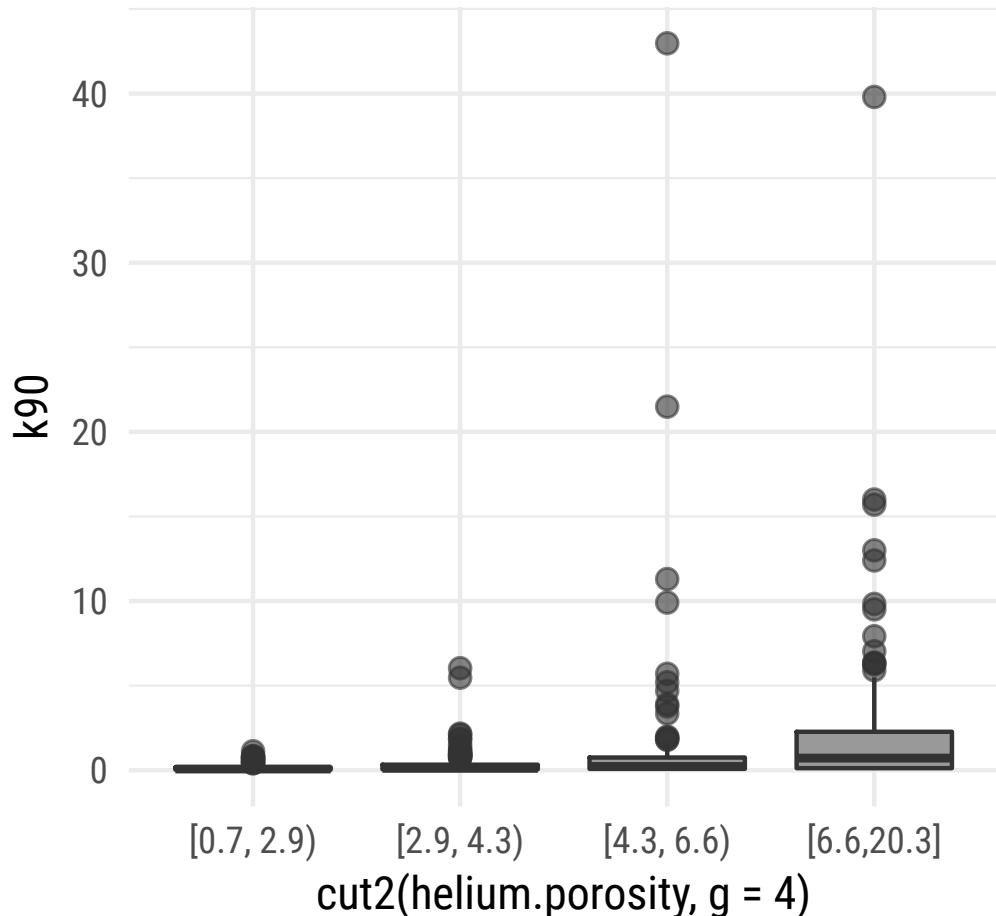


Scatterplot Matrix or Cross Plot

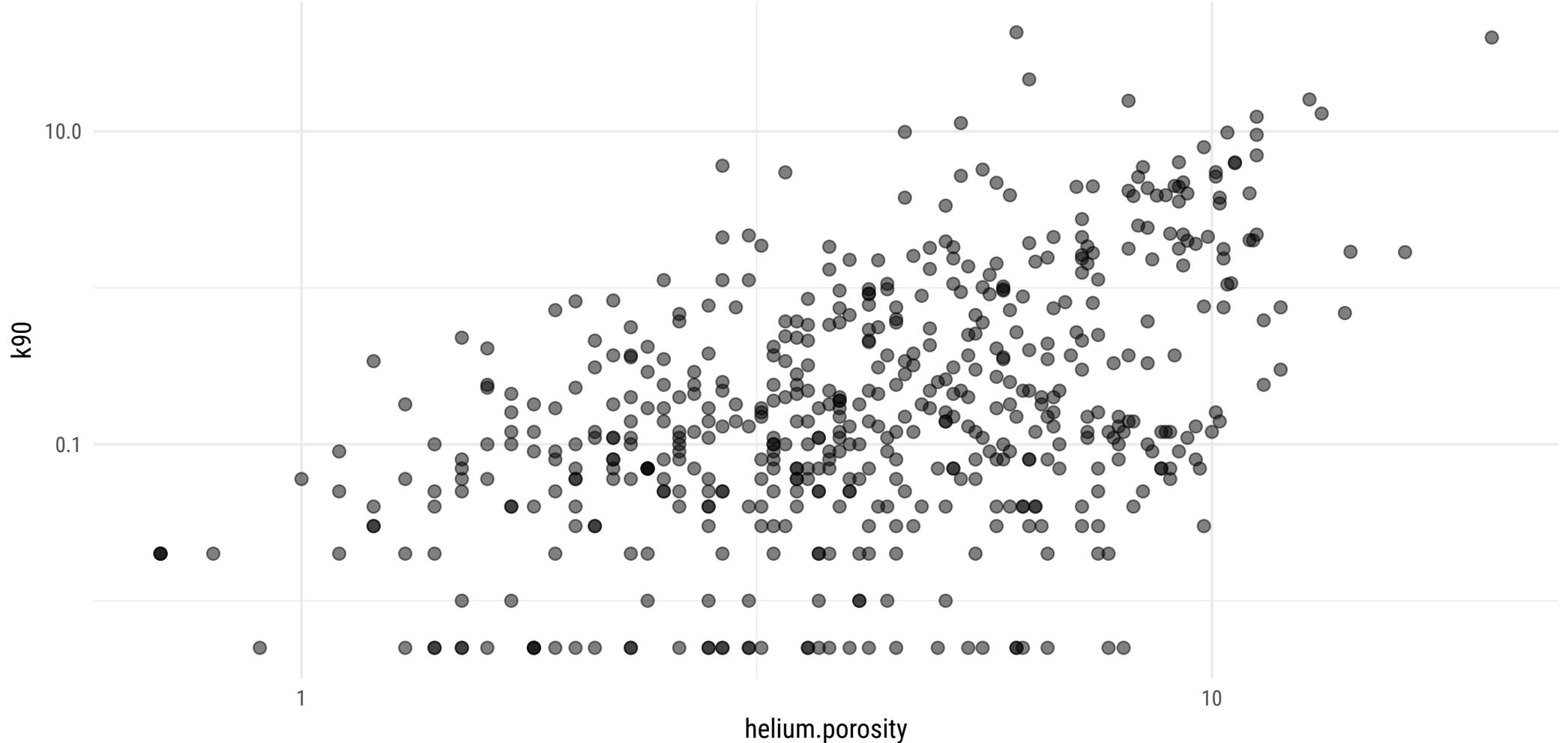
Show all pairwise combinations. Here, I've cheated by removing a few outliers.

Boxplots

Here we *cut* (bin) helium.porosity into quartiles (P25, P50, P75).



