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PART I

Author Request - The following author(s) request authority to disclose the following presentation at the MORS Event below with subsequent publication in the MORS Event Report and posting on the MORS website if applicable.

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Principal Author's Signature X Thomas A. Donnelly		Date 3 June 2021	
MORS Event 89th MORSS		Event Date(s) 21-24 June 2021	
Presentation Type <input type="checkbox"/> Plenary <input type="checkbox"/> Course <input checked="" type="checkbox"/> Tutorial <input type="checkbox"/> Special Session <input type="checkbox"/> Poster <input type="checkbox"/> Demonstration <input type="checkbox"/> Working/Composite/Distributed or Focus Group List All <input type="checkbox"/> Other			
Title of Presentation All Graphs are Wrong – Some are Useful		Presentation ID (if assigned) 56938	
Classification <input type="checkbox"/> SECRET <input type="checkbox"/> SECRET//REL TO FVEY <input type="checkbox"/> CONFIDENTIAL <input type="checkbox"/> CONFIDENTIAL//REL TO FVEY <input checked="" type="checkbox"/> UNCLASSIFIED <input type="checkbox"/> UNCLASSIFIED W/FOUO <input type="checkbox"/> Other			
Distribution Statement <input checked="" type="checkbox"/> A (Publicly Releasable) <input type="checkbox"/> B <input type="checkbox"/> C <input type="checkbox"/> D <input type="checkbox"/> E (see side 2 for definitions)			
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All Graphs Are Wrong, but Some Are Useful

89th MORSS
Webcast Tutorial 56938
June 21, 2021

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Xan Gregg
JMP Director R&D

Originally Presented at

2015

DISCOVERY SUMMIT

EXPLORING DATA
INSPIRING INNOVATION

View at <https://community.jmp.com/docs/DOC-8270>

Three Graphical Influences...

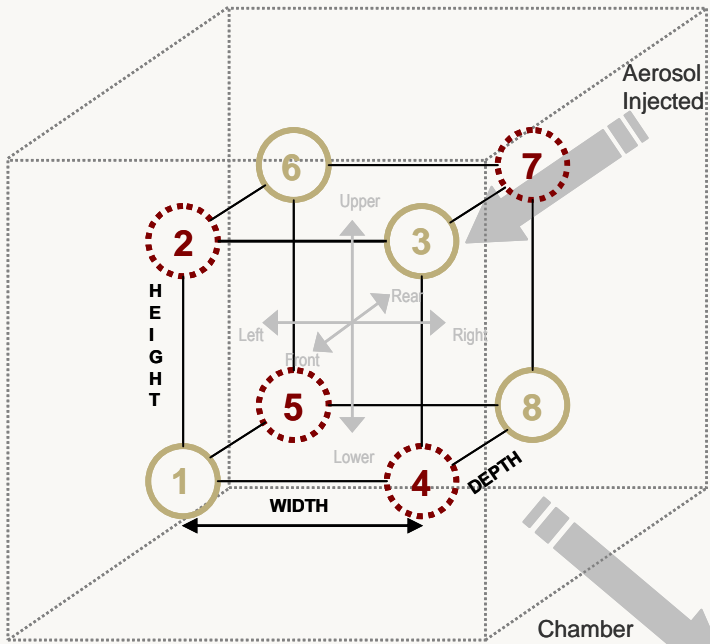
1. Edward Tufte - www.edwardtufte.com

2. Kaiser Fung - www.kaiserfung.com @junkcharts

3. Xan Gregg – <https://twitter.com/xangregg/media>
@xangregg, #onelesspie, #GraphBuilder, #DatViz, #DataScience,
#TieDye

Tufte's Big Ideas : "5 grand principles"

