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. Visualizations for Data Storytelling
3. Univariate Visualizations
4. Bivariate Visualizations
5. Visualizing Models
6. Tips & Best Practices
7. What to Look for in Visualization Tools? An Opinionated List
8. References

Data Manifesto

Data, in an 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 statistics and evidence based decision making.

1. Visualizations: Objectives and Constraints

Why Visualizations?

> *At their best, graphics are instruments for reasoning about quantitative information (Tufte, 1983)*
>
> *Graphs are exceptionally powerful tools for data analysis (Cleveland, 1985)*
>
> *There is no statistical tool that is as powerful as a well-chosen graph (Chambers, 1983)*
>
> *Diagrams prove nothing, but bring outstanding features readily to the eye (Fisher, 1925)*

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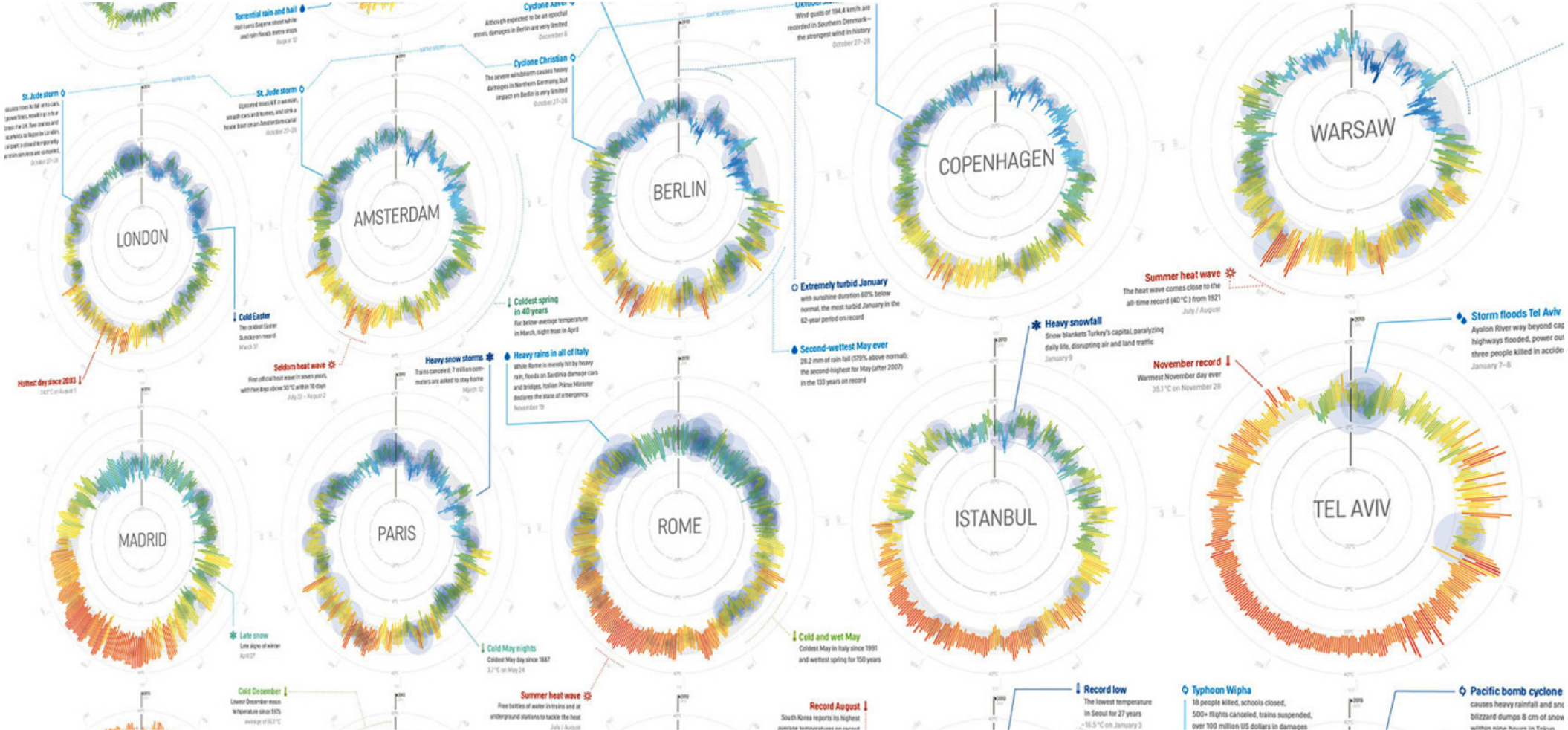
Two broad objectives:

- **Communication**: display a convincing pattern, attract reader's attention (first goal)
- **Discovery**: observe deviations from our expectations (second goal)

[1] *Gelman, Unwin. 2013*

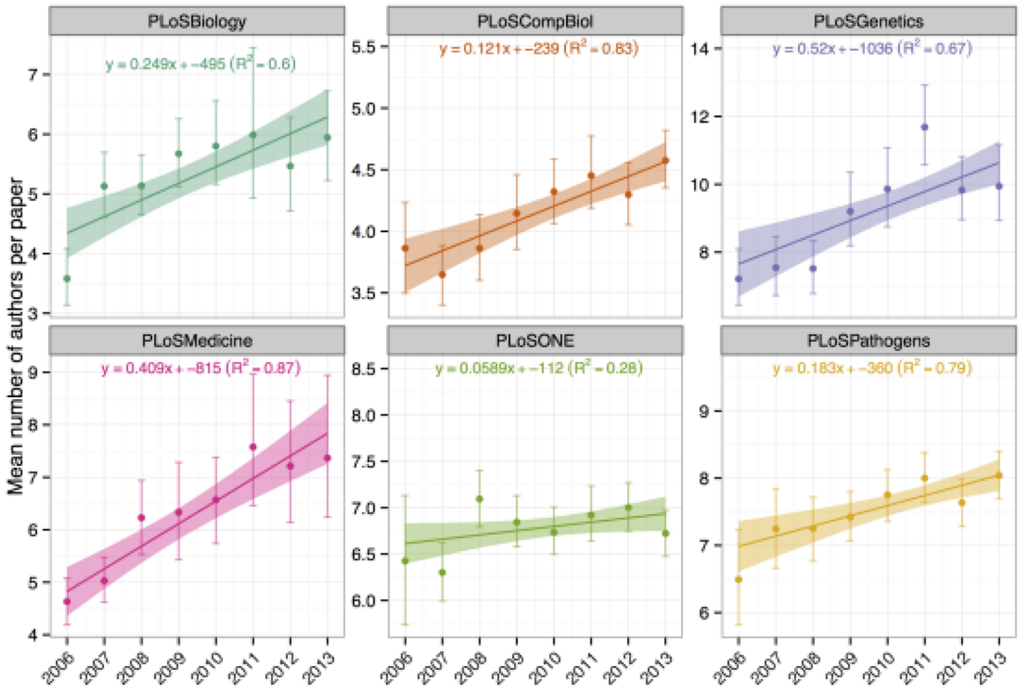
First Goal of Visualizations

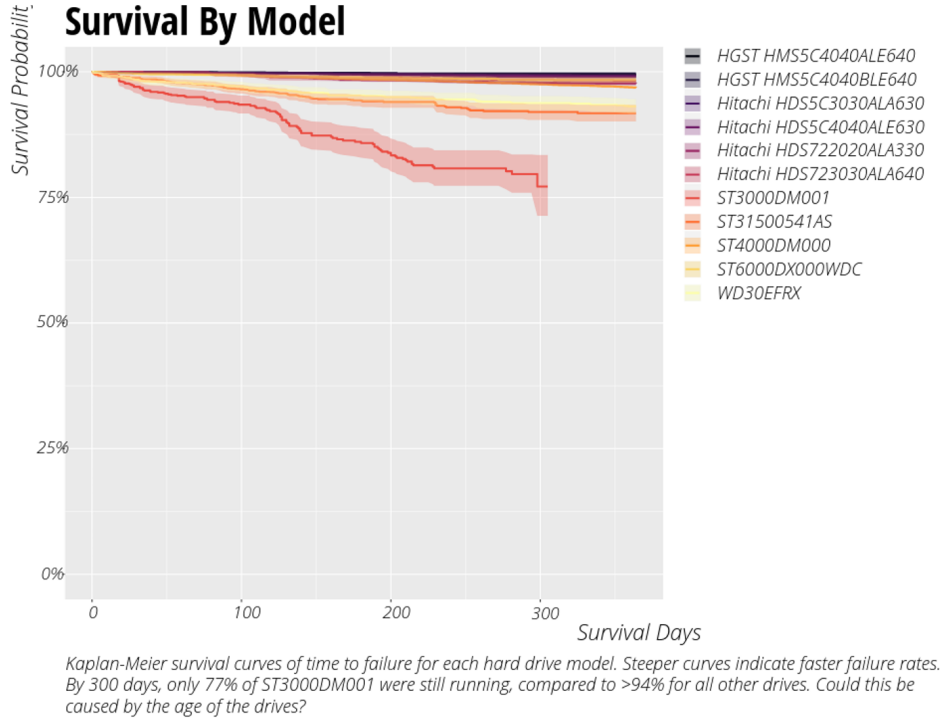
To summarize, communicate and engage (telling a story)



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 effectively at the same time!

To Persuade or to Inform?

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To Persuade

To Persuade or to Inform?

We **cannot** achieve both effectively 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.

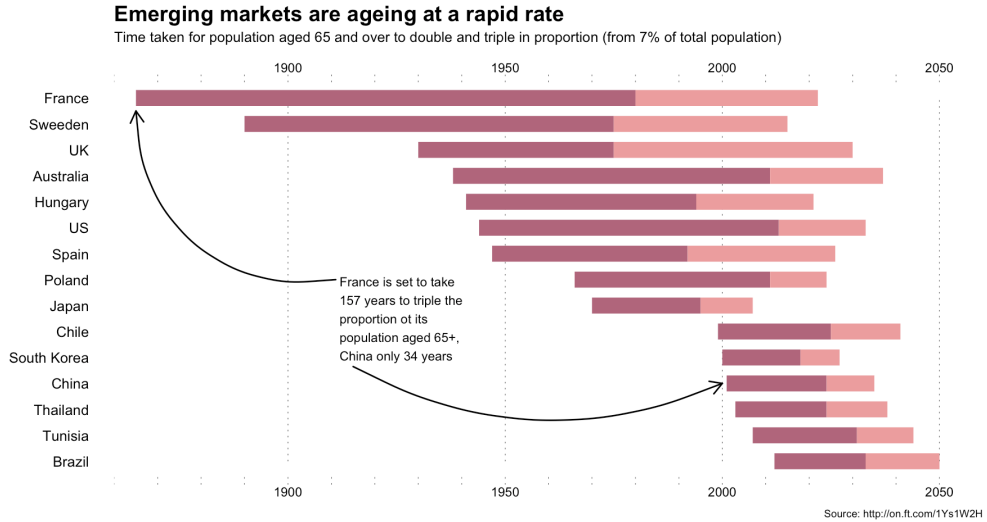
	Calories	2,000	2,500
Total Fat	Less than	65g	80g
Sat Fat	Less than	20g	25g
Cholesterol	Less than	300mg	300mg
Sodium	Less than	2,400mg	2,400mg
Total Carbohydrate		300g	375g
Dietary Fiber		25g	30g

[1] *Spiegelhalter, Pearson, Short. 2011*

To Remember or to Understand?

Can we achieve memory **and** understanding at the same time?

1. **Titles and annotations** help 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



[1] *Borkin et al. 2015. Beyond Memorability: Visualization Recognition and Recall*

[2] *Bob Rudis 2016.*

Example Dataset

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] *Thanks to D. Kaviani for pointing me to the data and for the preparatory work.*
[2] *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.*

Exploratory Data Analysis (EDA)

As the analsys 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.

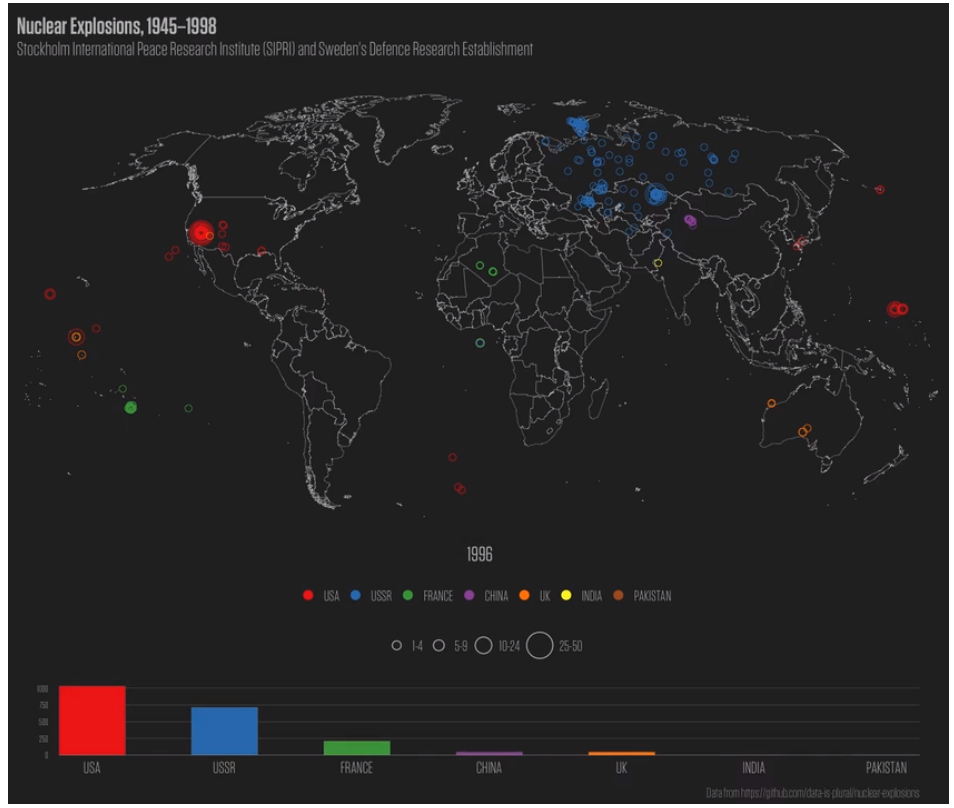
> *Graphs force us to note the unexpected; nothing could be more important.*
> -John Tukey