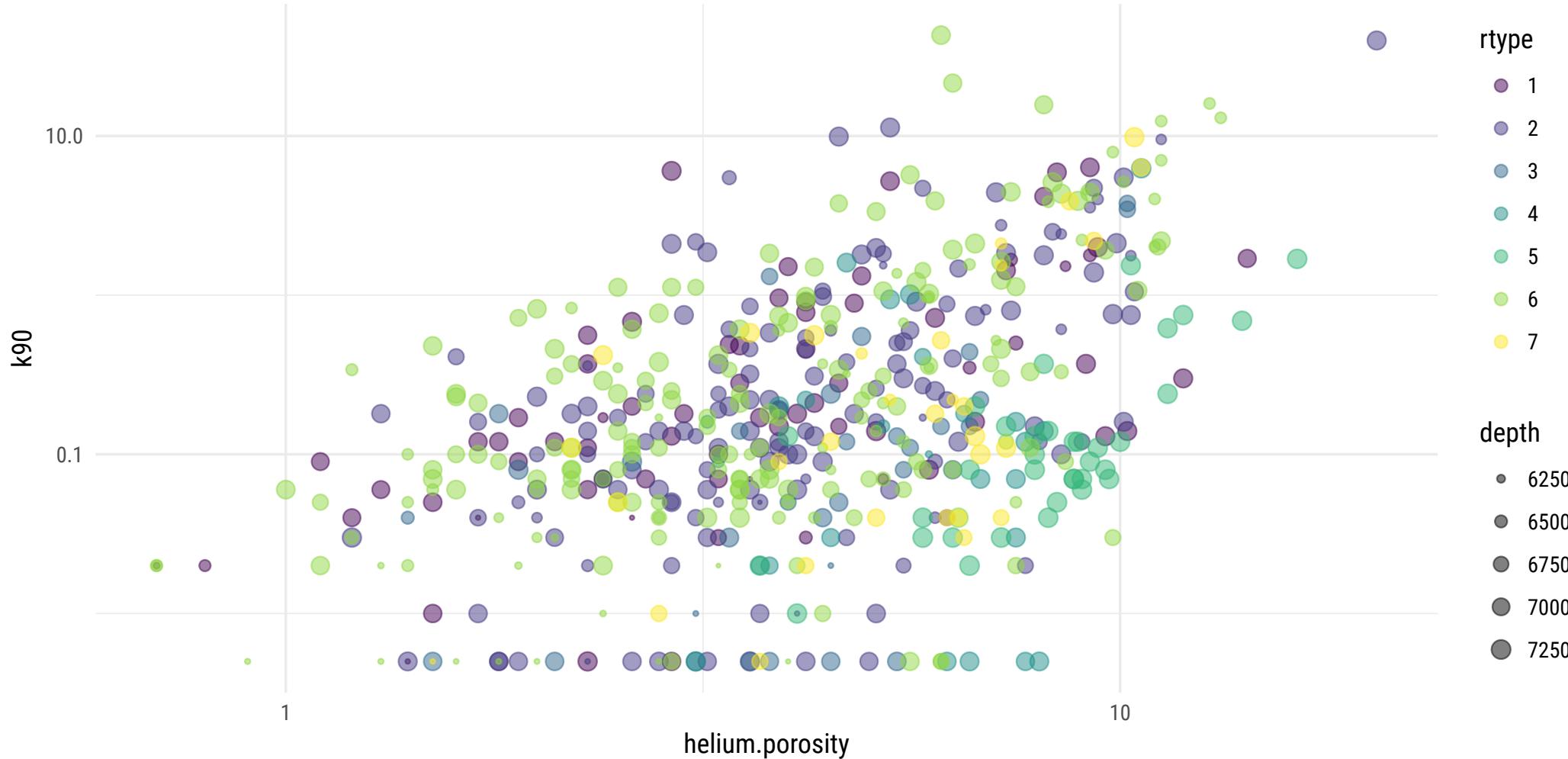
Scatterplots With 2 Variables



Scatterplots With 3 Variables



Scatterplots With 4 Variables



Correlation Matrix

							lls		
							lld	1	
						nphils	-0.7	-0.7	
					pe	-0.2	0.1	0.1	
				rholb	0.1	-0.7	0.7	0.7	
			gr	0.2	0	-0.2	0.2	0.2	
		k90	-0.1	-0.1	0	0.3	0	0	
	kmax	0.9	-0.1	0	0	0.3	0	0	
gdens	0	-0.1	0.2	0.4	0	-0.3	0.4	0.4	
helium.porosity	-0.4	0.4	0.4	-0.2	-0.5	0	0.6	-0.5	-0.6
depth	0.2	-0.4	0.1	0.1	-0.2	-0.4	0	0.1	-0.3
									-0.3

Graphs for Models

It's much easier to interpret a model by graphing it! Compare this:

Logistic (Proportional Odds) Ordinal Regression Model

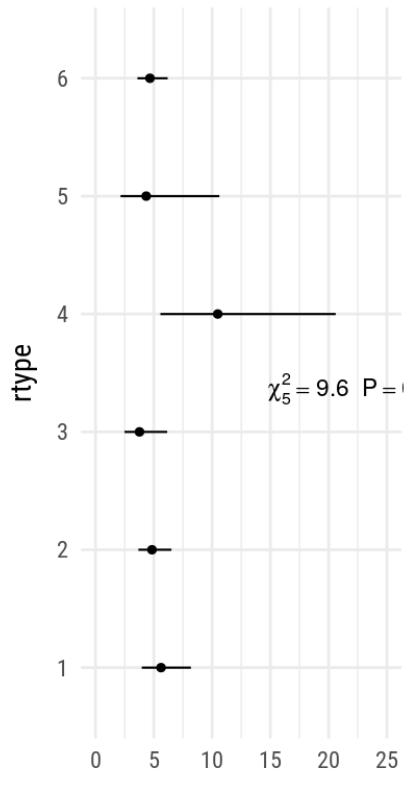
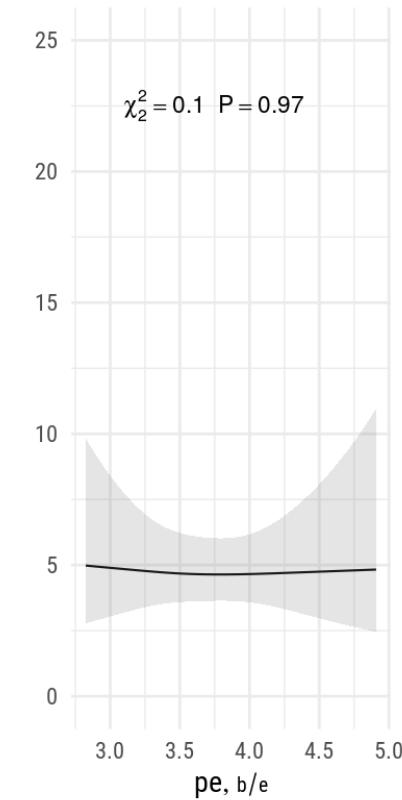
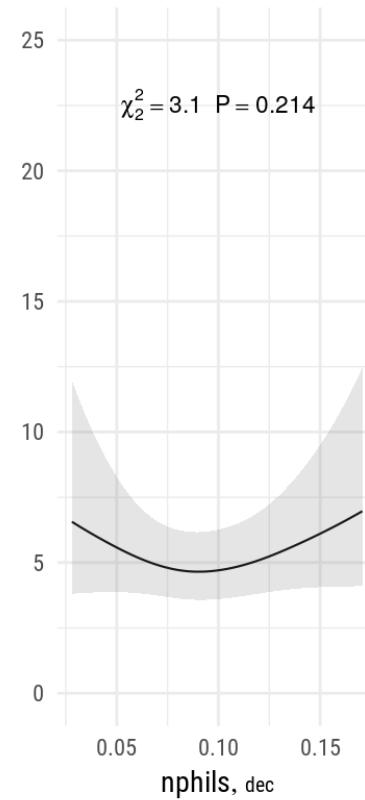
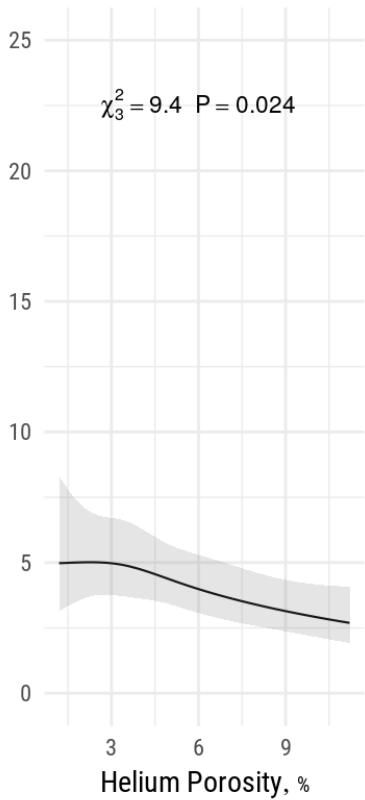
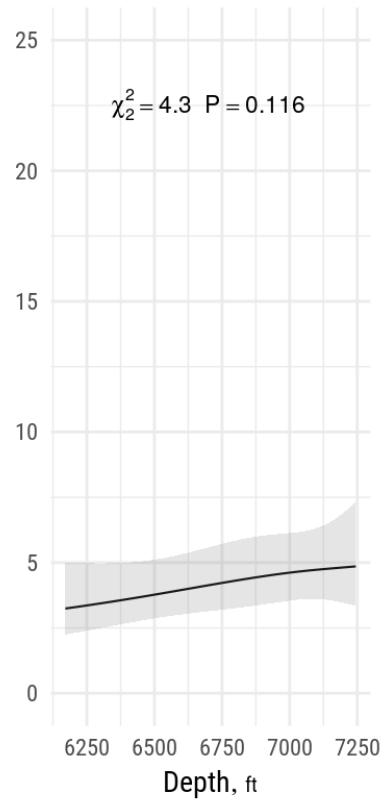
Frequencies of Missing Values Due to Each Variable