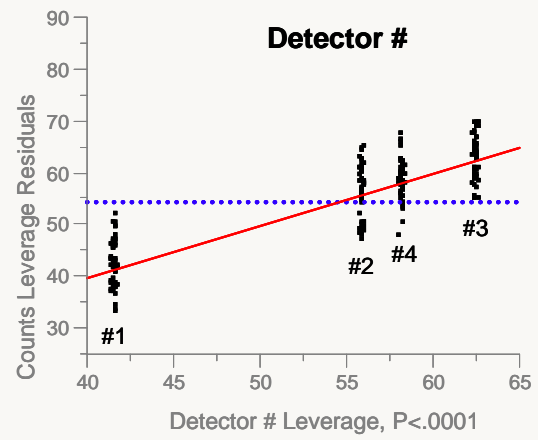
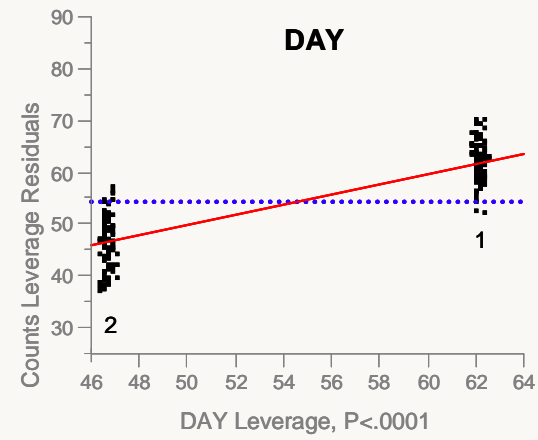
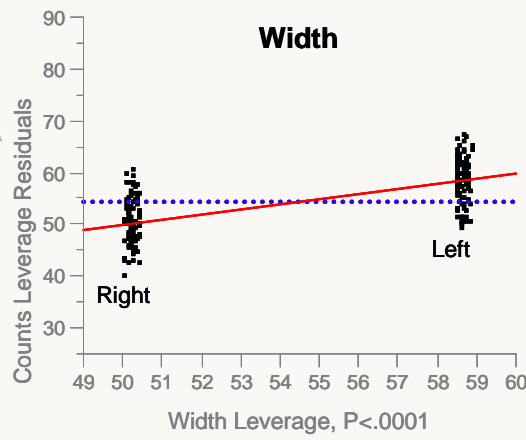
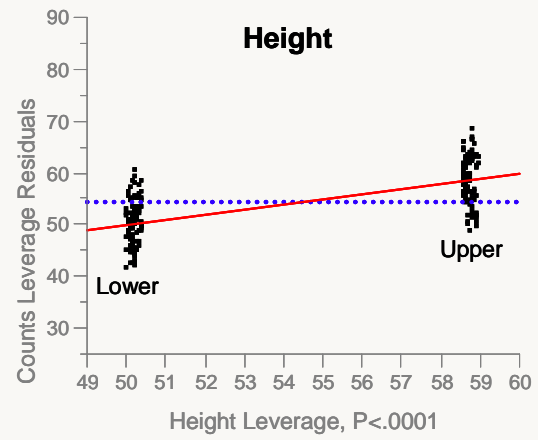
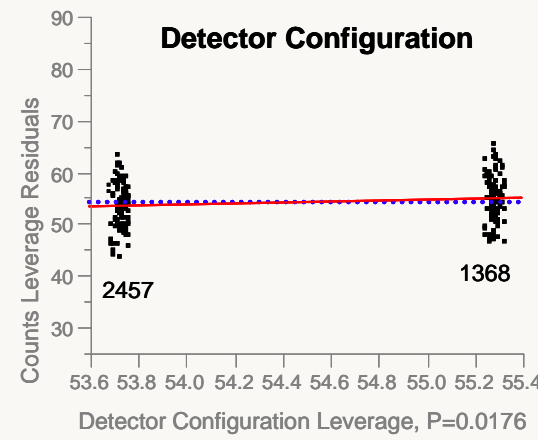
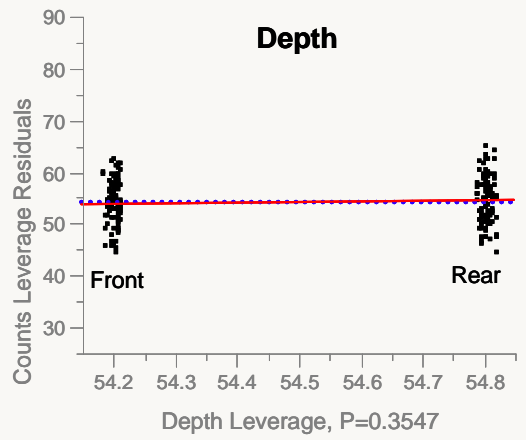
1. Enforce Wise Visual Comparisons
2. Show Causality
3. Show Multivariate Data
4. Integrate all visual elements (words, numbers, images)
5. Content-Driven Design