[1] *Grolemund, Wickham. R for Data Science, 2017*

2. Visualizations for Data Storytelling

Telling a Story

Display a convincing pattern, attract reader's attention

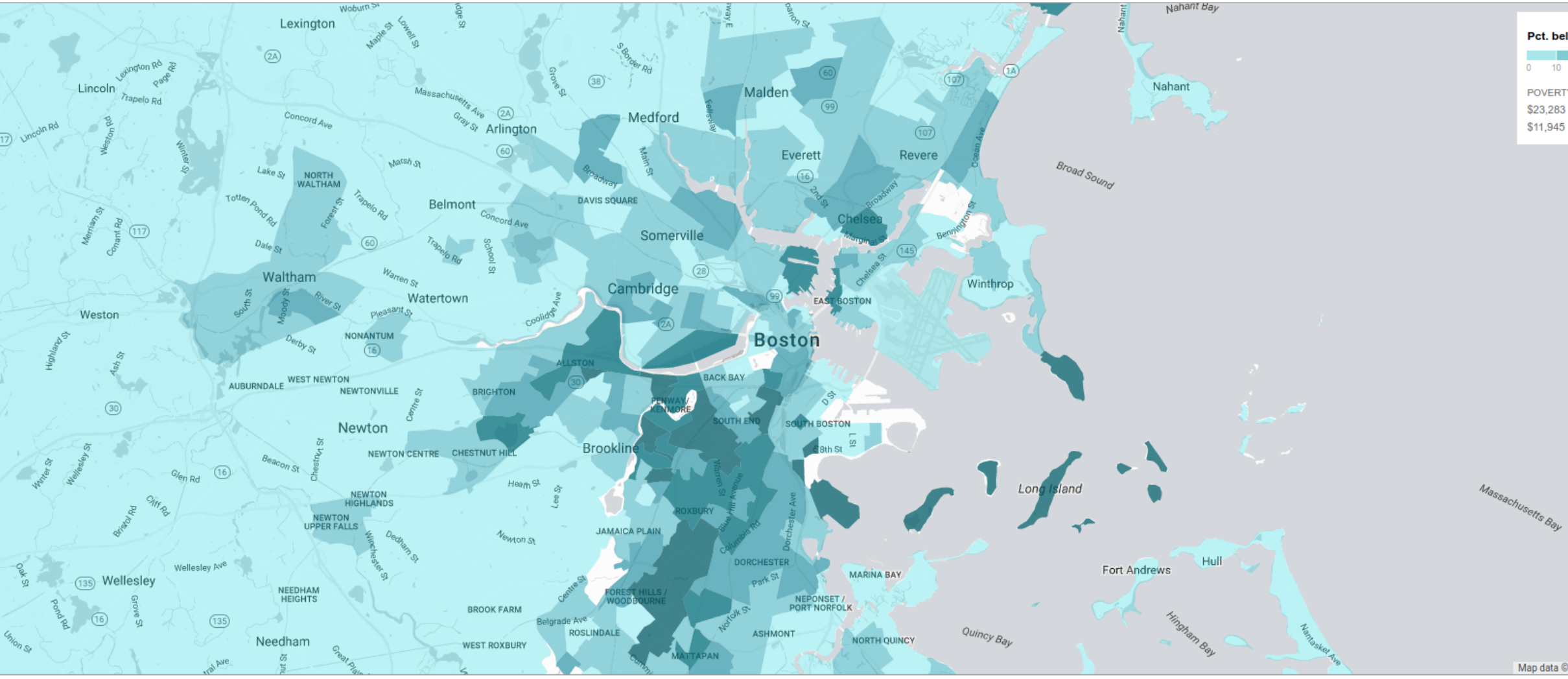


[1] *Bob Rudis 2016*

Mapping Poverty in America

Data from the Census Bureau show where the poor live.

VIEW Percentage below the poverty line

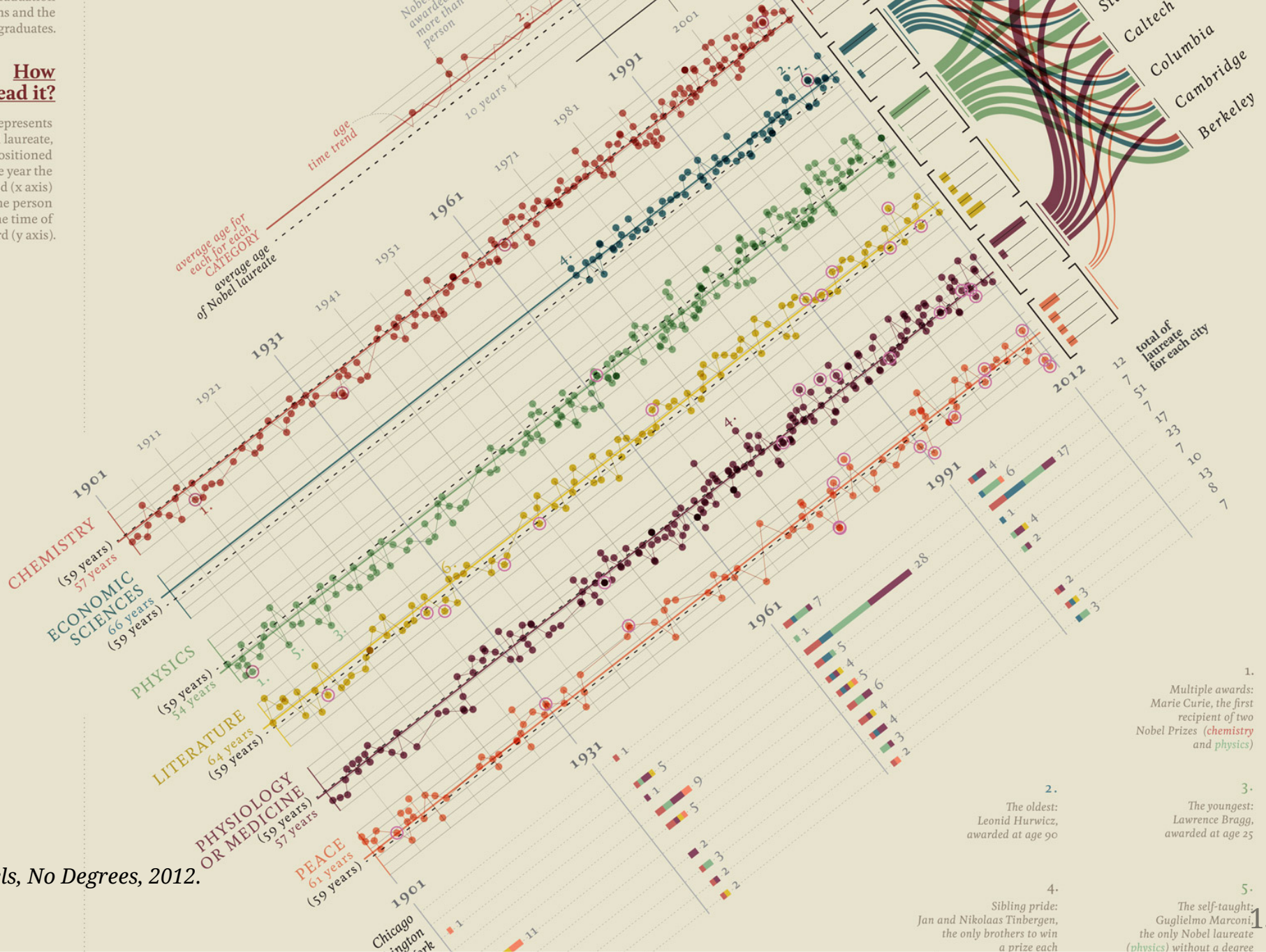


Washington | Boston | Philadelphia | Los Angeles | Atlanta | Houston | Dallas | Chicago | Minneapolis | Denver | Phoenix

[1] *New York Times. Mapping Poverty in America, 2014.*

MATTHEW ERICSON and TOM GIRATIKANON

vel data from the 2008-12 American Community Survey. County-level data from the 2012 Small Area Income and Poverty Estimates (SAIPE); socialexplorer.com.



[1] *Giorgia Lupi. Nobels, No Degrees, 2012.*

3. Univariate Visualizations

Summary Statistics

.

1 Variables 625 Observations

helium.porosity

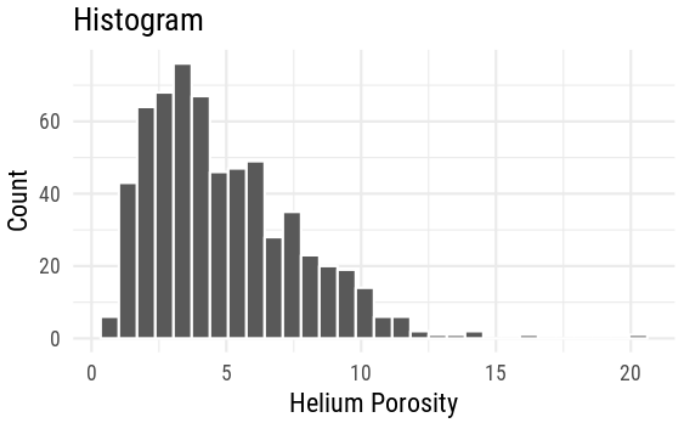
n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
625	0	110	1	4.875	2.986	1.5	1.8	2.8	4.2	6.5	8.8	10.0

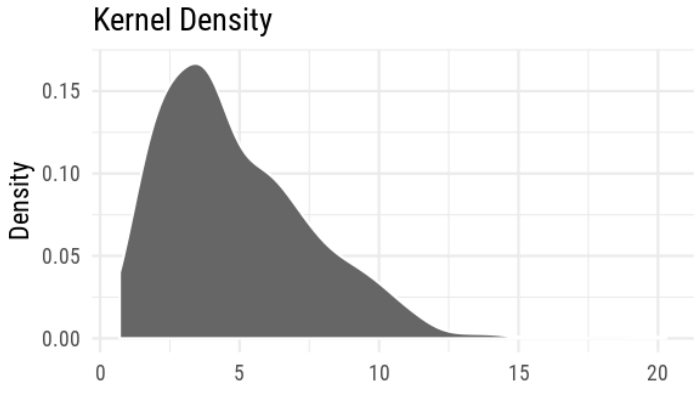
lowest : 0.7 0.8 0.9 1.0 1.1 , highest: 13.2 14.0 14.2 16.3 20.3

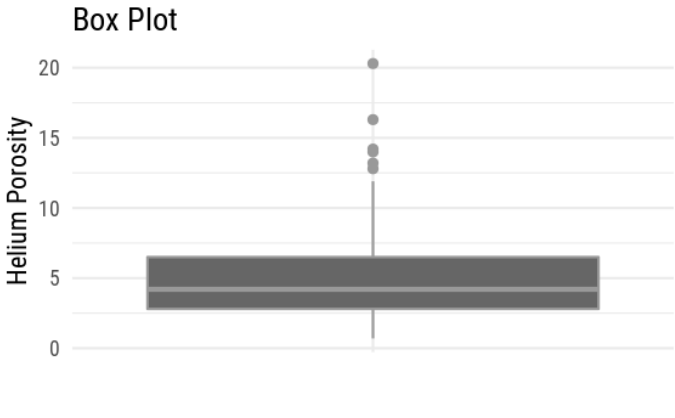
*Gmd stands for **Gini mean difference**, a scale independent measure of dispersion (it is the mean absolute difference between any pairs of observations).*

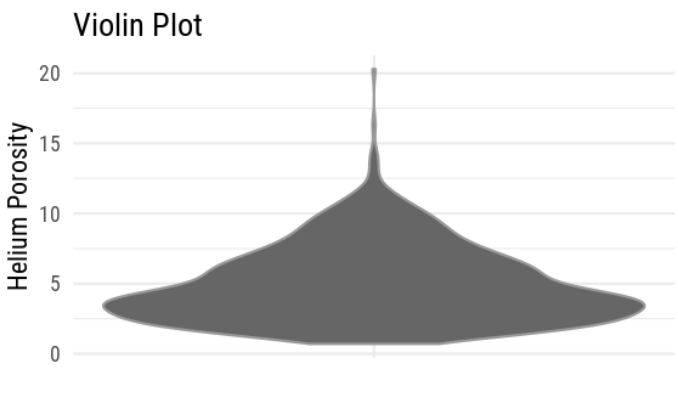
Info is a measure of how continuous the variable is.

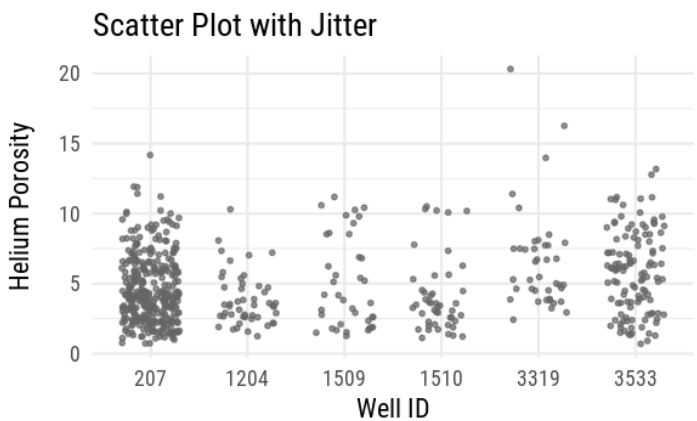
Alternative Univariate Visualizations

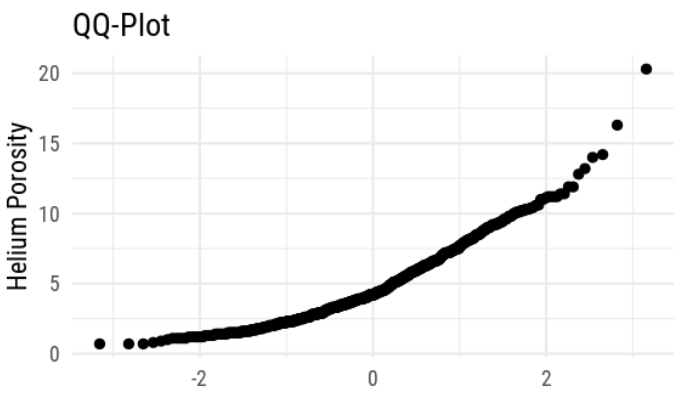












4. Bivariate Visualizations

> *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	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
gdens	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	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. $x \pm s$ represents $\overline{X} \pm 1$ SD.
Test used: Kruskal-Wallis test .