k.ratio	helium.porosity	pe	nphils
81	0	0	0
depth	rtype		
0	0		

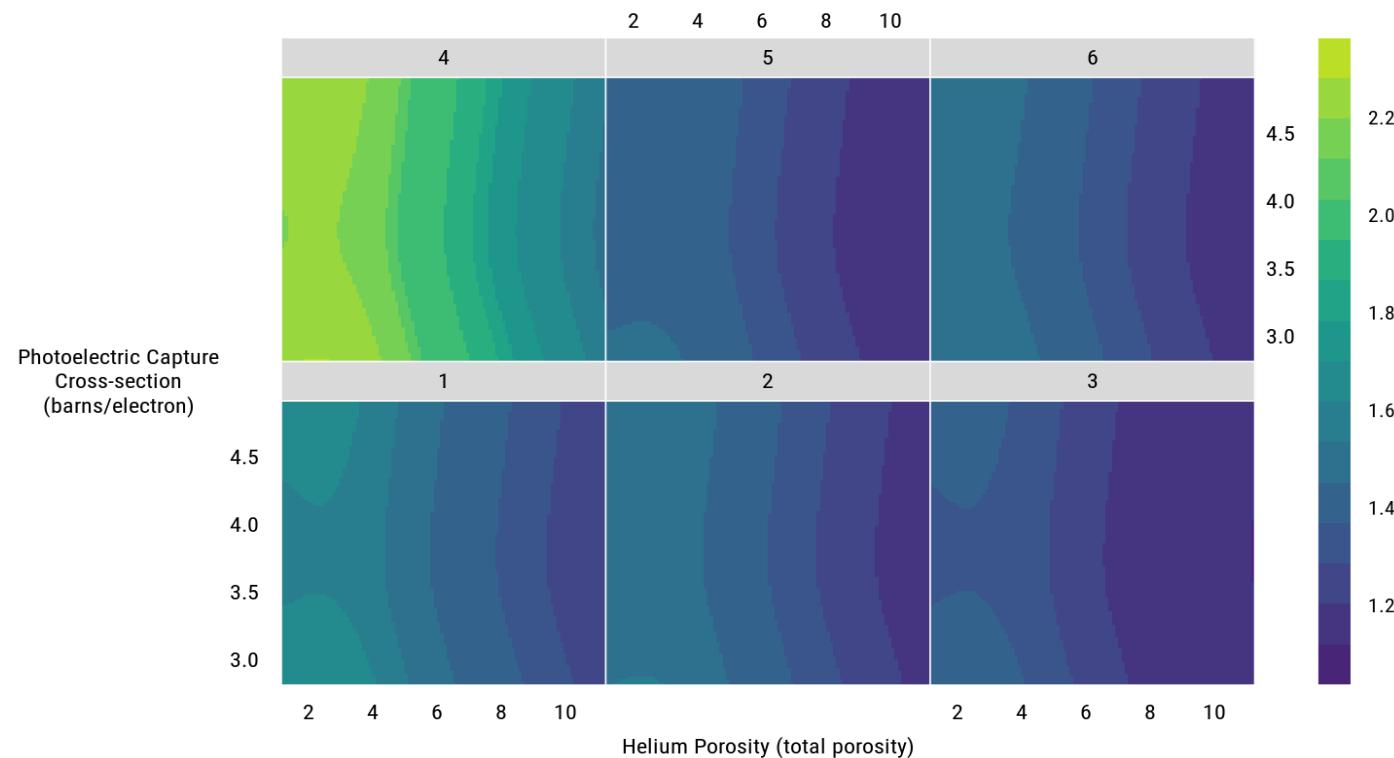
	Model Likelihood Ratio Test	Discrimination Indexes	Rank Discrim. Indexes
Obs 511	LR χ^2 34.84	R^2 0.066	ρ 0.234
Unique Y 318	d.f. 14	g 0.493	
$Y_{0.5}$ 1.433628	$Pr(>\chi^2)$ 0.0016	g_r 1.637	
max $ \partial \log L / \partial \beta $ 1×10^{-6}	Score χ^2 36.21	$ Pr(Y \geq \text{median})^{-1/2} $ 0.083	
	$Pr(>\chi^2)$ 0.0010		

	β	S.E.	Wald Z	$Pr(> Z)$
helium.porosity	0.012	0.195	0.06	0.9494
helium.porosity'	-0.492	0.965	-0.51	0.6100
helium.porosity''	0.987	2.134	0.46	0.6437
pe	-0.140	0.578	-0.24	0.8086
pe'	0.204	0.906	0.23	0.8214

... with this:



... or this:



Non-linear regression model showing the simultaneous effect, on the dependent variable permeability ratio (K_{max}/k_{90}), of changing two continuous variables (helium porosity and photoelectric capture cross-section log) while holding (marginalizing) all other variables fixed at their median.