Chamber Width = twice test volume WIDTH

○ 2-4-5-7 **Detector Configuration**
○ 1-3-6-8 **Detector Configuration**

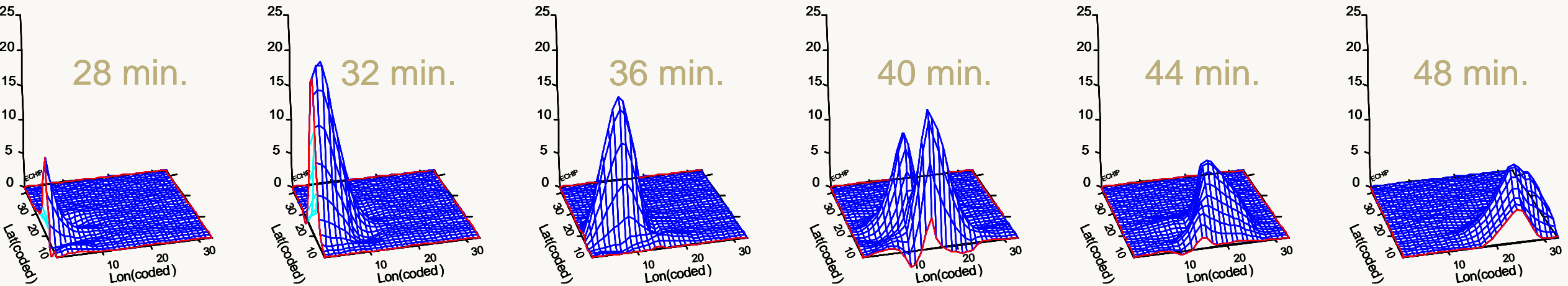
Leverage Plots for the Response Data 'Counts' for Six Explanatory Variables



The second example shows aerosol concentration versus location variables for 6 time steps from analysis of simulation data using a Kriging or Gaussian Process regression technique that smoothly interpolates deterministic data.

Tufte's Grand Principles:

- Enforce wise visual comparisons
- Content counts most of all
- Show causality
- Complete integration of evidence - words, numbers, images, diagrams
- Use multivariate displays
- Use small multiples (format constancy)
- Put everything on universal grid
- Give reasons to believe
- Don't de-quantify data



Tufte's advice...

If you ever get 5 minutes with the Admiral, you don't want to be giving a PowerPoint presentation.

Instead, hand the Admiral an 11" X 17", 4-page handout that in 250 words or less describes the *problem* and its *importance*, and in 250 words or less describes the *solution* you propose.

The rest of the handout *shows your credibility*...

Tutorial on “Real-World DOE Problems”

Tom Donnelly, 20 June 2011, 79th MORSS

This tutorial is intended to complement the introductory Design of Experiments (DOE) tutorial. You may not learn as much “how to,” but will learn to recognize real-world problems and when you need to get help from a knowledge source or someone with experience. It’s far better to go to a DOE subject matter expert (SME) before you experiment than after.

Why use Design of Experiments (DOE) methods?

It is the most cost effective way to get quick answers to multivariable problems. Another way to think about it is for your existing budget you can solve more and/or bigger problems.

Why is using DOE methods important?

DOE is one of the more powerful tools we can use to quickly and efficiently develop and optimize the multivariable technologies needed to best equip and protect our warfighters. It enables us to provide decision makers not just data, but information, and understanding of a process so that they can make better tradeoffs and judgments.

Summary Part 3 – Algorithmic Design:

It is better to make your design fit your problem than to make your problem fit the available design!

Algorithmic designs can be created for all these problems:

- special models,
- combinations of any or all three types of variables:
 - continuous (quantitative), - finely adjustable like temperature, speed or force
 - categorical (qualitative), - comes in types like material = wood, plastic or metal with mixed numbers of levels (3 materials, 4 machines, and 5 operators)
 - mixture (formulation) - blending ingredients - process depends more on the proportions than on the amount and blocking - a variable for which there “shouldn’t be” a causal effect - day, lot, batch, tray
- constrained regions (constraints),
- adding on to existing trials (augmentation),
- repairing broken designs (both constraints and augmentation).

Summary Part 4 – Modern Screening Designs:

“Definitive” screening design can collapse into a response-surface design. Leverage these assumptions to do more than screening.

- Factor sparsity – only a few variables are active in a factorial experiment
- Effect heredity – significant interactions only appear among these active factors
- A 10-variable example is shown that in 23 unique trials yields a response surface model in the most important factors.
- Jones B. and Nachtsheim, C.J., “A Class of Three-Level Designs for Screening in the Presence of Second-Order Effects,” *Journal of Quality Technology*, Vol. 43, No. 1 (2011)
- Jones B. and Nachtsheim, C.J., “Efficient Designs with Minimal Aliasing,” *Technometrics*, Vol. 53, No. 1 (2011)
- Jones B., Lin, D. K. J., and Nachtsheim, C.J., “Bayesian D-optimal Supersaturated Designs,” *Journal of Planning and Statistical Inference*, Vol. 138, (2008)

Summary Part 5 – Mixtures & Combining Variable Types:

One complex design example was demonstrated with 10 variables – 6 mixture, 2 continuous, 1 categorical and 1 blocking - with additional constraints. Issues specific to some mixture designs:

- Absence (0%) vs. presence (0.1%) can have greater effect than change from 1% to 10% for catalysts, dopants, etc.
- “Additive” (in a mathematical sense) mixture component doesn’t take part in the chemistry – filler, binder, colorant, diluent
- Some components (e.g. held at a constant value forcing balance to sum to less than 1).
- Trace quantities act like process variables (0.0001 to 0.0002).