Combining Tables with Graphs

Show 10 entries Search:

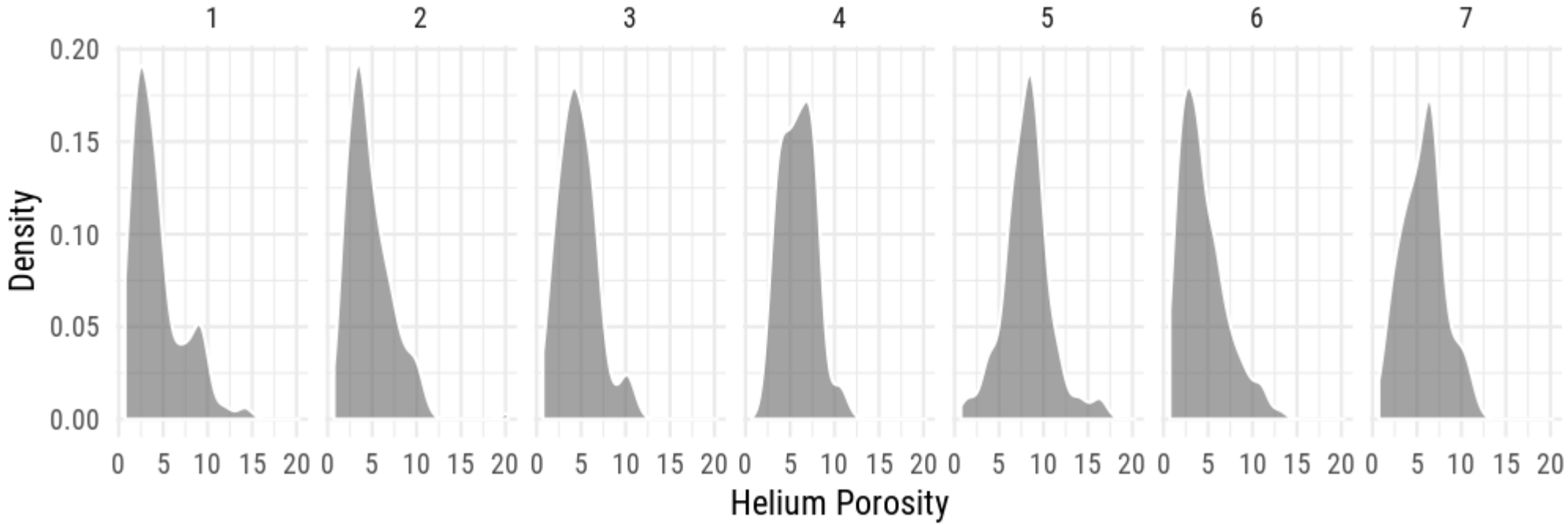
Location	Month	Var	Decade	Mean	SD	Min	Max	Samples	Series
Edmonton, Alberta	Aug	Temperature	1950s	14.8	1.2	13.1	17		
Edmonton, Alberta	Aug	Temperature	1960s	15.7	1.61	13	18.2		
Edmonton, Alberta	Aug	Temperature	1970s	15.2	1.82	12.4	17.9		
Edmonton, Alberta	Aug	Temperature	1980s	15.5	2.03	13	18.8		
Edmonton, Alberta	Aug	Temperature	1990s	16	1.64	13.1	18.5		
Edmonton, Alberta	Aug	Temperature	2000s	15.3	1.22	14	17.3		

Showing 1 to 6 of 6 entries Previous 1 Next

[1] *Matthew Leonawicz*

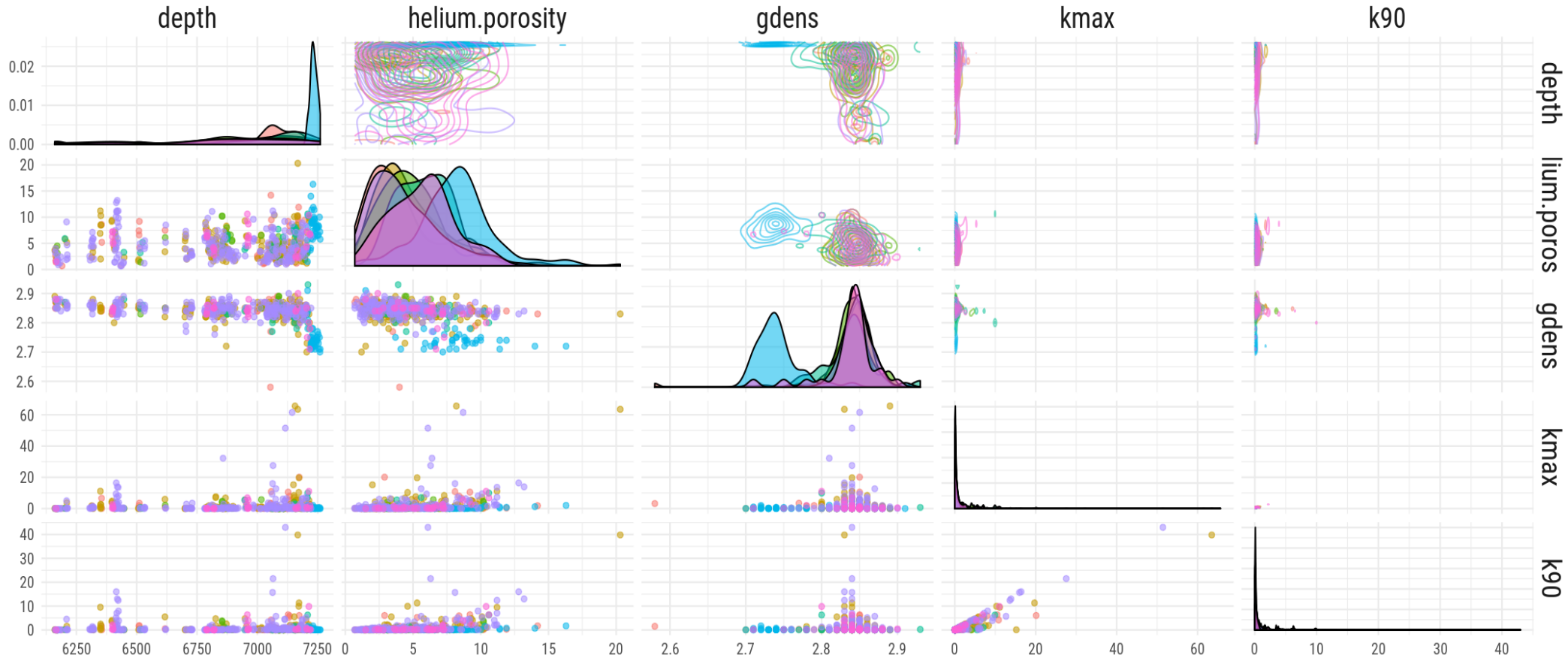
Kernel Density

Kernel density plots have the unique advantage that they are self-standardizing. They are also more effective than histograms. This makes them useful to **compare distributions** when the units aren't the same (not here).



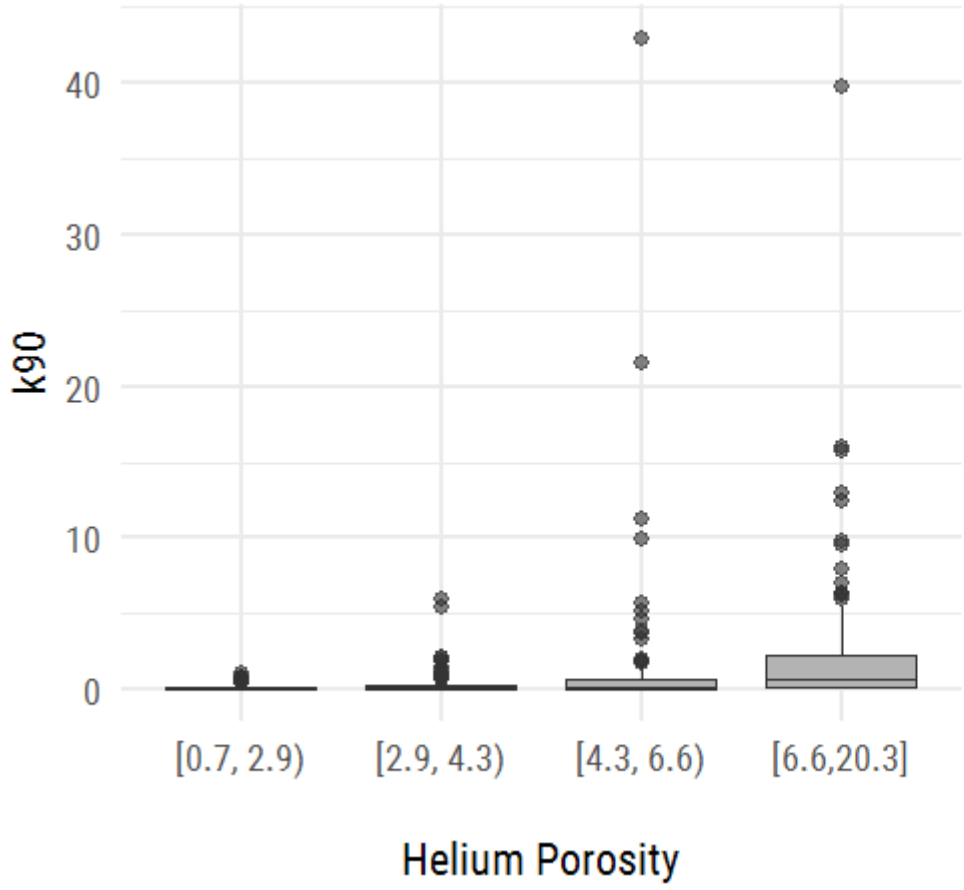
Scatterplot Matrix or Cross Plot

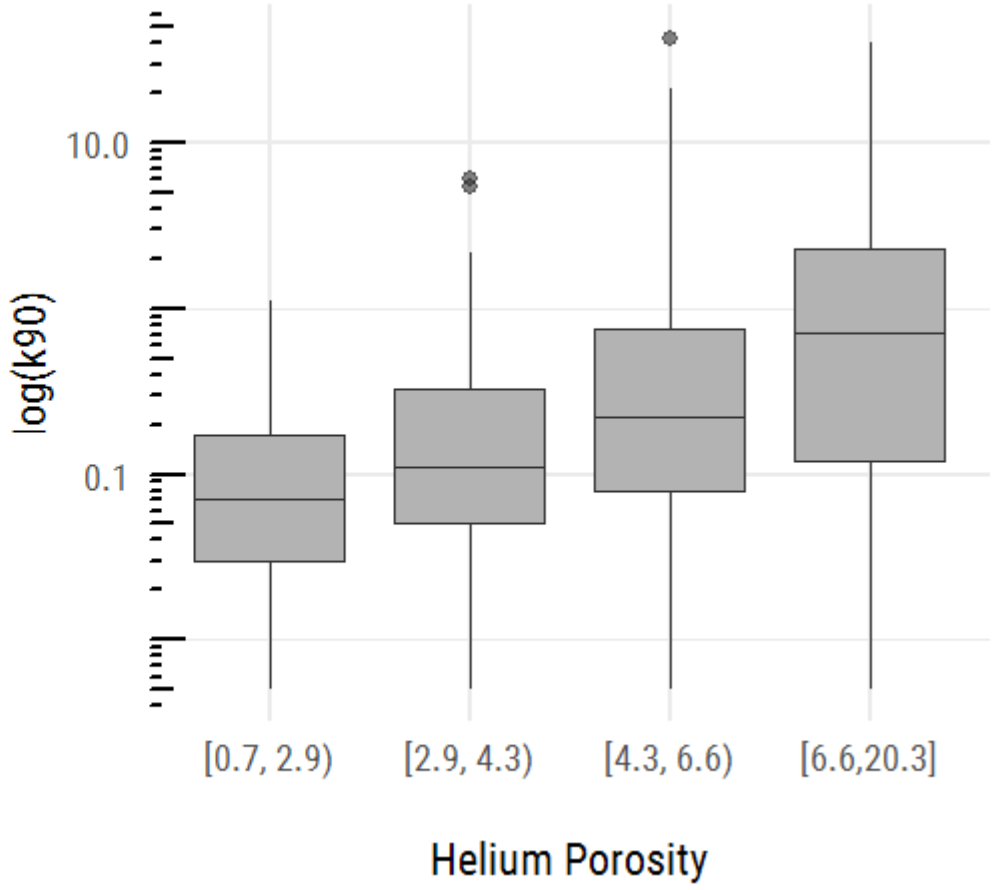
One of the very first plots you ant to make. Shows all pairwise combinations. Here, I've cheated by removing a few outliers.