4. Tips & Best Practices

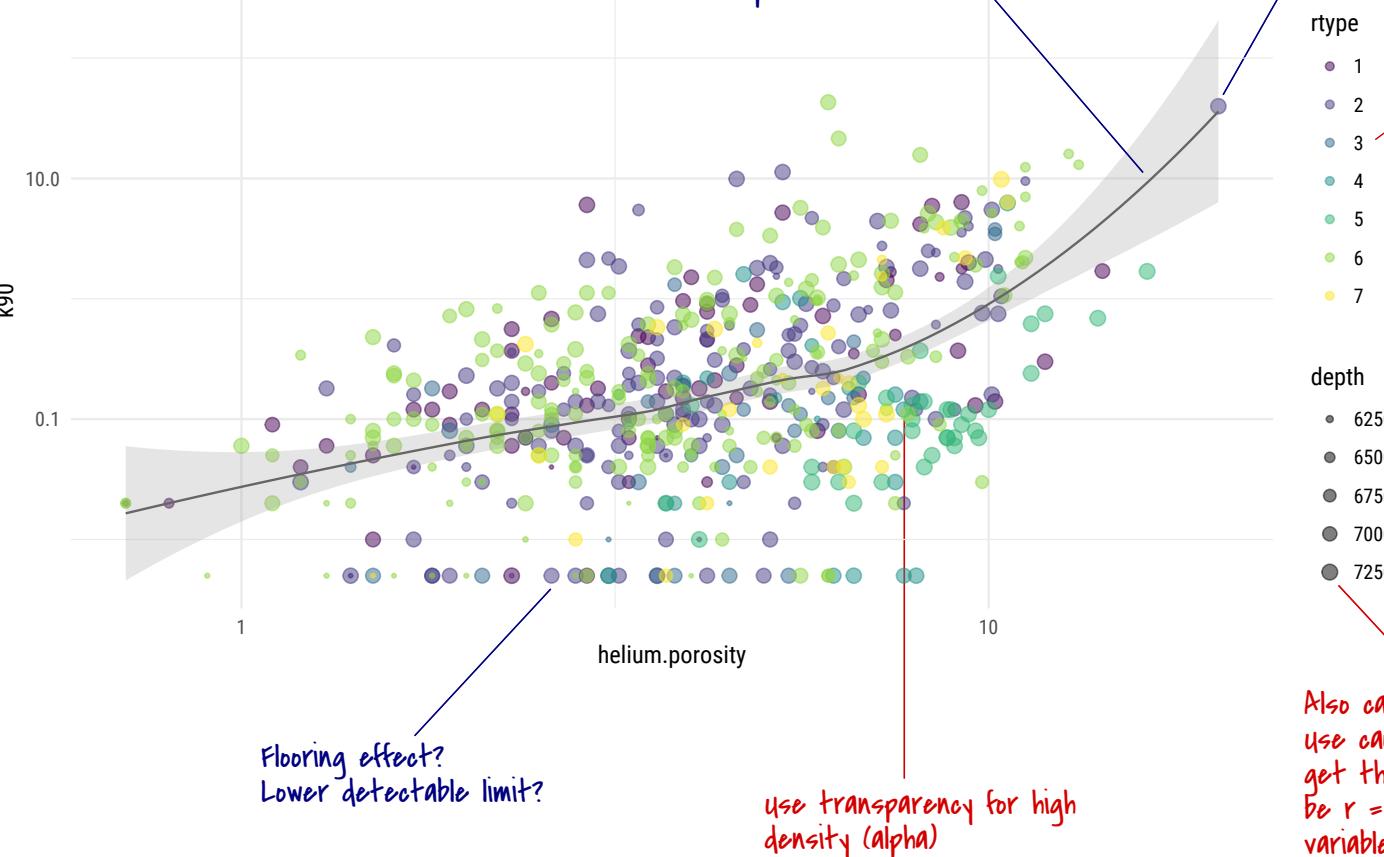
Information displays should be documentary, comparative, causal and explanatory, quantified, multivariate, exploratory, skeptical.

-Edward R. Tufte, Visual Explanations: Images & Quantities, Evidence & Narrative (1997)

General Graphing

— ANALYTICAL NOTES
— VISUALIZATION NOTES

By convention we put the variable of interest on the Y-axis



outlier?

rtype

- 1
- 2
- 3
- 4
- 5
- 6
- 7

use of colors:
1. Wide gamut
2. Perceptually uniform
3. Colorblind friendly
(e.g. colorbrewer, viridis)

depth

- 6250
- 6500
- 6750
- 7000
- 7250

Also called bubble charts.
use cautiously. Some viz tools
get this wrong! Scaling should
be $r = (z / p)^{0.5}$ where z =scaling
variable

Table Tips

Sales in £ '000	QI	QII	QIII	QIV	Average
Sheffield	230	220	190	220	220
Leeds	280	190	220	340	270
Edinburgh	140	130	130	210	150
Hull	70	81	71	84	76
Swansea	62	66	62	77	67
Plymouth	41	44	33	50	42
Luton	23	27	23	27	25
Boston	31	29	25	29	29
Average	110	107	94	130	110

Elements to be compared across columns

Marginal averages gives visual focus, provides a summary and the sorting order

Decrease effective digits (faced with long numbers we all tend to be non numerate)

Largest to smallest

Do not sort alphabetically

White space aids in readability

Right-aligned

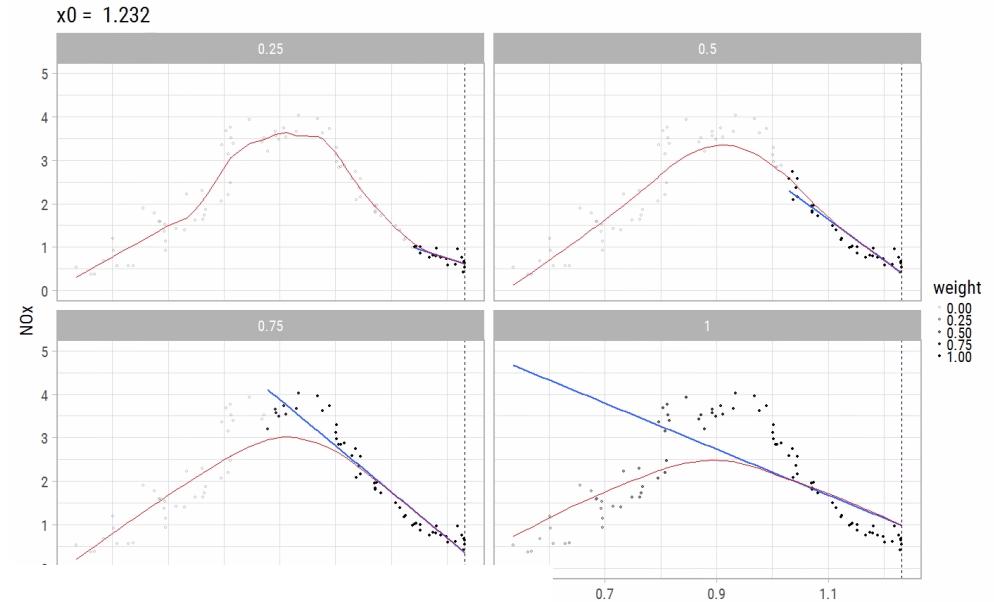
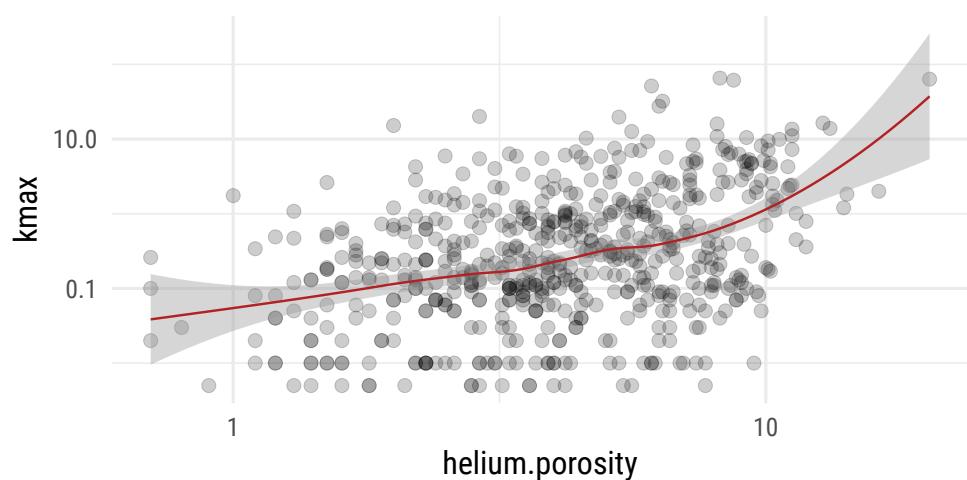
All numbers are rounded off to a minimum (faced with long numbers we all tend to be non numerate)