Summary Part 6 – Transformations:

They’re free in the sense that you don’t need more data! - Can help data meet regression assumption of being normally distributed with constant variance with the benefits of often eliminating lack-of-fit and improving model predictions from being nonsensical (e.g. negative % of defects/unit area, yield > 100%, etc.) - Especially useful when data values run up against a boundary. For data bounded on the low side (e.g. μ , defects, resistivity, hardness, etc.)

$Y = \text{Log}(Y)$ – used when values range over several orders of magnitude
 $Y = Y^2$ – used with counting data

For data bounded on two sides (e.g. percentage range of 0-100%, or a range of 1 = worst to 9 = best)

$Y = 2^{\text{arcsin}(Y)}$ – used for values scaled between 0 and 1

To scale a bounded range (low, high) to the unit range (0, 1) use $Y = (y - \text{low}) / (\text{high} - \text{low})$

For Pass/Fail (Binary) data, IF all trials have the same number of attempts, then you can use the transformation $Y = 2^{\text{arcsin}(Y^2)}$, but a better tool is logistic regression. First time using logistic regression I strongly suggest you edit the page of a SME.

A great reference: *Plots, Transformations and Regression*, A.C. Atkinson, (1984), Oxford University Press

Summary Part 7 – DOE for Computer Experiments:

Currently becoming a hot topic since so many DoD programs require M&S. DOE is used to understand the long-running simulation model. Both traditional (factorial type) designs and “space-filling” designs are discussed. Traditional designs were run in a sequential fashion until adequate accuracy was obtained for one example. Space-filling designs can be analyzed using kriging methods when the response is - non-stochastic (non-random) and when all variables are continuous although these limitations are actively being pursued in academic study. Neural regression methods as well as partitioning methods are useful for analyzing stochastic simulation data that exhibits more complex behavior than can be modeled using a thin low to moderate order polynomial.

“The purpose of models is not to fit the data but to sharpen the questions.” – Samuel Karlin

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Tutorial on “Real-World DOE Problems”

Tom Donnelly, 20 June 2011, 79th MORSS

This tutorial is intended to complement the introductory Design of Experiments (DOE) tutorial. You may not learn as much “how to,” but will learn to recognize real-world problems and when you need to get help from a knowledge source or someone with experience. It’s far better to go to a DOE subject matter expert (SME) before you experiment than after.

Why use Design of Experiments (DOE) methods?

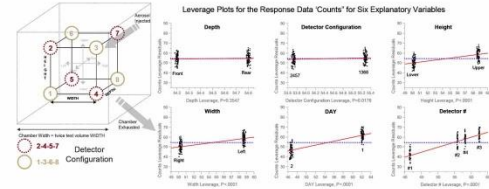
It is the most cost effective way to get quick answers to multivariable problems. Another way to think about it is for your existing budget you can solve more and/or bigger problems.

Why is using DOE methods important?

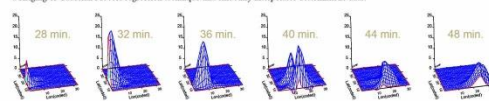
DOE is one of the more powerful tools we can use to quickly and efficiently develop and optimize the multivariable technologies needed to best equip and protect our warfighters. It enables us to provide decision makers not just data, but information, and understanding of a process so that they can make better tradeoffs and judgments.

Some easy things to do:

Plot the data. Plot ALL the data when possible. Leverage plots are handy. Present plots in small multiples. See books by Edward Tufte (www.edwardtufte.com). Tufte’s first grand principle is “Enforce Visual Comparisons.” Here are two examples: The first shows plots of all the observed data from a study of aerosol particle counts in a chamber for six explanatory variables.



The second example shows aerosol concentration versus location variables for 6 time steps from analysis of simulation data using a Kriging or Gaussian Process regression technique that smoothly interpolates deterministic data.