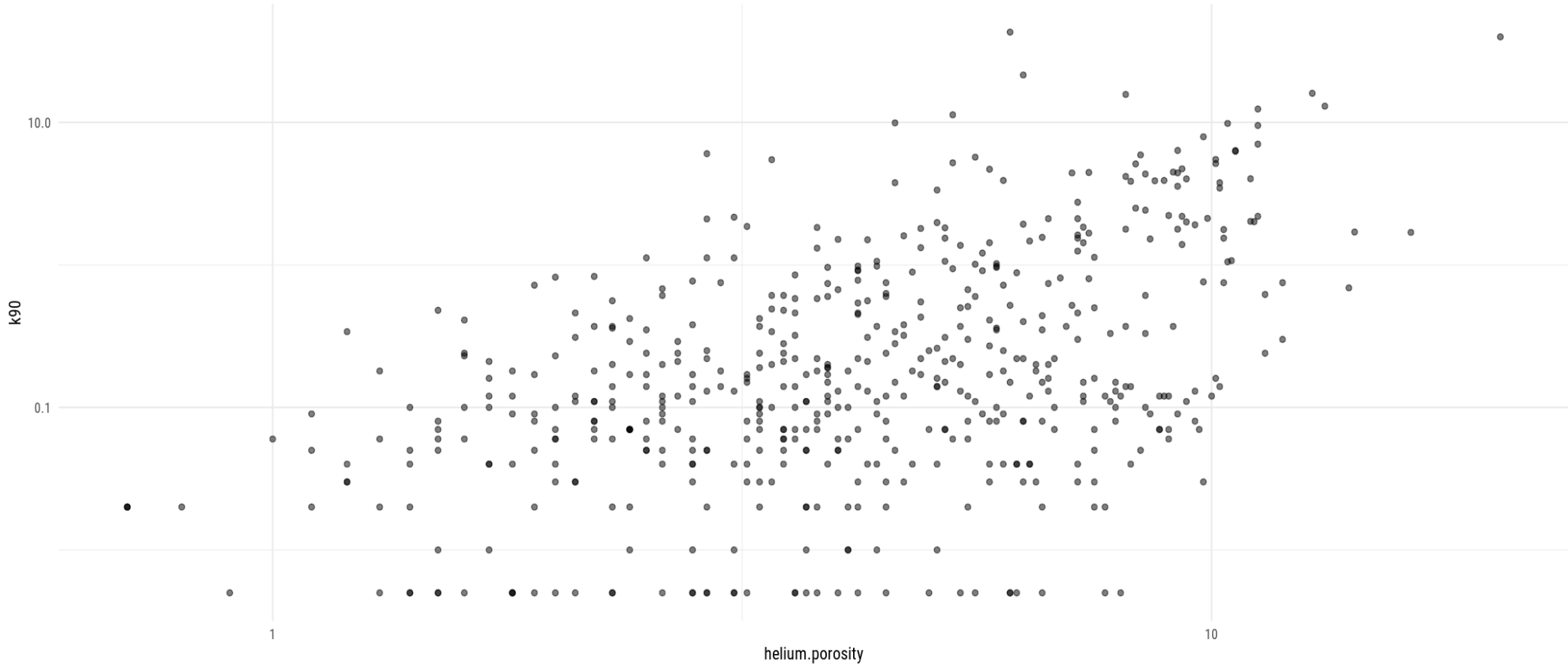
Boxplots

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

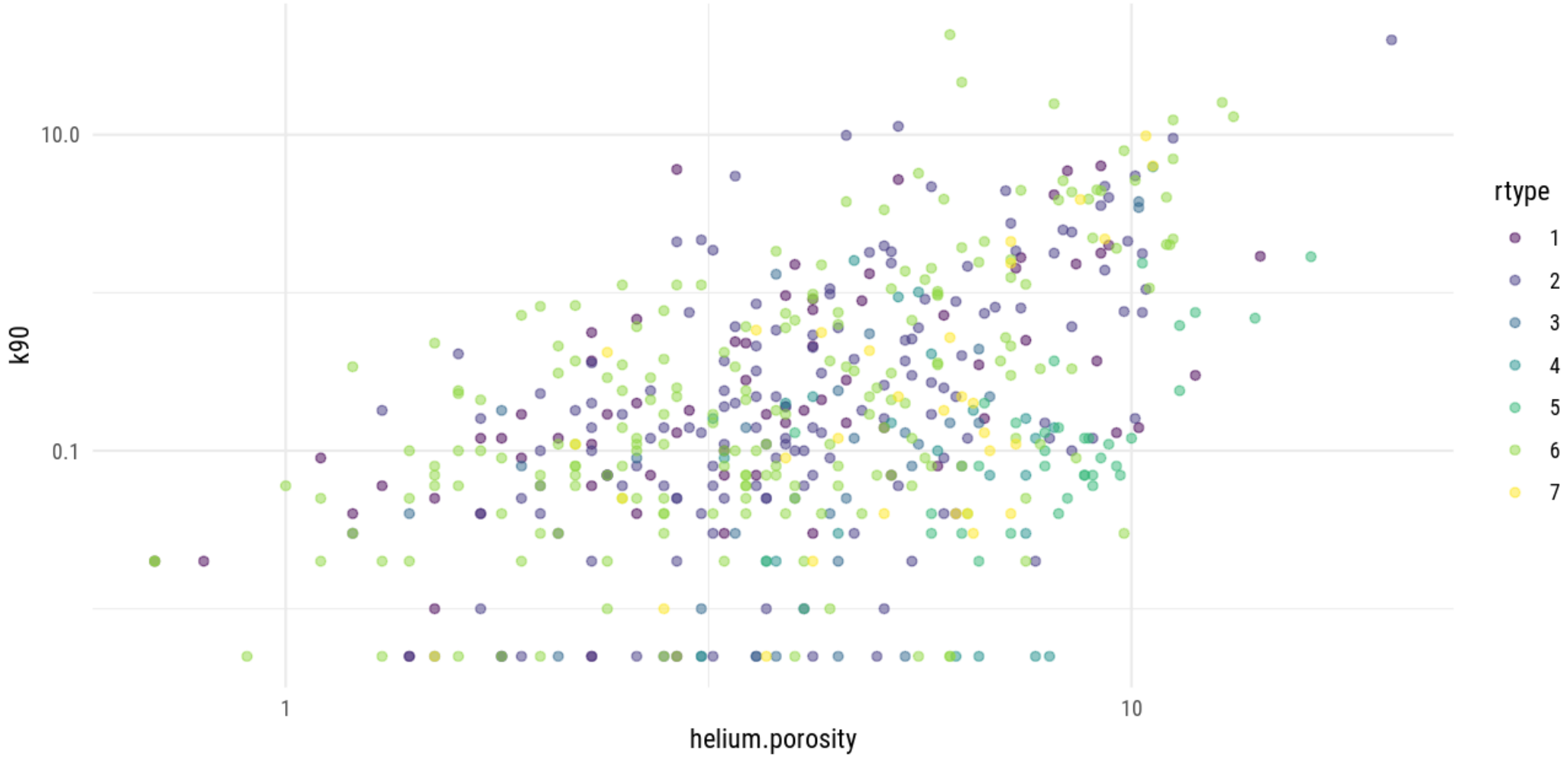




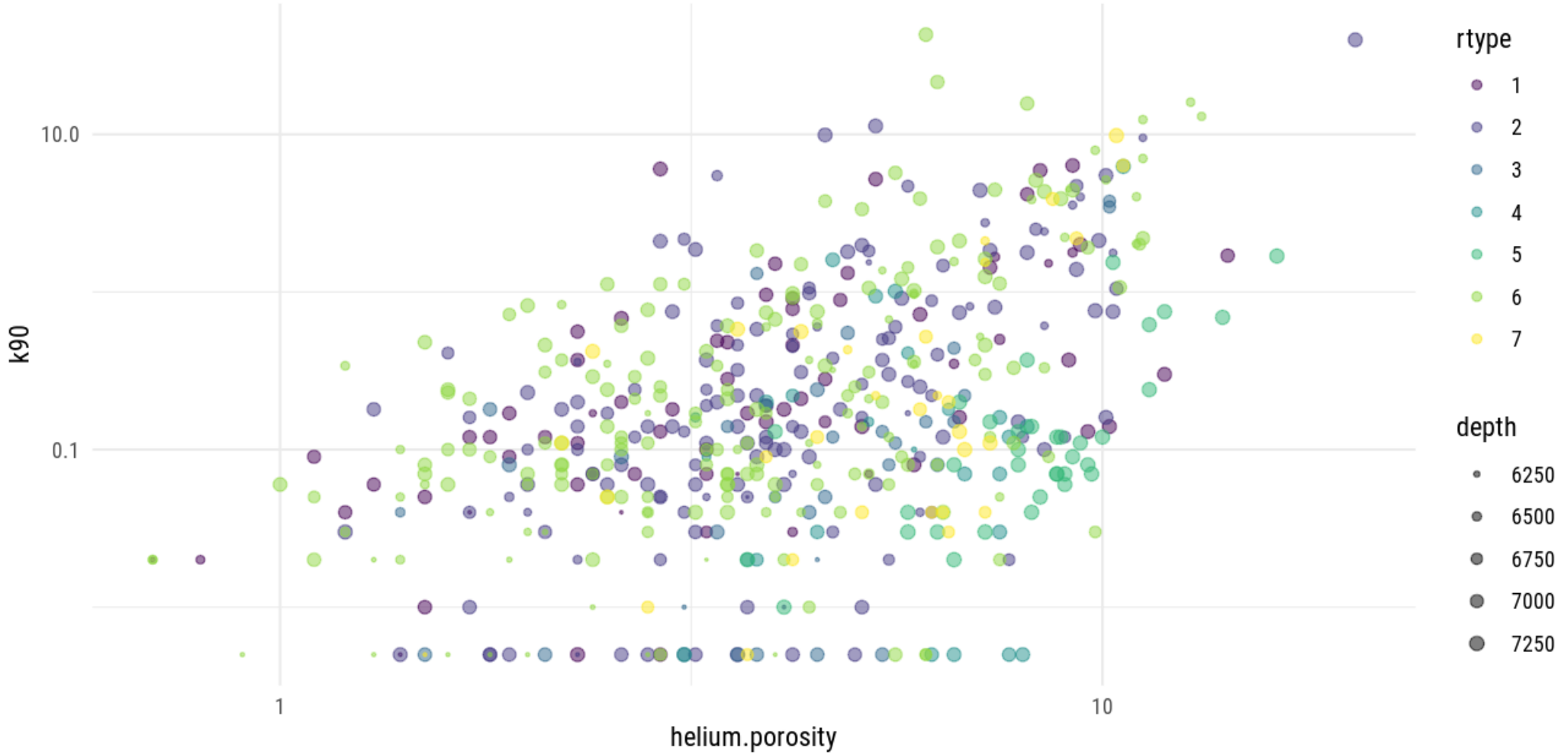
Scatterplots With 2 Variables



Scatterplots With 3 Variables



Scatterplots With 4 Variables



Correlation Matrix

A unitless measure of the strength of the association between pairs of variables.

5. Visualizing Models

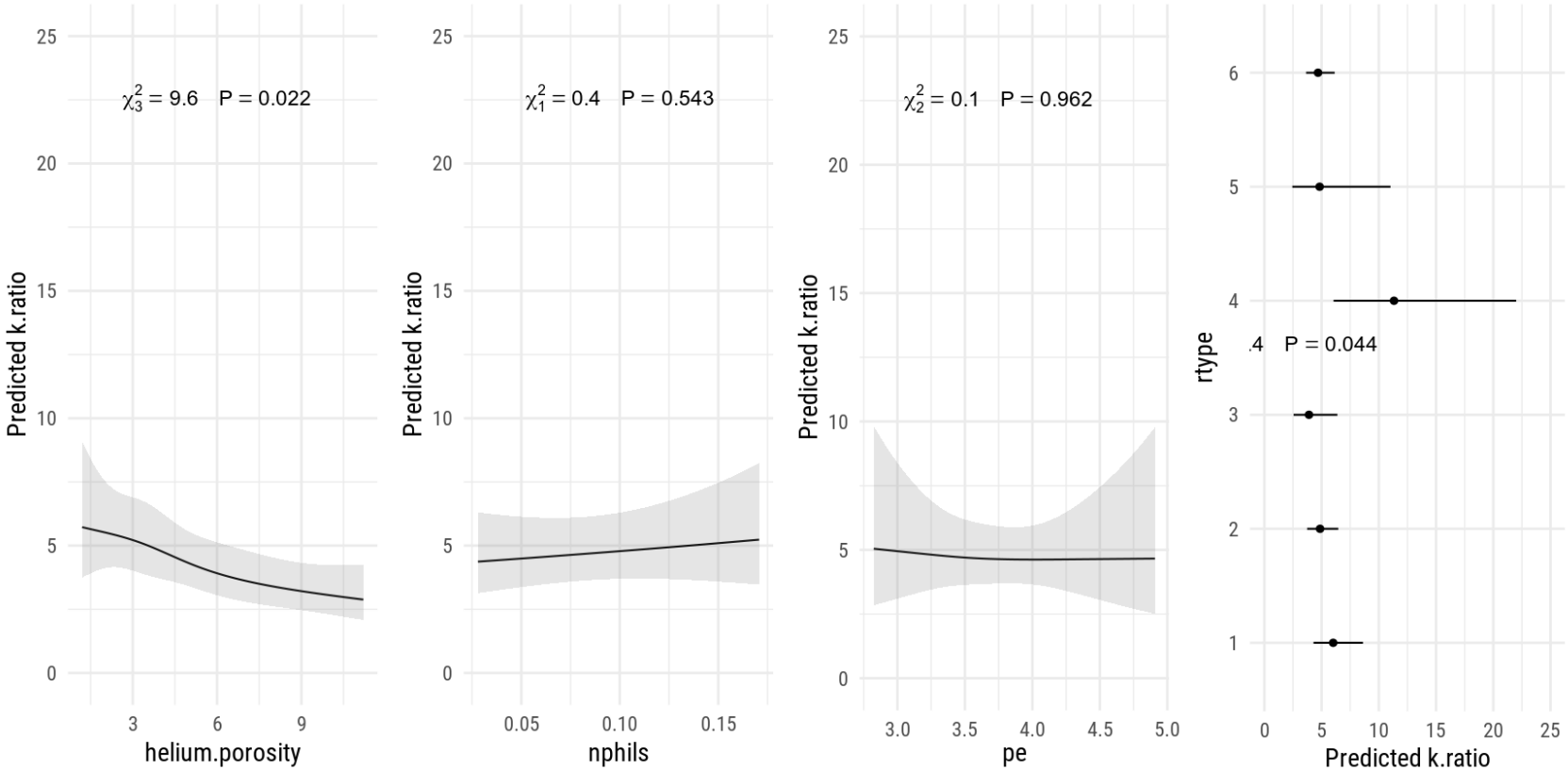
Graphs for Models

It's much easier to interpret a model by graphing it! Here's a regression model of `k.ratio` on several variables. Compare this:

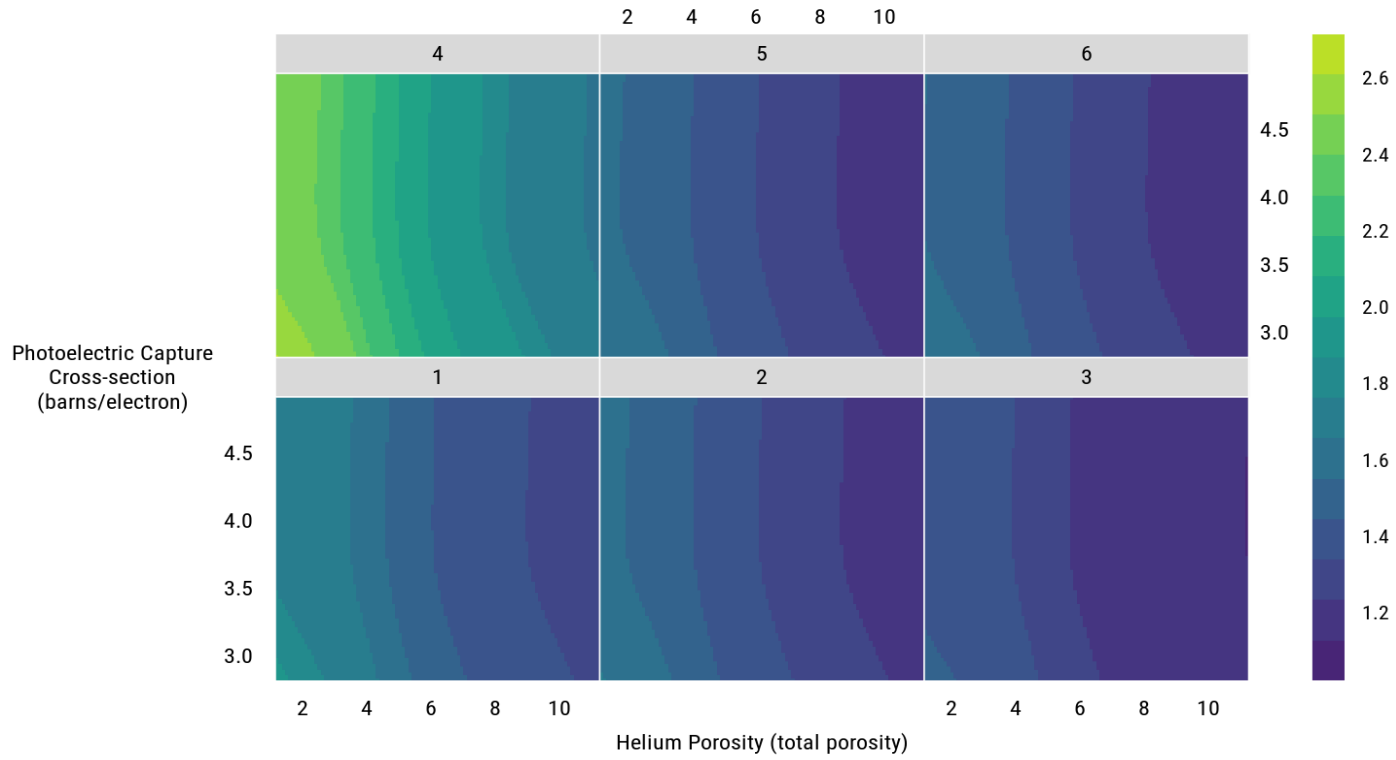
Effects Response: `k.ratio`

	Low	High	Δ	Effect	S.E.	Lower 0.95	Upper 0.95
helium.porosity	2.80000	6.4000	3.60000	-0.47850	0.2176	-0.9049	-0.0521
Odds Ratio	2.80000	6.4000	3.60000	0.61970		0.4046	0.9492
pe	3.30600	3.8450	0.53980	-0.04675	0.1789	-0.3974	0.3039
Odds Ratio	3.30600	3.8450	0.53980	0.95430		0.6721	1.3550
nphils	0.06198	0.1115	0.04952	0.08786	0.1443	-0.1950	0.3707
Odds Ratio	0.06198	0.1115	0.04952	1.09200		0.8228	1.4490
rtype --- 1:6	6.00000	1.0000		0.34150	0.2686	-0.1849	0.8679
Odds Ratio	6.00000	1.0000		1.40700		0.8312	2.3820
rtype --- 2:6	6.00000	2.0000		0.05197	0.2484	-0.4348	0.5388
Odds Ratio	6.00000	2.0000		1.05300		0.6474	1.7140
rtype --- 3:6	6.00000	3.0000		-0.26770	0.3832	-1.0190	0.4834
Odds Ratio	6.00000	3.0000		0.76520		0.3611	1.6220
rtype --- 4:6	6.00000	4.0000		1.15000	0.4418	0.2845	2.0160
Odds Ratio	6.00000	4.0000		3.16000		1.3290	7.5110
rtype --- 5:6	6.00000	5.0000		0.04104	0.4848	-0.9092	0.9913
Odds Ratio	6.00000	5.0000		1.04200		0.4028	2.6950