[1] Recreated from Ehrenberg, 1981 ↗

Use (and abuse) Smoothers

Smoothers are incredibly useful in order to highlight possible **trends** in the data. One of the most popular and flexible smoother is Cleveland's **LOESS** (locally weighted least squares method).

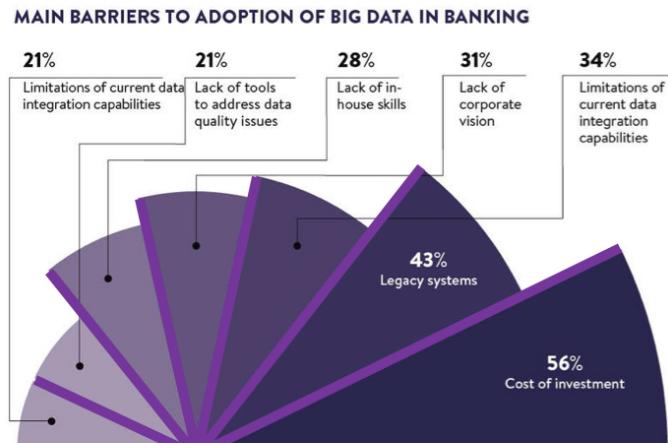
- Non-linear
- Built-in outlier control
- Can control degree of smoothness
- Works well even when one of the variables is binary



Data-to-Ink Ratio

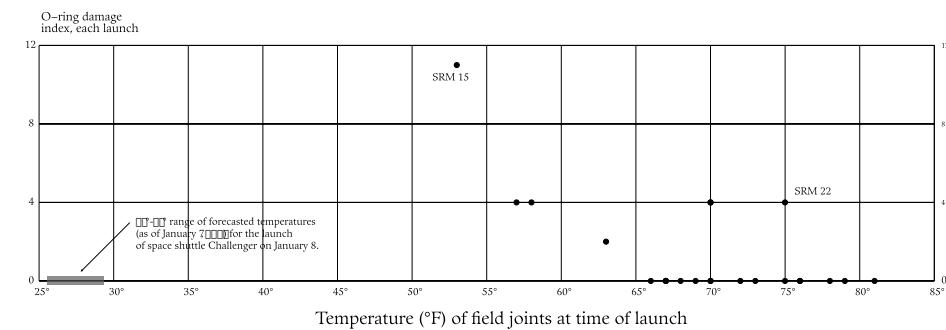
Chartjunk

All visual elements in charts and graphs that are not necessary to comprehend the information represented on the graph, or that distract the viewer from this information. Instead, we want to achieve **rapid visual perception**. (Tufte, 1983, 2006)



Data-to-ink ratio

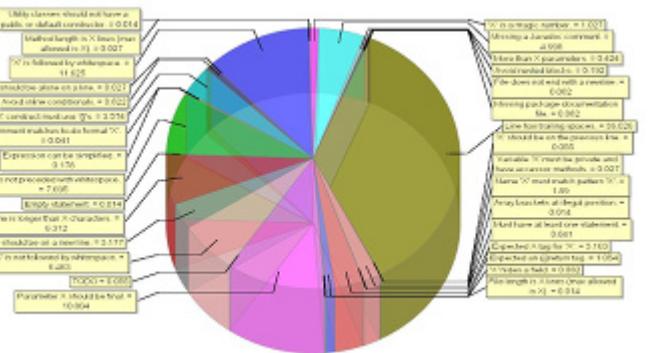
Of all the ink used in a graph, the amount of ink that **transports information**. We want this to be high. (Tufte, 1983, 2006)



Avoid Pies

Why

Plenty of scientific evidence shows that humans are **bad at judging size and making comparisons from angles**. Pie charts do not facilitate comparison when slices are close in size nor can one sort numbers.



Exceptions

Ok to use when there are few well distinct slices to represent. Because we are only good at judging slices that are $\frac{1}{2}$ or $\frac{1}{4}$ of the total, we should aim to have **2-4 slices** at most.

Avoid the **doughnut types**: they remove the angular information we need to draw visual comparisons.

Alternatives

Use bar charts or dot plots.

The Type of Chart Affects Visual Judgement

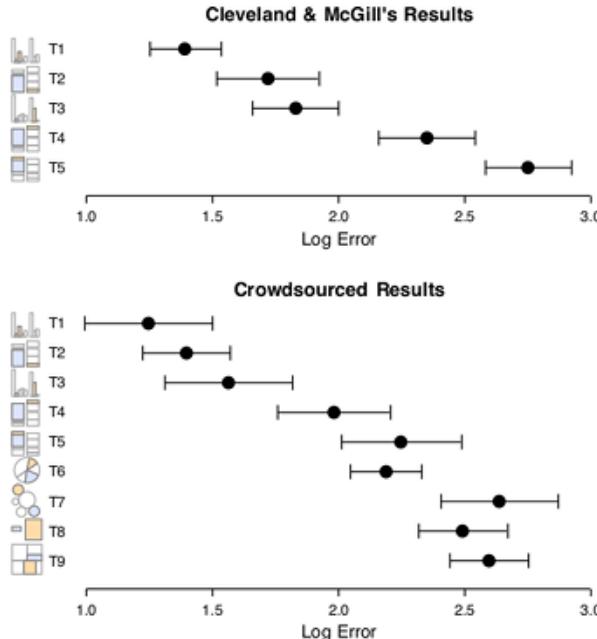


Figure 4: Proportional judgment results (Exp. 1A & B).
Top: Cleveland & McGill's [7] lab study. Bottom: MTurk studies. Error bars indicate 95% confidence intervals.