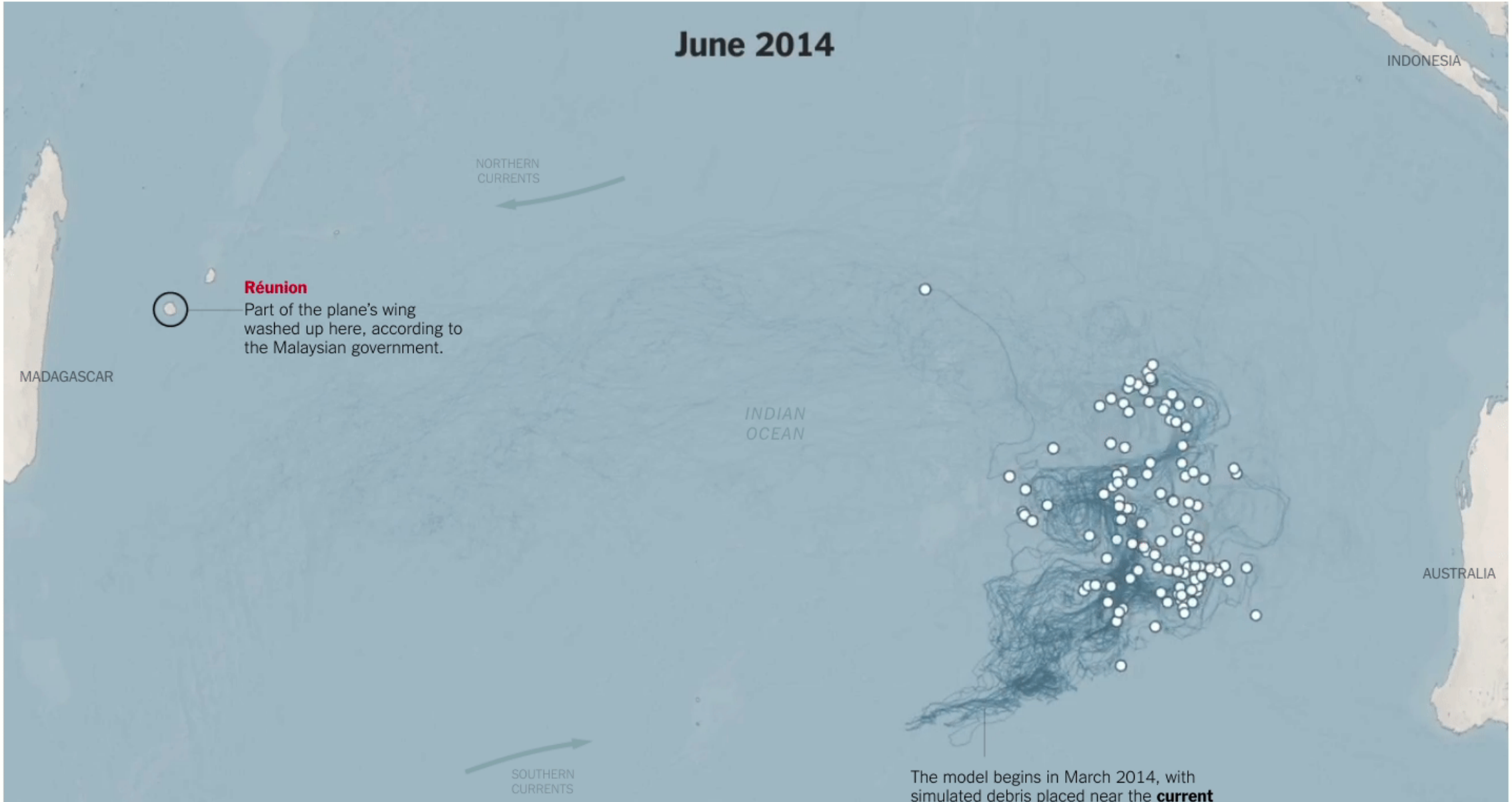
... with this:


$\chi^2_3 = 9.6$ P = 0.022
Predicted k.ratio
helium.porosity
$\chi^2_1 = 0.4$ P = 0.543
Predicted k.ratio
nphils
$\chi^2_2 = 0.1$ P = 0.962
Predicted k.ratio
pe
.4 P = 0.044
rtype
Predicted k.ratio

... or this:



Non-linear regression model showing the simultaneous effect, on the dependent variable permeability ratio (Kmax/k90), of changing two continuous variables (helium porosity and photoelectric capture cross-section log) while holding (marginalizing) all other variables fixed at their median.



[1] *New York Times. How Missing Jet's Debris Could Have Floated to Réunion, 2015.*

Visualizing Principal Components

Principal components allow us to describe our data with fewer new variables. These new variables are linear combinations of multiple variables. We call these new variables principal components.

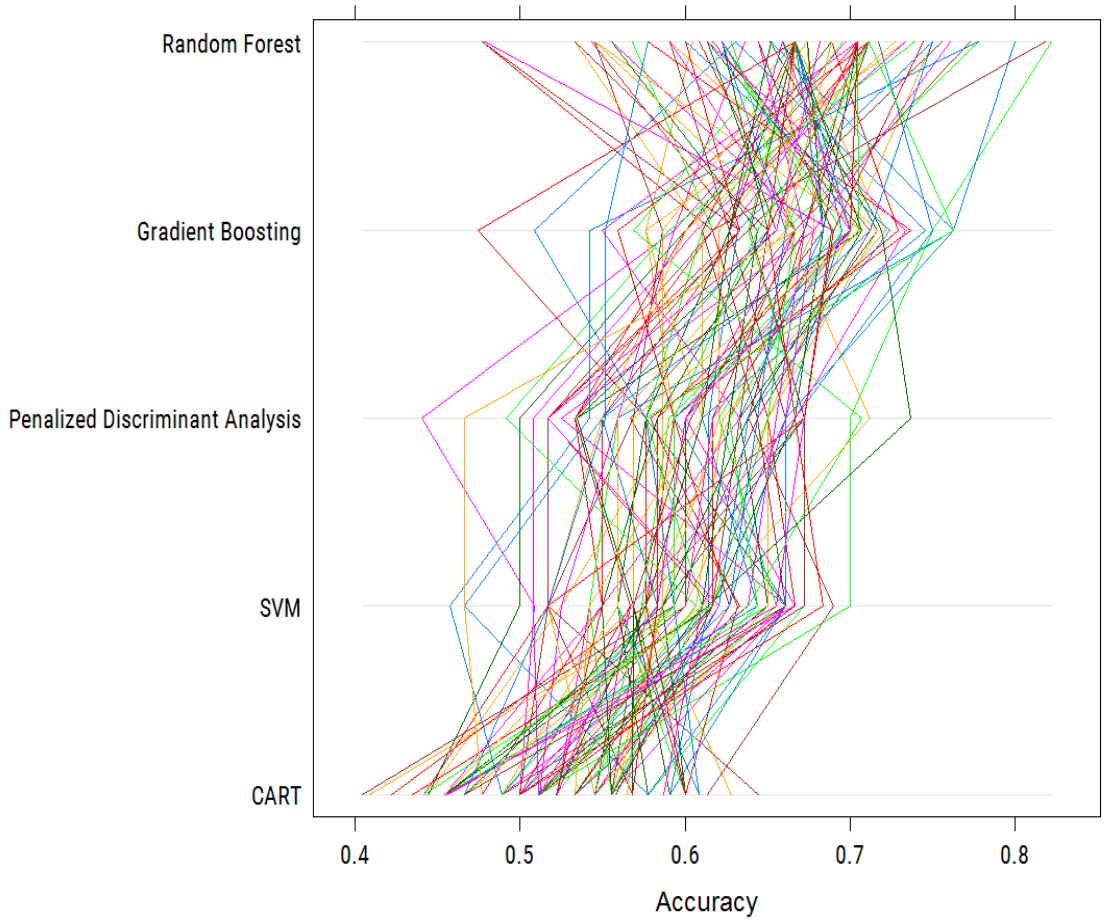
```
## Standard deviations (1, .., p=6):
## [1] 1.6000316 1.0858936 0.9579714 0.8818079 0.5800918 0.4784693
##
## Rotation (n x k) = (6 x 6):
##                 PC1          PC2          PC3         PC4          PC5
## gr       0.22818282  0.137547398 -0.934774742 -0.2328681  0.03109767
## rhob     0.43271157  0.453422040  0.265822874 -0.2945947  0.63176533
## pe       0.03040547 -0.830000205  0.003589022 -0.4300128  0.34543234
## nphils -0.48514647 -0.001751888 -0.221395134  0.5036248  0.67809619
## lld      0.54616385 -0.153463229  0.042668603  0.3027975  0.12771134
## lls      0.47550685 -0.251067310 -0.068447679  0.5733682 -0.06676349
##                 PC6
## gr       0.003858898
## rhob    -0.224930842
## pe      -0.076991994
## nphils   0.046493127
## lld      0.753881245
## lls     -0.610708536
```

Visualizing Principal Components

Visualizing CART Models

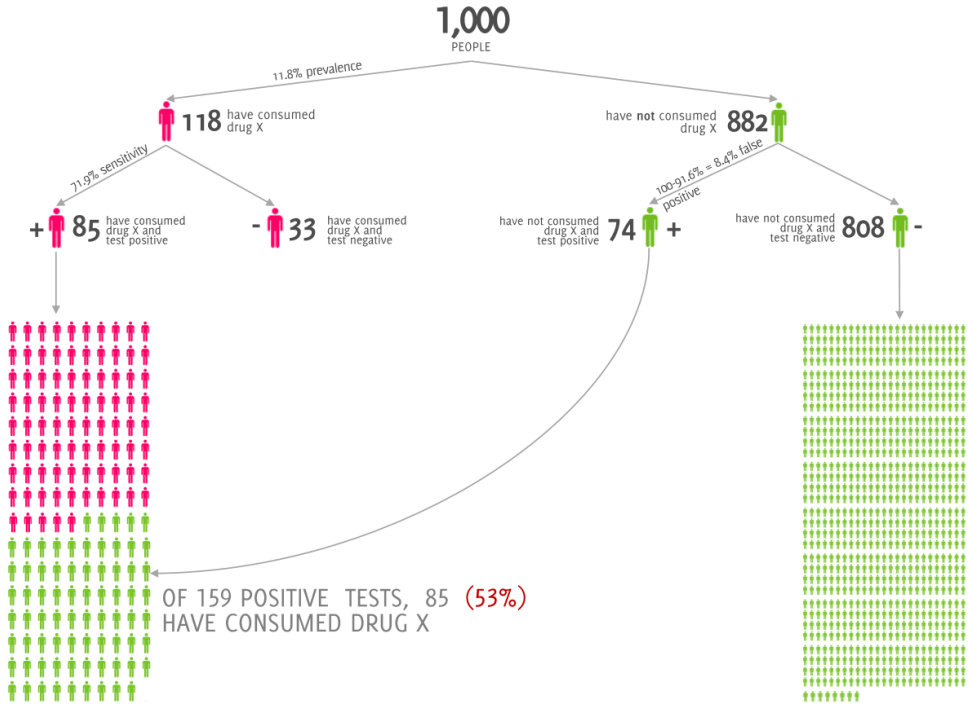
CART stands for **Classification and Regression Trees** a non-parametric type of model. Hypothetically, let's fit a model to predict rock type using `depth` and `helium.porosity` and visualize the results:

Visually Comparing Multiple Models



Diagrams to Explain

While not showing a model per-se, diagrams can help make unintuitive topics more transparent. Here, because of the low prevalence of drug consumption, we observe a high **false positive rate** (test says a person has consumed a drug, but in truth s/he has not), despite high test accuracy.



[1] *Spiegelhalter et al. Visualizing Uncertainty About the Future. 2011*

6. 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

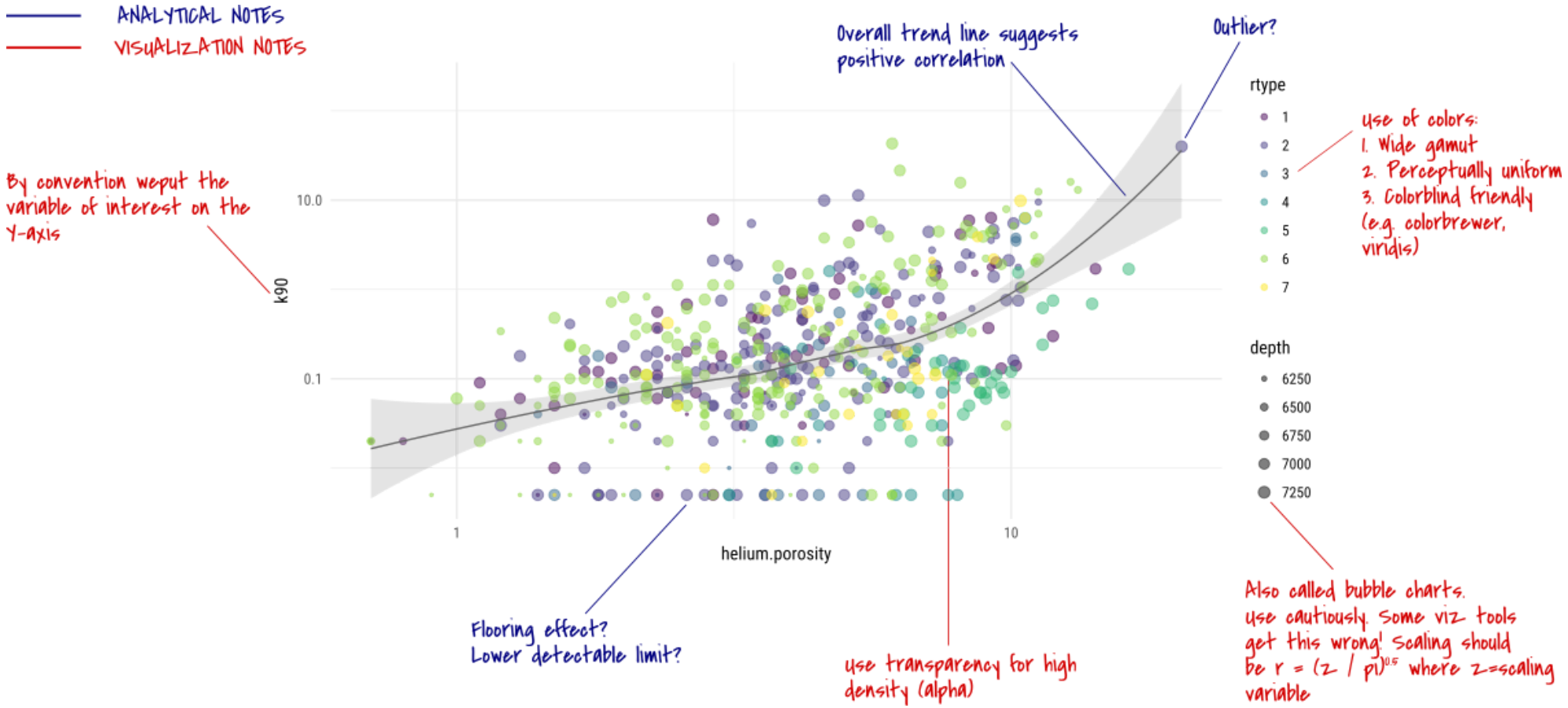
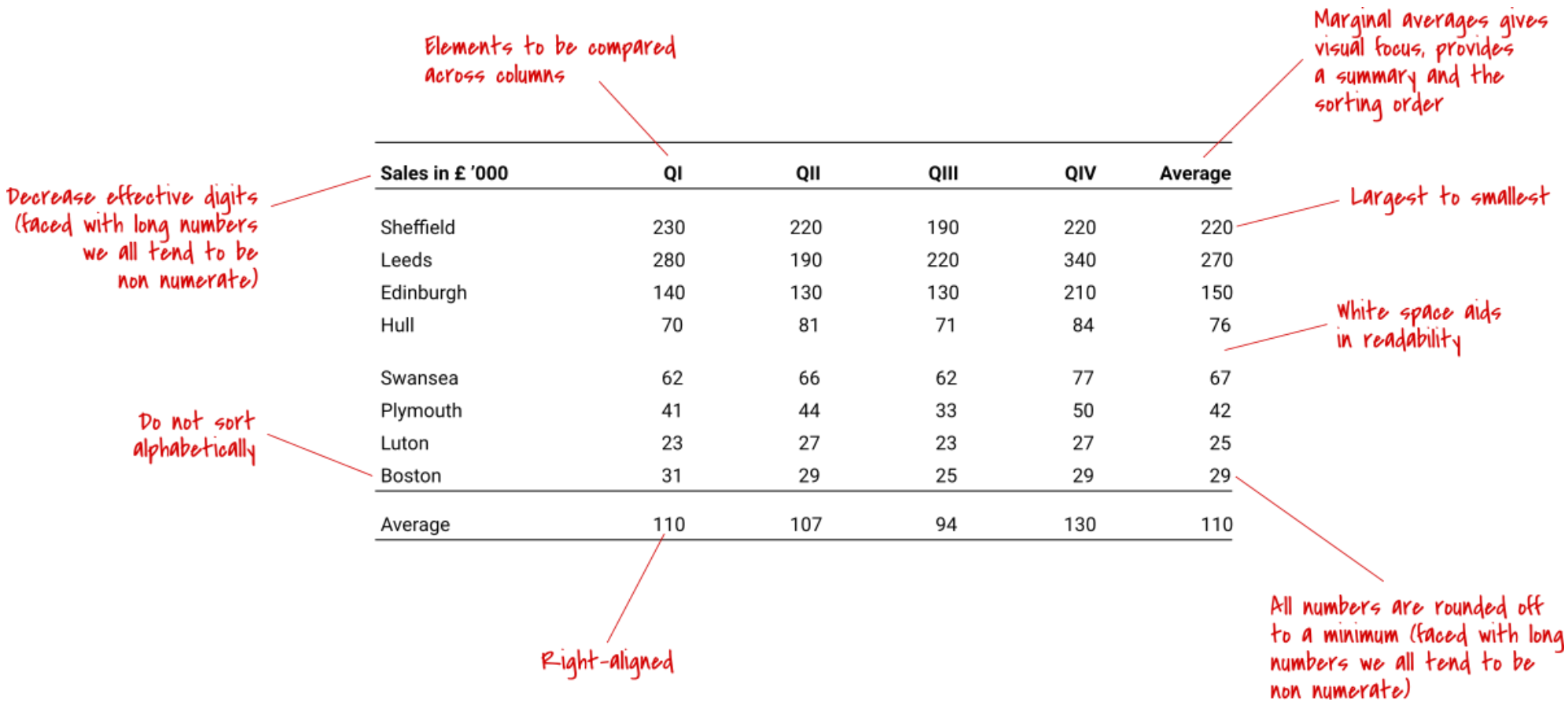


Table Tips



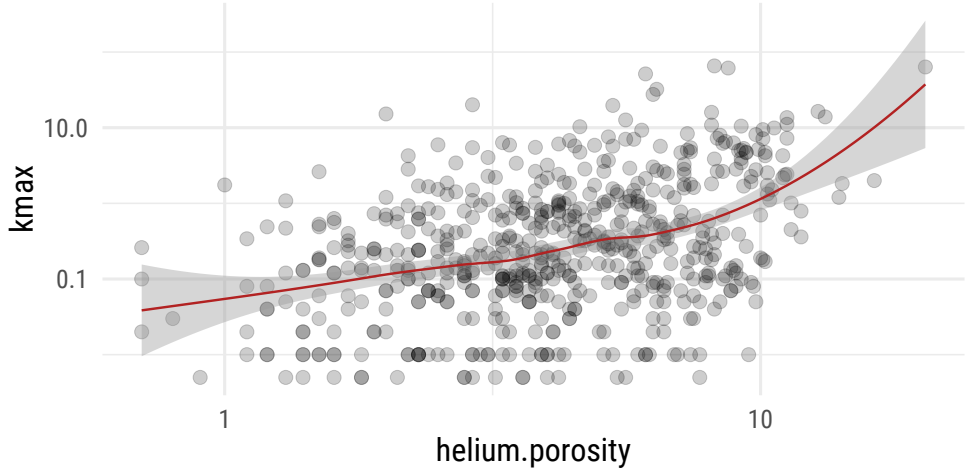
Sales in £ '000	QI	QII	QIII	QIV	Average
Sheffield	230	220	190	220	220
Leeds	280	190	220	340	270
Edinburgh	140	130	130	210	150
Hull	70	81	71	84	76
Swansea	62	66	62	77	67
Plymouth	41	44	33	50	42
Luton	23	27	23	27	25
Boston	31	29	25	29	29
Average	110	107	94	130	110

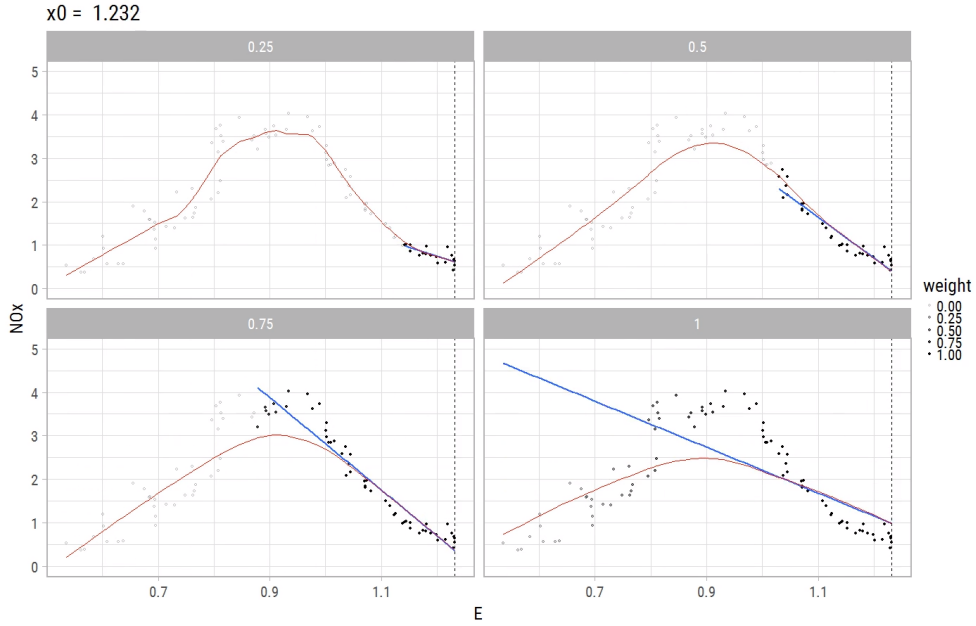
[1] *Recreated from Ehrenberg, 1981*

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

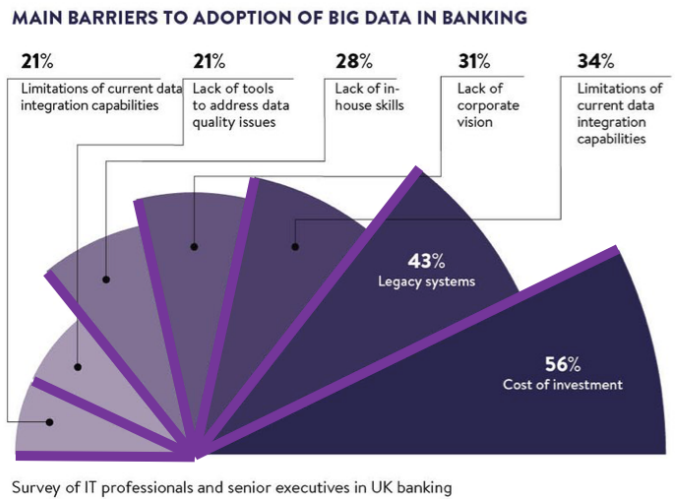




Data-to-Ink Ratio

Chartjunk

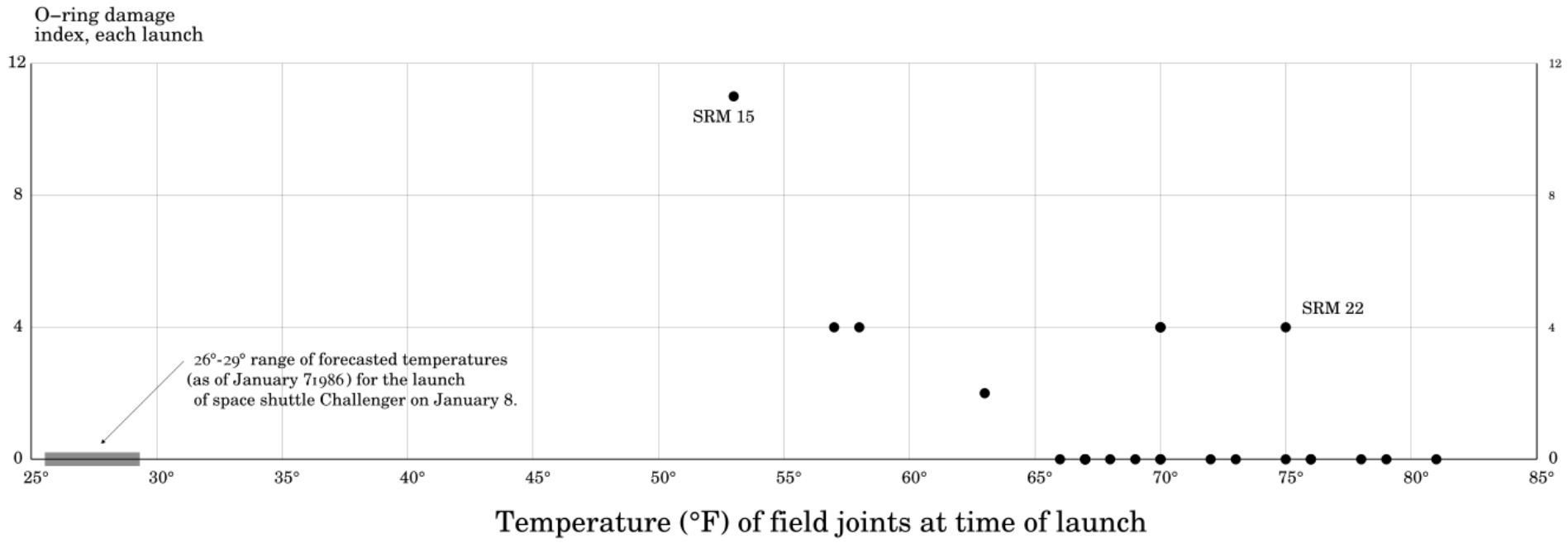
All visual elements in charts and graphs that are not necessary to comprehend the information represented on the graph, or that distract the viewer from this information. Instead, we want to achieve **rapid visual perception**. (Tufte, 1983, 2006)



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)

Data-to-ink ratio

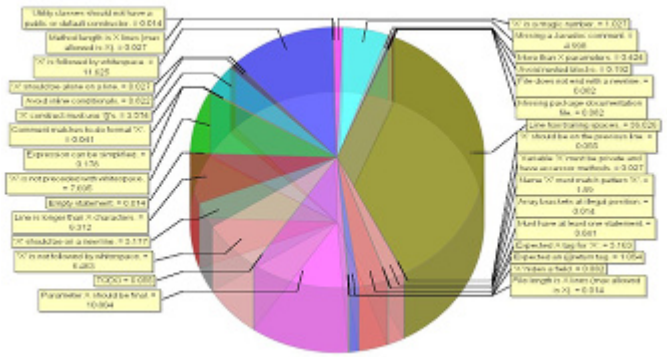


[1] *Recreated from Tufte, 1983. Visual Explanations: Images and Quantities, Evidence and Narrative*

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 ½ or ¼ of the total, we should aim to have **2-4 slices** at most.

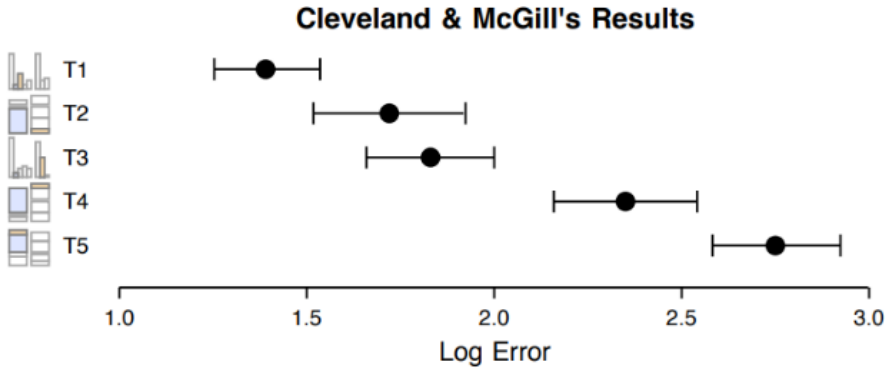
Avoid the **doughnut types**: they remove the angular information we need to draw visual comparisons.

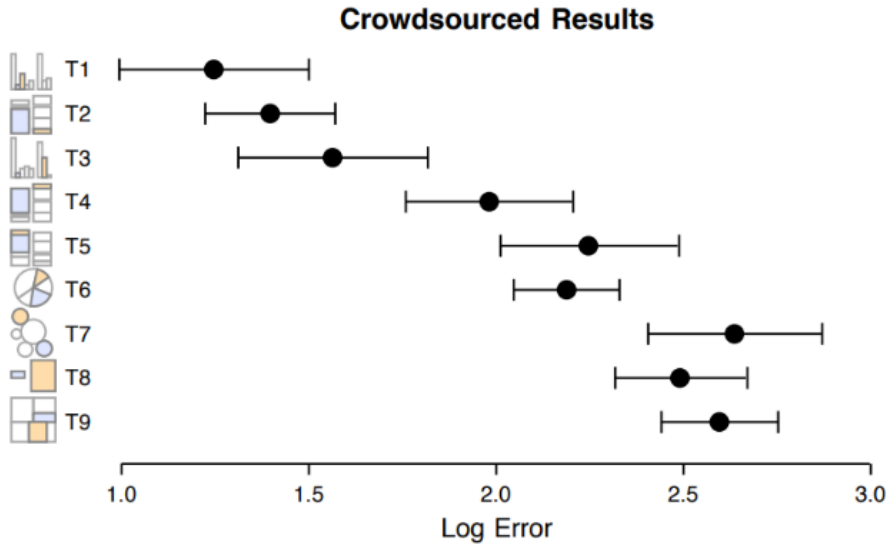
Alternatives

Use bar charts or dot plots.

The Type of Chart Affects Visual Judgement

Experiments performed to quantify visual judgment of graphs: 25 years later, results have not changed.





[1] *Cleveland and McGill, 1984* *and Heer and Bostok, 2010*

Avoid 3D

Why

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

Exceptions

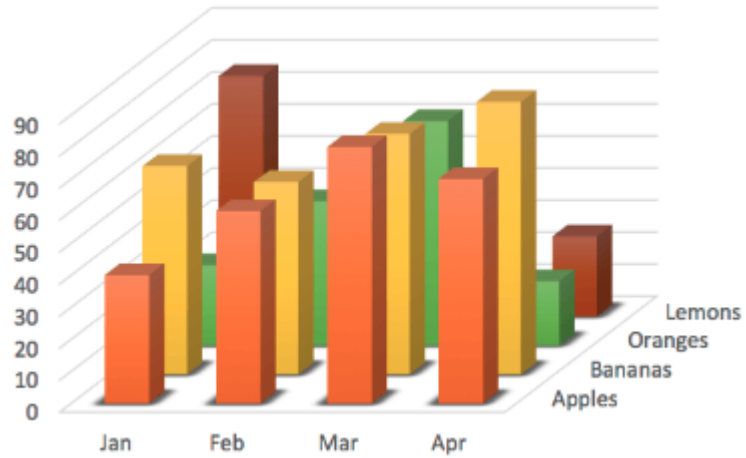
Spatial data, interaction surfaces.