Graphical Perception: Theory, Experimentation, and Application to the Development of Graphical Methods

WILLIAM S. CLEVELAND and ROBERT McGILL*

The subject of graphical methods for data analysis and for data presentation needs a scientific foundation. In this article we take a few steps in the direction of establishing such a foundation. Our approach is based on *graphical perception*—the visual decoding of information encoded on graphs—and it includes both theory and experimentation to test the theory. The theory deals with a small but important piece of the whole process of graphical perception. The first part is an identification of a set of *elementary perceptual tasks* that are carried out when people extract quantitative information from graphs. The second part is an ordering of the tasks on the basis of how accurately people perform them. Elements of the theory are tested by experimentation in which subjects record their judgments of the quantitative information on graphs. The experiments validate these elements but also suggest that the set of elementary tasks should be expanded. The theory provides a guideline for graph construction: Graphs should employ elementary tasks as high in the ordering as possible. This principle is applied to a variety of graphs, including bar charts, divided bar charts, pie charts, and statistical maps with shading. The conclusion is that radical surgery of these popular graphs is needed, and as replacements we offer alternative graphical forms—*dot charts*, *dot charts with grouping*, and *framed-rectangle charts*.

KEY WORDS: Computer graphics; Psychophysics.

1. INTRODUCTION

Nearly 200 years ago William Playfair (1786) began the serious use of graphs for looking at data. More than 50 years ago a battle raged on the pages of the *Journal of the American Statistical Association* about the relative merits of bar charts and pie charts (Ellis 1926; Croxton 1927; Croxton and Stryker 1927; von Huhn 1927). Today graphs are a vital part of statistical data analysis and a vital part of communication in science and technology, business, education, and the mass media.

Still, graph design for data analysis and presentation is

largely unscientific. This is why Cox (1978) argued, "There is a major need for a theory of graphical methods" (p. 5), and why Kruskal (1975) stated "in choosing, constructing, and comparing graphical methods we have little to go on but intuition, rule of thumb, and a kind of master-apprentice passing along of information. . . . there is neither theory nor systematic body of experiment as a guide" (p. 28–29).

There is, of course, much good common sense about how to make a graph. There are many treatises on graph construction (e.g., Schmid and Schmid 1979), bad practice has been uncovered (e.g., Tuft 1983), graphic designers certainly have shown us how to make a graph appealing to the eye (e.g., Marcus et al. 1980), statisticians have thought intensely about graphical methods for data analysis (e.g., Tukey 1977; Chambers et al. 1983), and cartographers have devoted great energy to the construction of statistical maps (Bertin 1973; Robinson, Sale, and Morrison 1978). The ANSI manual on time series charts (American National Standards Institute 1979) provides guidelines for making graphs, but the manual admits, "This standard . . . sets forth the best current usage, and offers standards 'by general agreement' rather than 'by scientific test'" (p. iii).

In this article we approach the science of graphs through human graphical perception. Our approach includes both theory and experimentation to test it.

The first part of the theory is a list of elementary perceptual tasks that people perform in extracting quantitative information from graphs. In the second part we hypothesize an ordering of the elementary tasks based on how accurately people perform them. We do not argue that this accuracy of quantitative extraction is the only aspect of a graph for which one might want to develop a theory, but it is an important one.

The theory is testable; we use it to predict the relative performance of competing graphs, and then we run experiments to check the actual performance. The experiments are of two types: In one, once the graphs are drawn, the evidence appears so strong that it is taken *prima facie* to have established the case. When a strong effect is perceived by the authors' eyes and brains, it is likely that it will appear to most other people as well. In

* William S. Cleveland and Robert McGill are members at AT&T Bell Laboratories, Murray Hill, NJ 07974. The authors are grateful to John Chambers, Ram Gnanadesikan, David Kmentz, William Kruskal, Colin Mallows, Frederick Mosteller, Henry Pollak, Paul Tukey, and the JASA reviewers for important comments on an earlier version of this article.

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Applications Section

(1)

Avoid 3D

Why

Removes clarity, adds obfuscation, inhibits comprehension, does not help retain information, third dimension is usually nonexistent (and if it did exist, you would try to avoid it).

Exceptions

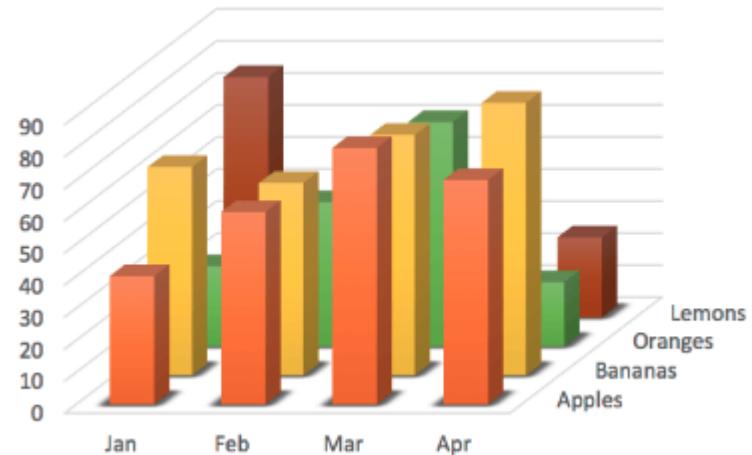
Spatial data, interaction surfaces.