Advantages

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

Disadvantage

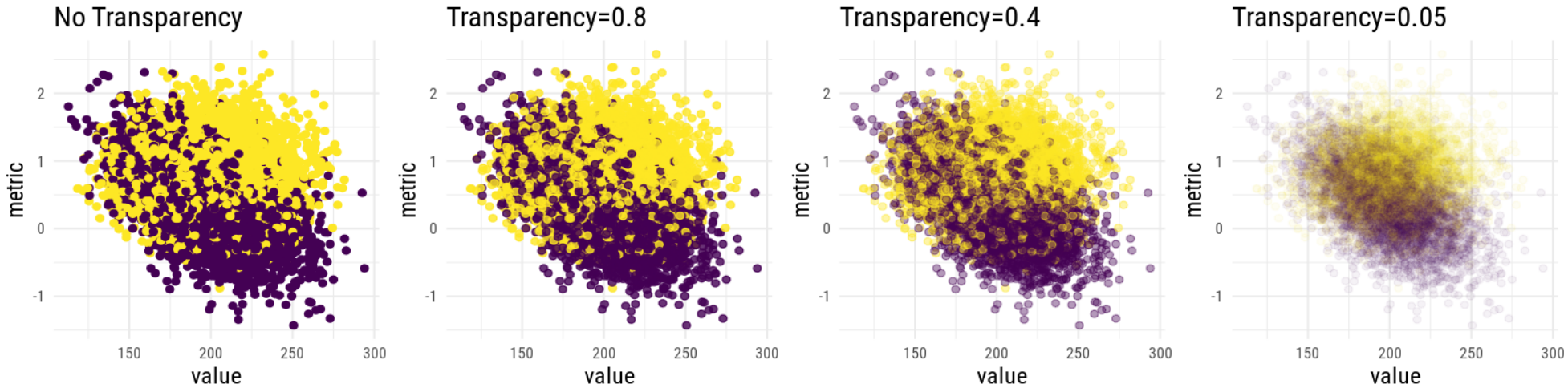
A reader is more likely to be confused by a 3D graph than a plain graph.



Visualizing High Density Data

Good...

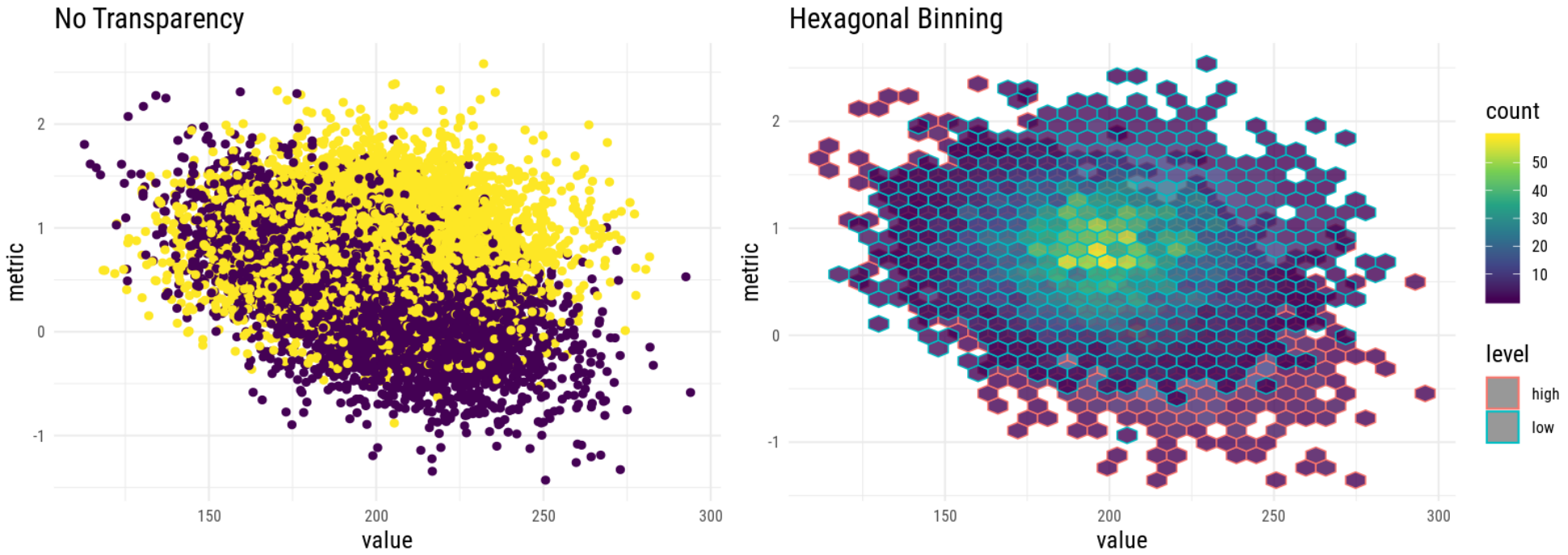
Add **transparency** (alpha). Easy and quick to implement: reveals underlying patterns but hides outliers and sparse data points.



Visualizing High Density Data

Better...

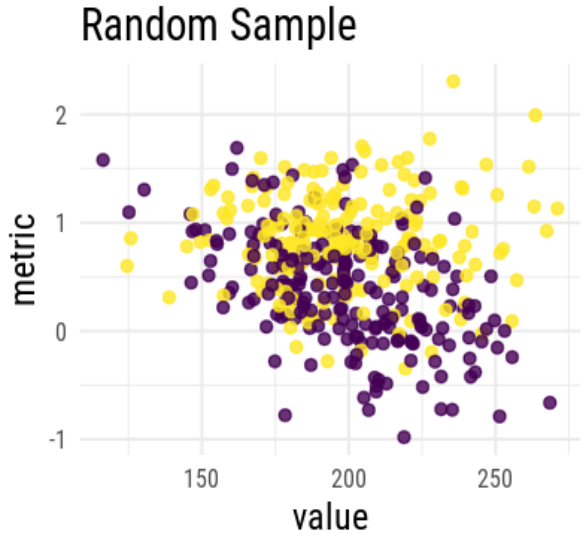
Use **binning techniques** for high density data (they've been around since the mid 80's!). A little harder to read, but won't miss outliers and sparse data.



Visualizing High Density Data

Best...

Critically assess whether you need BIG data in the first place: unless outliers are the main focus of analysis, it's often satisfactory to **sample** the data.



[1] *If you are unconvinced, ask yourself: do I really have the whole population despite a huge dataset? Big data provides no protection against bias*

Visualizing Changes Over Time

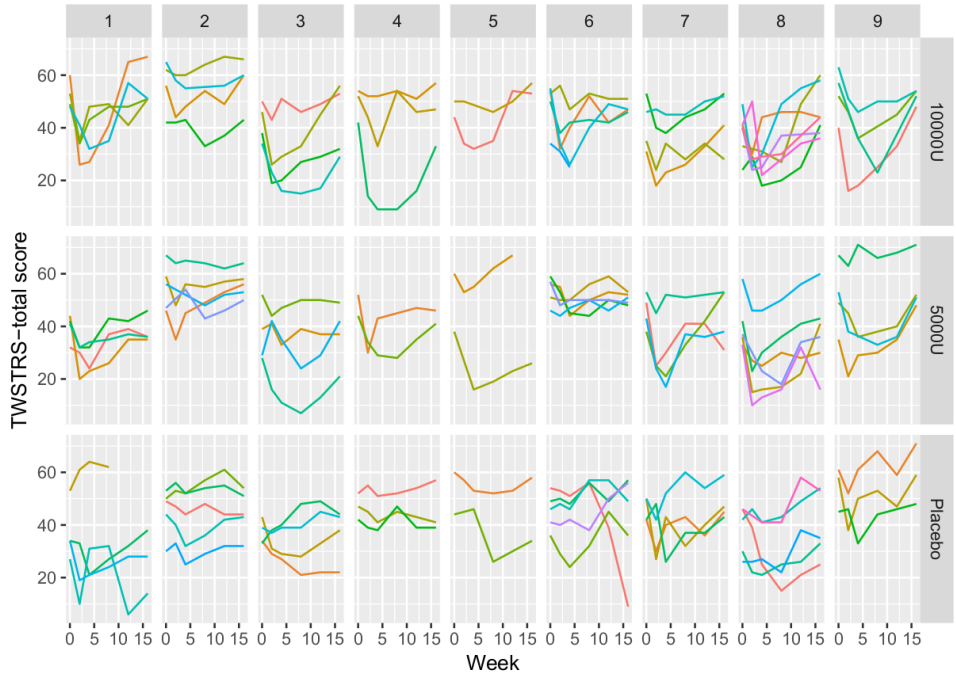


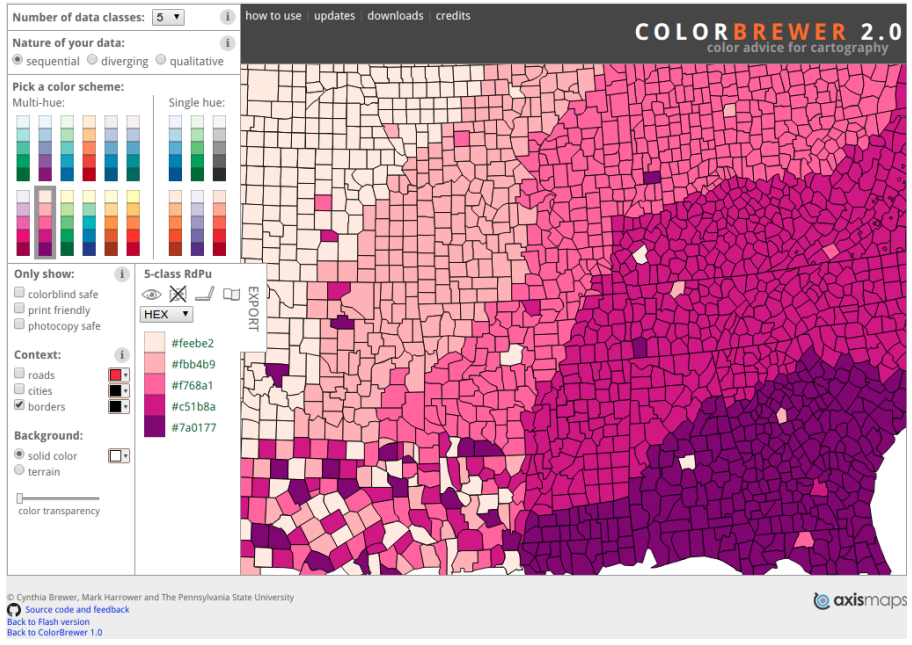
Figure 4.7: Spaghetti plot showing all the raw data on the response variable for each subject, stratified by dose and study site (1–9). Importantly, week 0 (baseline) measurements are included.

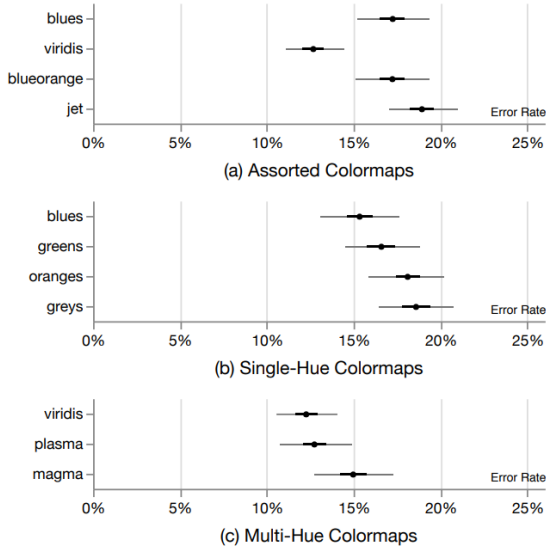
- Works well when the data is not huge.
- Best if stratified.
- x-axis needs not be time, but best if ordinal.

[1] *Harrell, 2017*

Choosing Appropriate Color

Choice of color is often subject to "*misguided artistry*". There are numerous empirically validated color scales, so the analyst's job is made significantly easier.





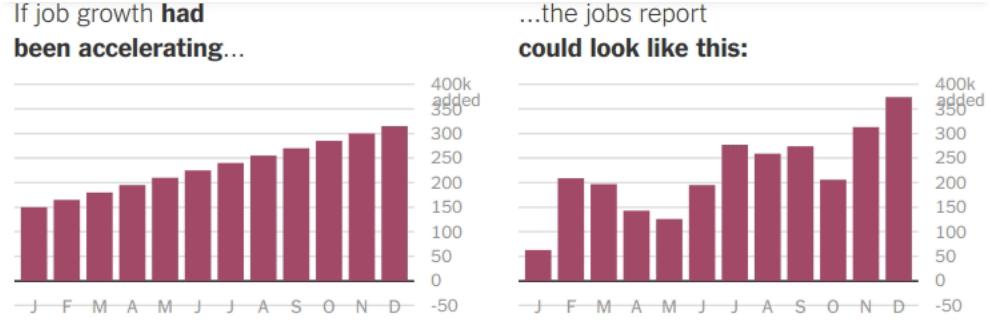
...finally, we confirmed that a rainbow colormap (jet) does indeed perform the worst overall in terms of both time and error, and should be jettisoned.

[1] *Brewer. Colorbrewer 2.0: Color Advice for Cartography*

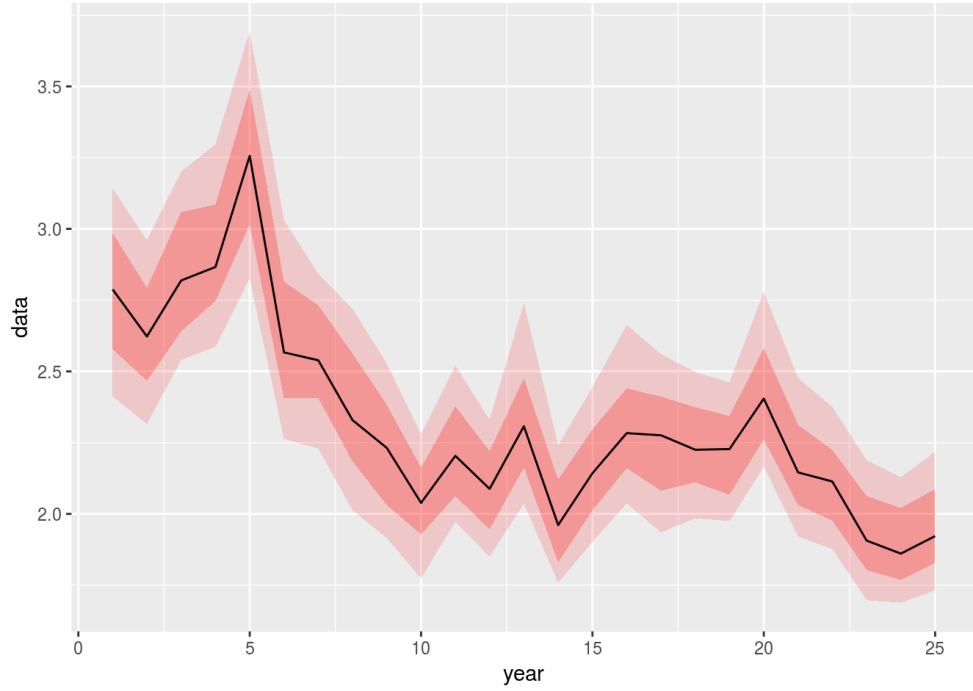
[2] *Liu, Heer. Somewhere Over the Rainbow: An Empirical Assessment of Quantitative Colormaps. 2018*

Show the Uncertainty

We need to visualize the uncertainty in order to make optimal decisions.



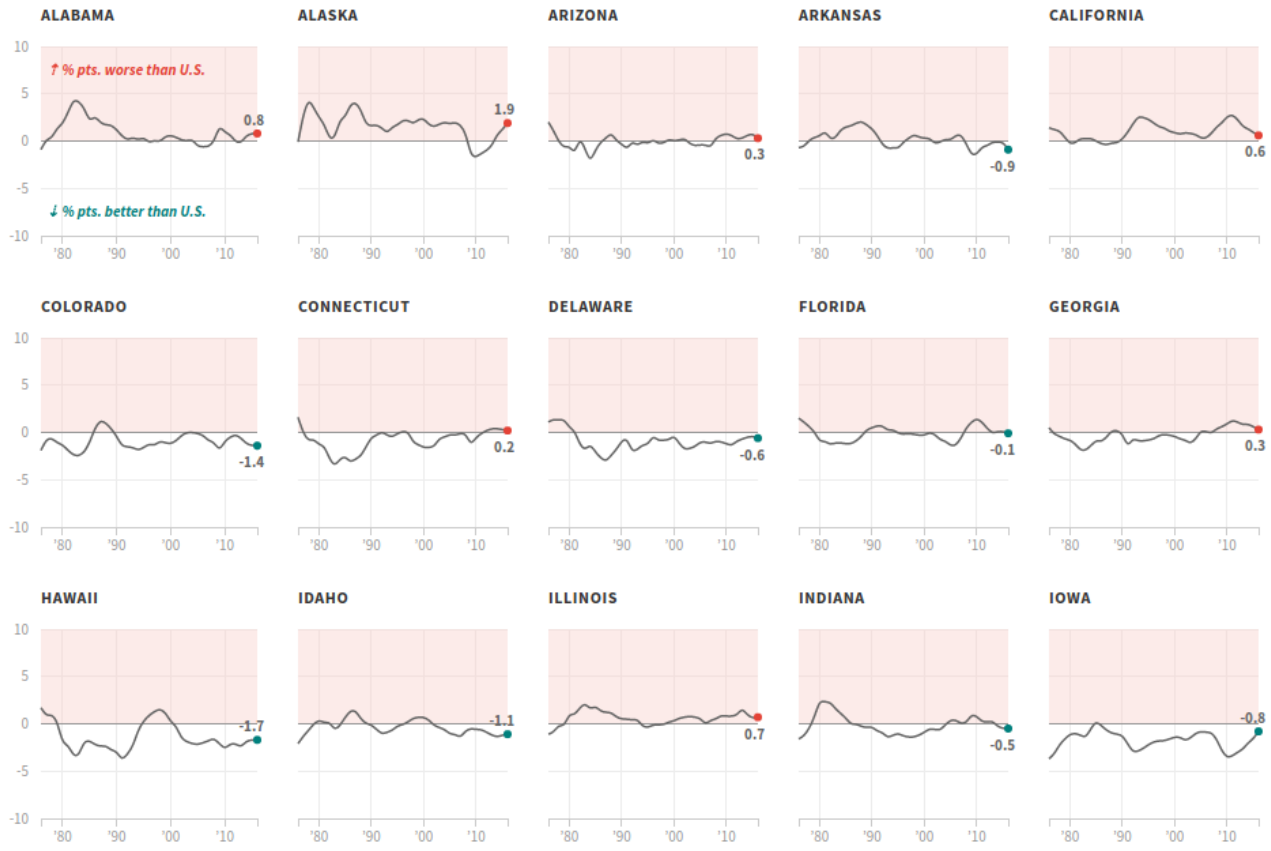
If you squint, you can see evidence of the upward trend, with stronger growth apparent in the second half of the year. But month by month, you wouldn't have any way of knowing if it was a true acceleration, or just a false signal generated by sampling error.



[1] *New York Times. How Not to Be Misled by the Jobs Report, 2014*
[2] *Chato Osio and Hamon. 2017*

Small Multiples

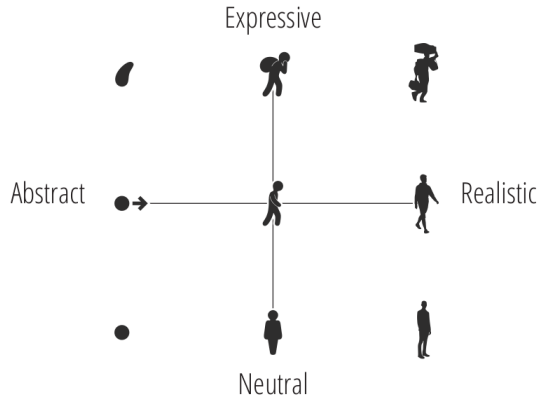
A series of very similar graphs where the eye is drawn on comparing differences among them.



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 particpants. 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?

7. 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 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. 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**.

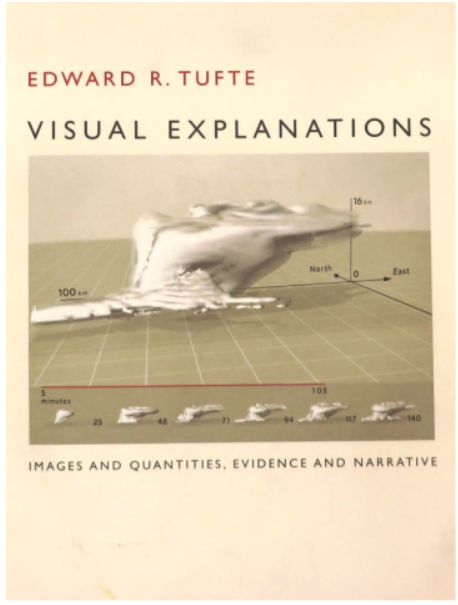
[1] *Cox LA Jr. What's wrong with risk matrices? Risk Anal. 2008 Apr*

What to Look for in Visualization Tools? An Opnionated List

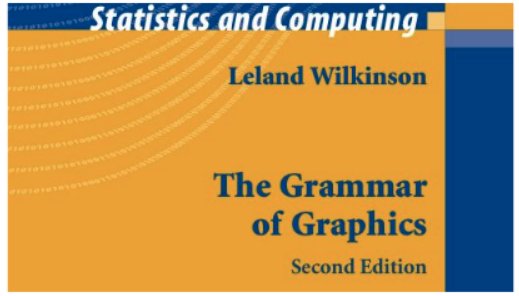
Remember Tufte: *Numbers become evidence by being in relation to*. Does the tool encourage comparisons? Does it make it easy? A simple test is to plot a stratified box-plot.

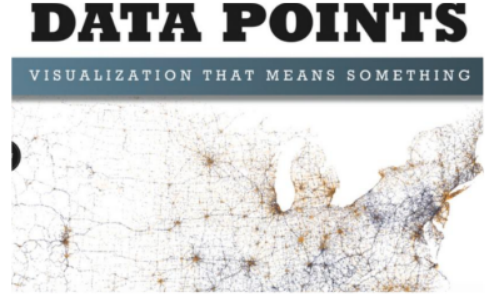
> *An approximate answer to the right problem is worth a good deal more than an exact answer to an approximate problem*
>
> -John Tukey

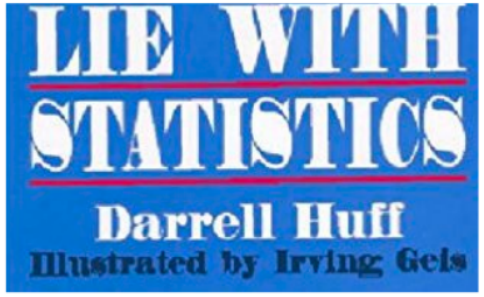
8. References

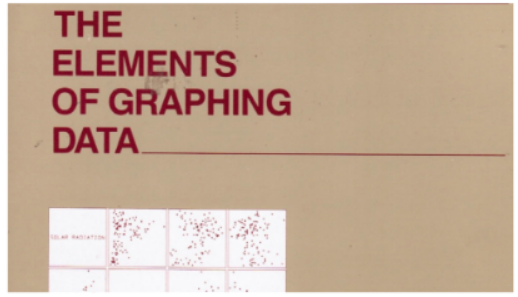

EDWARD R. TUFTE
VISUAL EXPLANATIONS
IMAGES AND QUANTITIES, EVIDENCE AND NARRATIVE

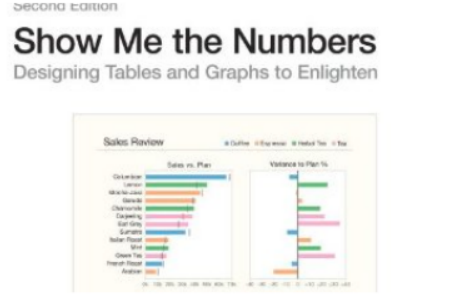

EDWARD TUFTE
BEAUTIFUL EVIDENCE

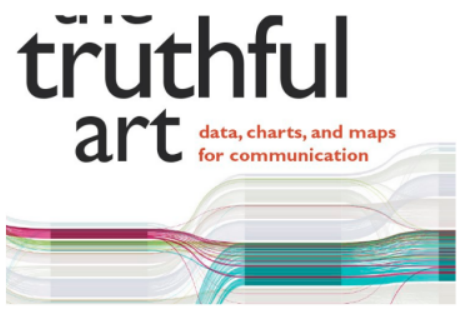

Statistics and Computing
Leland Wilkinson
The Grammar of Graphics
Second Edition

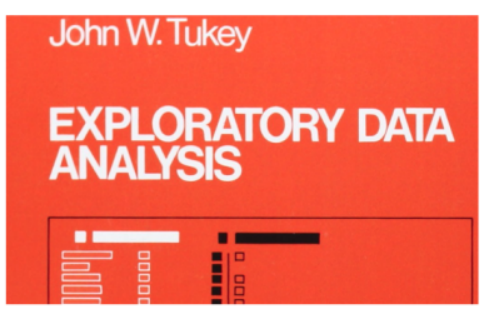

DATA POINTS
VISUALIZATION THAT MEANS SOMETHING

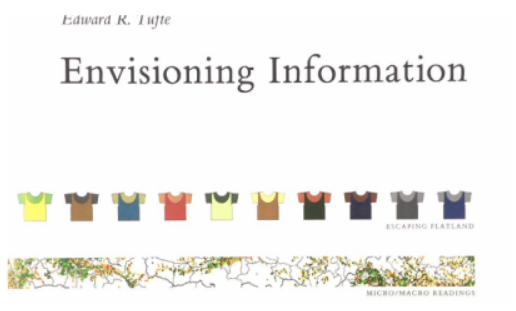

LIE WITH STATISTICS
Darrell Huff
Illustrated by Irving Geis

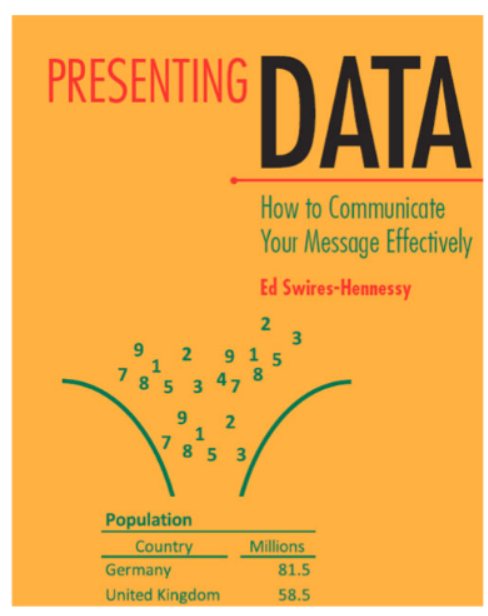

THE ELEMENTS OF GRAPHING DATA

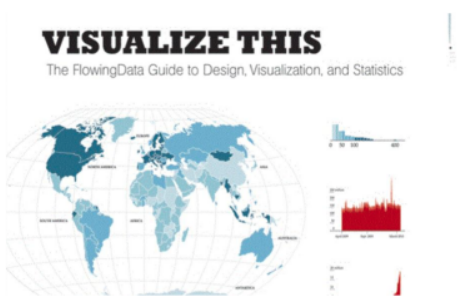

Second Edition
Show Me the Numbers
Designing Tables and Graphs to Enlighten

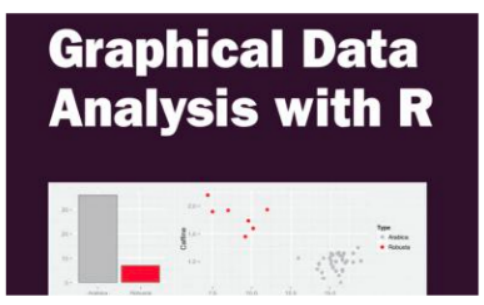

truthful art
data, charts, and maps for communication

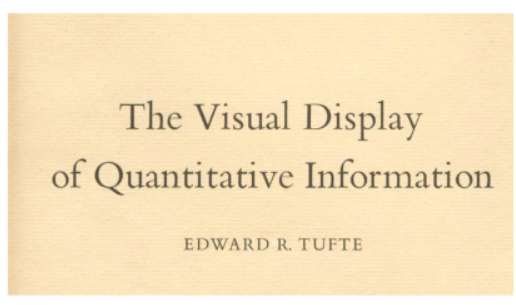

John W. Tukey
EXPLORATORY DATA ANALYSIS


Edward R. Tufte
Envisioning Information


PRESENTING DATA
How to Communicate Your Message Effectively
Ed Swires-Hennessy
Population
Country
Millions
Germany
81.5
United Kingdom
58.5


VISUALIZE THIS
The FlowingData Guide to Design, Visualization, and Statistics


Graphical Data Analysis with R


The Visual Display of Quantitative Information
EDWARD R. TUFTE

Author	Title
Tufte, E. R. (1983)	The Visual Display Of Quantitative Information
Tufte, E. R. (1990)	Envisioning Information
Tukey, J. W. (1977)	Exploratory Data Analysis
Few, S. (2012)	Show Me The Numbers. Designing Tables And Graph To Enlighten.
Chiasson T., Gregory D. et al. (2014)	Data + Design
Ehrenberg, A.S.C. (1981)	The Problem Of Numeracy. The American Statistician, Vol. 35, N. 2
Wilkinson, L. (2005)	The Grammar Of Graphics
Simon, H.A. (1996)	The Sciences Of The Artificial.
Cleveland, W.S. (1985)	The Elements Of Graphing Data.
Yau, N. (2011)	Visualize This. The Flowingdata Guide To Design, Visualization And Statistics
Good P.I., Hardin J.W. (2012)	Common Errors In Statistics (And How To Avoid Them)
Gelman A., Unwin A. (2012)	Infovis And Statistical Graphics: Different Goals, Different Looks

Thank you

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ca.linkedin.com/in/speidel/
alternative-stats.netlify.com

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 as the presentation template.