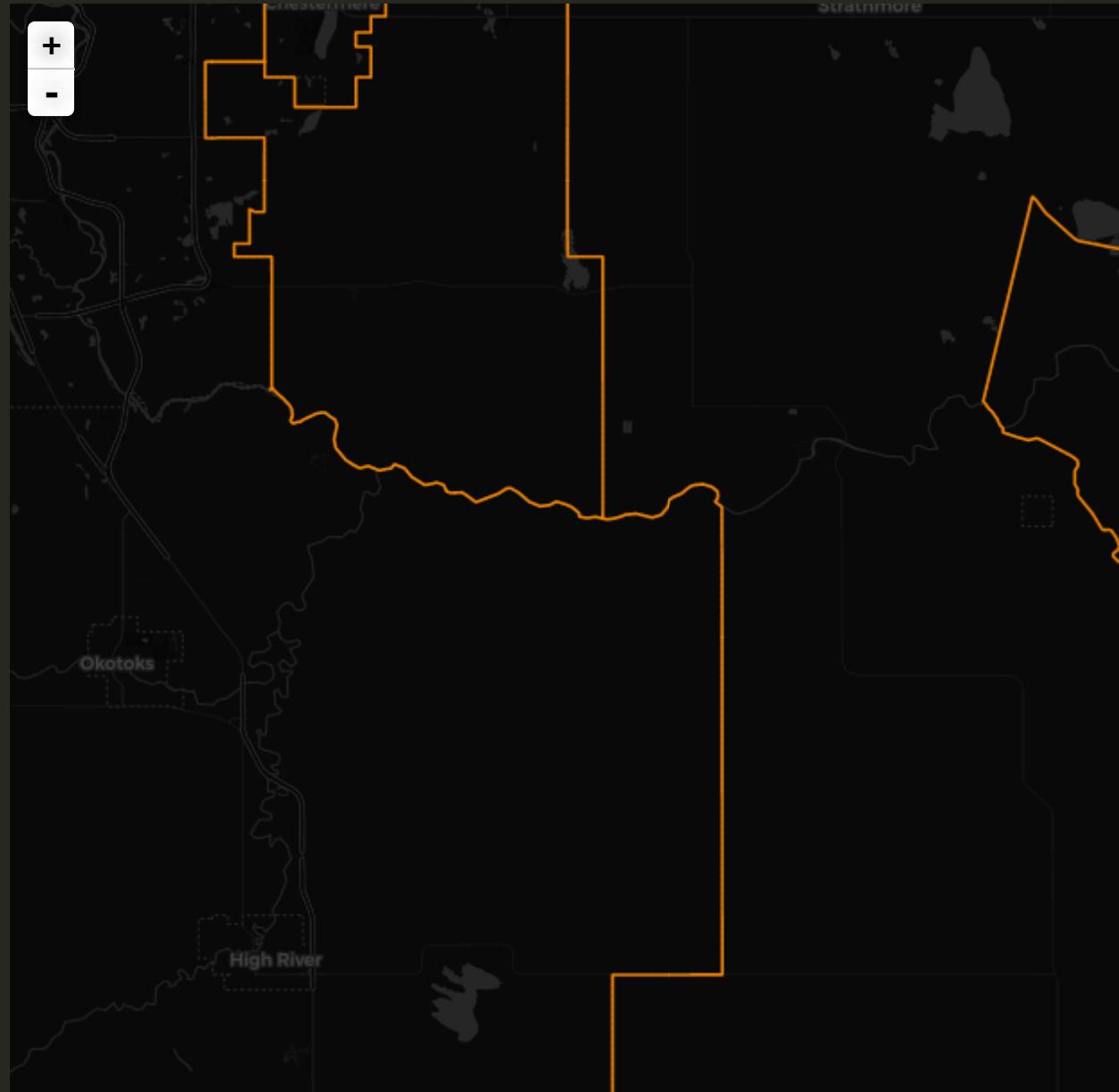
Advantages

A reader is more likely to remember a 3D graph than a plain graph.

Disadvantage

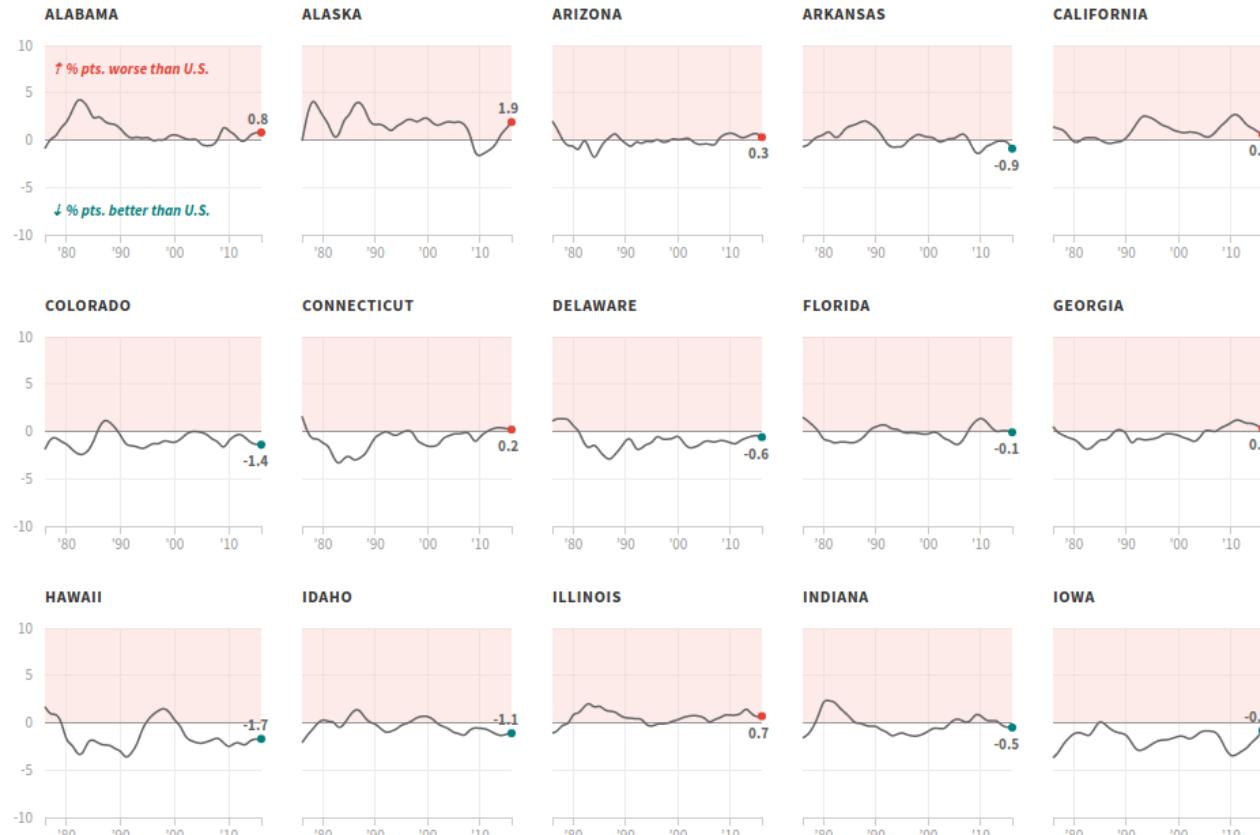
A reader is more likely to be confused by a 3D graph than a plain graph.





Small Multiples

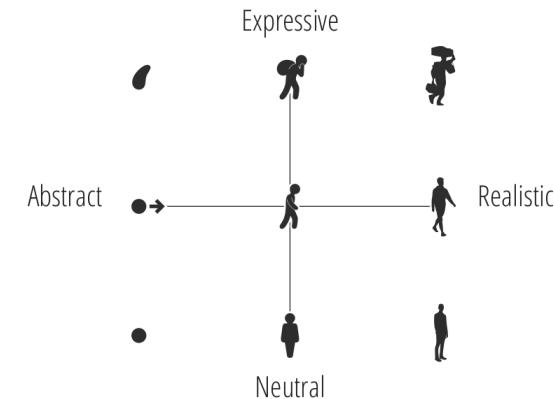
A series of very similar graphs where the eye is drawn on comparing differences among them.



Should We Anthropomorphize Visualizations?

...to attribute human form or personality to things not human

In 2017, Boy et al. (1) conducted visual experiments on 284 participants. They found no evidence that anthropomorphizing visualizations has benefits on empathy.



(1) Boy J. et al. *Showing People Behind Data: Does Anthropomorphizing Visualizations Elicit More Empathy for Human Rights Data?* ↗

5. What to Look for in Visualization Tools? An Opinionated List

What to Look for in Visualization Tools? An Opinionated List

Goal 1: *to identify, highlight features or relationships*

Goal 2: *to summarize, communicate and engage (telling a story)*

Evaluation Item	Notes
Who is it for?	Identify the users and consumers. Likely 2-3 streams.
Goal 1 or goal 2?	Data visualization vs. visual storytelling
No one size fits all	General purpose vs. special purpose
Data preparation approach	Visual composition framework
Data preparation capabilities	Joins, filter, aggregate, sample, rank, reshape, append, grouping, text extraction, logical operators, mathematical expressions
Handling of dates and times	Human readable and adherence to ISO standards.
Time series data preparation	Rolling windows, date padding, durations, rolling statistics, smart aggregations
Breadth of statistics for aggregation	Mean, percentiles, ranks, min/max, counts, totals, conditional statistics, proportions, duration, harmonic mean, geometric mean, sd, IQR...
Missing values	Appropriate handling/warning of missing data
Ability to show uncertainty	Confidence bands, error bars, rangeplots
General purpose smoothers	LOESS, exponential smoothing
Quality of visualizations	Avoids or encourage chartjunk
Breadth of visualizations	Standard graphs and modern graphs (e.g. ridgeline plots, violin plots, circular migration plots, word clouds)

What to Look for in Visualization Tools? An Opinionated List

Evaluation Item	Notes
Learning curve	Effort and time
Community size	Extremely important! Forum, discussion boards, conferences, books, blogs, YouTube, MOOC's
Extensibility	Community contribute added features
Extensibility	Play nice with R, Python?
Connectivity	Beyond common connections. E.g. API's Bloomberg, weather, social media

Don't over-rely on IT advisory and consulting firms.

When evaluating tools, **weighting** and **scoring** tend to be arbitrary and subjective. Scales are also arbitrary with little scientific basis. This usually results in poor choices. Weights are easy to manipulate in order to favour one tool over another. The resulting scoring matrices can be "*worse than useless, leading to worse-than-random decisions*"(1).

Favour a **thorough qualitative evaluation**, ideally from a **pilot** rather than a pseudo-scientific scoring matrix.

[1] Cox LA Jr. What's wrong with risk matrices? Risk Anal. 2008 Apr ↗

What to Look for in Visualization Tools? An Opinionated List

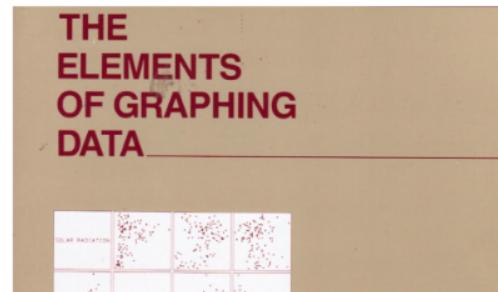
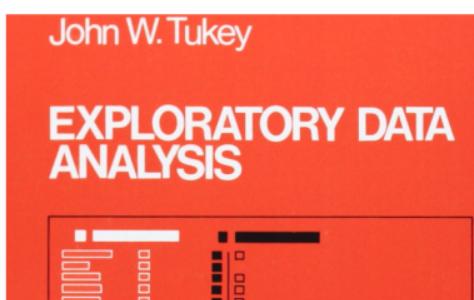
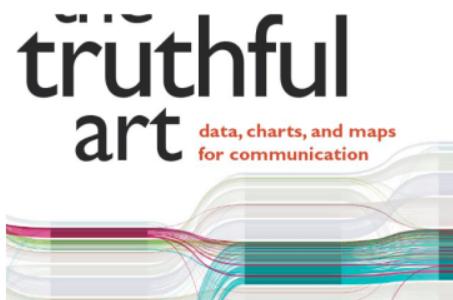
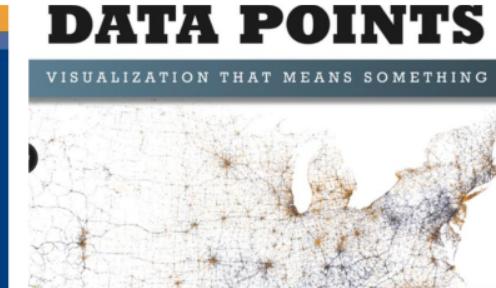
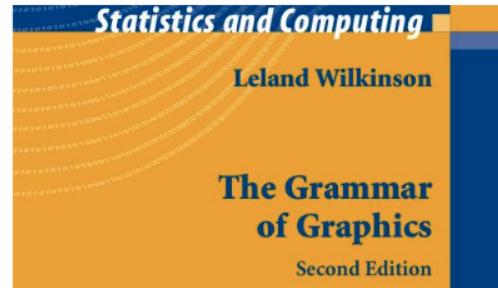
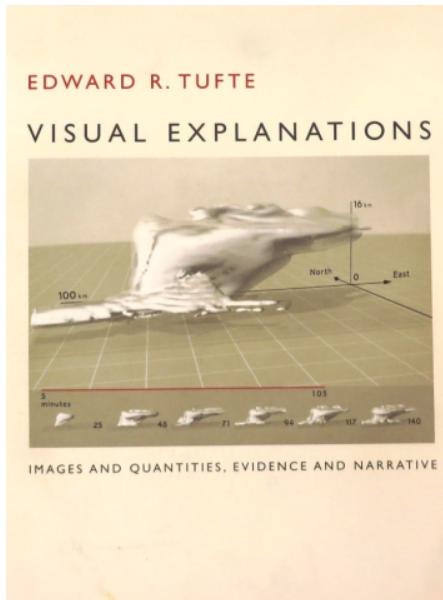
Remember Tufte: *Numbers become evidence by being in relation to.* Does the tool encourage comparisons? Does it make it easy?

A simple test: I could not create a similar graph in a popular visualization tool:

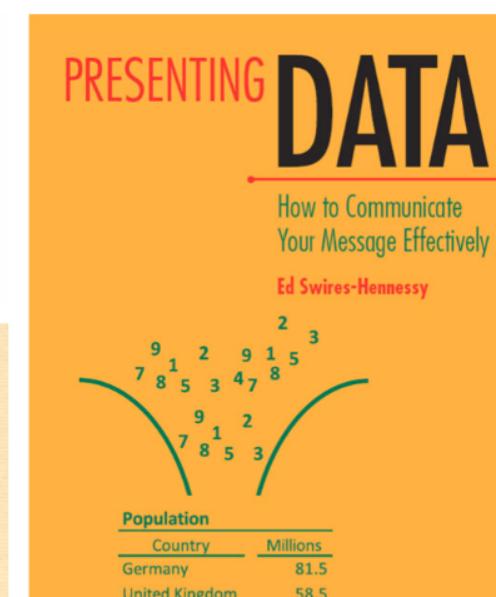
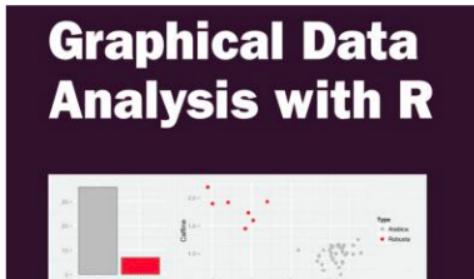
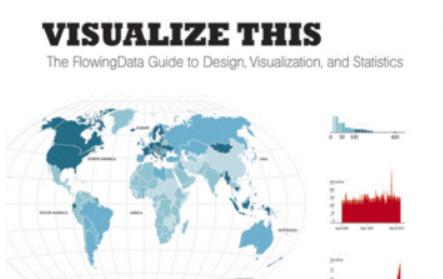
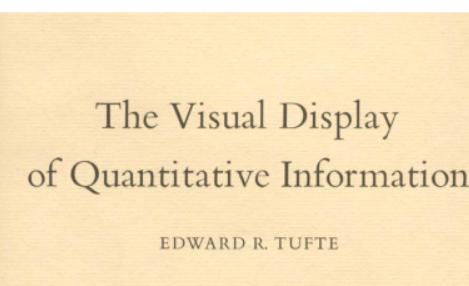
An approximate answer to the right problem is worth a good deal more than an exact answer to an approximate problem

-John Tukey

6. References



Edward R. Tufte
Envisioning Information



Population	Country	Millions
81.5	Germany	
58.5	United Kingdom	

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Thank you

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This presentation and most of the graphs were produced in R), a programming language and software environment for statistical computing and graphics. The Xaringan package was used for the presentation.