Tufte’s Grand Principles:

- Enforce wise visual comparisons
- Use multivariate displays
- Complete integration of evidence - words, numbers, images, diagrams
- Content counts most of all
- Put everything on universal grid
- Show causality
- Use small multiples (format constancy)
- Give reasons to believe
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Checkpoints, checkpoints, checkpoints... If you can’t predict your response within a certain tolerance, how good can your model be? Consider taking checkpoints inside and outside design space, at optima, where unusual behavior is observed, that support the

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next higher model, the boss’ suggestion, during the design... Compare observed value and model prediction \pm limits. Compare residual SD (model error) and checkpoint RMS (checkpoints error) – they should be similar.

Replicate at Least 5 Trials – and 10 would be better. Then you can conduct a lack-of-fit test comparing model error (Residual SD) to pure error (duplicate SD). The actual F-test uses compares the variances (squares of the SDs) and takes into account the number of degrees of freedom in each variance estimate.

Before running your real-world design, do an analysis with fictitious data to check the correlation among the factors. Also be sure to run a feasibility analysis of the trials and consider doing the hardest one first.

Historical (Historical?) Data – Existing data may hold some useful information, certainly about the process variability, but way too often it doesn’t broadly cover the variable space of interest – lots of data, but too much of the same thing. Use data mining methods to search historical data for correlations that might suggest causality to be tested in your DOE.

RESOURCES: By no means is this an exhaustive listing!

The first DOE book: Fisher, R. A. (1935), *The Design of Experiments*, Oliver and Boyd

Textbooks this Century: 1. Box, G. E. P., Hunter, W. G. and Hunter, J. S. (2005), *Statistics for Experimenters*, 2nd ed., Wiley, New York - The standard – classic 1978 text recently revised

2. Wu, C. F. J. and Hamada, M. (2009), *Experiments, Planning, Analysis and Parameter Design Optimization*, 2nd ed., Wiley, New York

3. Both classic approaches and orthogonal arrays & orthogonal main effects plans

4. Montgomery, D. C. (2009), *Design and Analysis of Experiments*, 7th ed., Wiley, New York

5. Popular text, solution book available, examples illustrated with JMP® software.

More Specialized Texts – Optimal Design, Mixtures, Response Surface:

- Atkinson, A. C., Donev, A. N. and Tobias R. D. (2007), *Optimum Experimental Designs*, Clarendon Press, 2nd ed., Oxford
- Cornell, J. A. (2002), *Experiments with Mixtures, Designs, Models and the Analysis of Mixture Data*, 2nd ed., Wiley, New York
- Khuri, A. and Cornell, J. A. (1996), *Response Surfaces, Designs and Analysis*, 2nd ed., Marcel Dekker, New York
- Box, G. E. P. and Draper, N. A. (2007), *Response Surfaces, Mixtures and Ridge Analysis*, 2nd ed., Wiley, New York
- Meyer, R. H. and Montgomery, D. C. (2002), *Response Surface Methodology: Process and Product Optimization Using Designed Experiments*, 2nd ed., Wiley, New York

Texts Specifically on DOE for Computer Experiments:

- Kleijnen, J. P. C. (2008), *DAE: design and analysis of simulation experiments*, Springer, New York
 - Sartore, T. J., Williams, B. J., and Notz, W. I. (2003), *The Design and Analysis of Computer Experiments*, Springer, New York
 - Fang, K. T., Li, R. Z., and Sudrajat, A. (2005), *Design and Modeling for Computer Experiments*, Chapman & Hall/CRC Press, New York
- One more book:
Good, P. J. and Hadjin, J. W. (2006), *Common Errors in Statistics (and How to Avoid Them)*, Wiley, New York
- *Metric data can be grouped so as to evaluate it by statistical methods applicable to categorical or ordinal data. But to do so would be to throw away information, and to reduce the power of any tests and the precision of any estimates.* Page 220

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20 (some) Questions I Like to Ask at the Start of DOE Discussions:

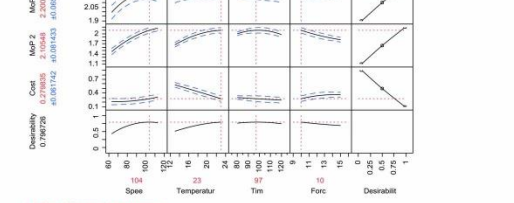
- What is the goal of the experimentation?
- How do you measure success?
- What response variables do you measure?
- What are all the control factors that may affect these responses?
- Over what ranges does it make sense to operate these variables?
- Do any combinations of variable settings cause problems? (Safety? Cost? Breaks the equipment? Impossible to achieve?)
- Do you currently run control samples for this process?
- If you do exactly the same process on separate days do you ever get obviously/surprisingly different results?
- How big is the variability (What is the standard deviation)? for each response?
- Do you have past records of replicated trials for each response?
- Are the replicate trials close together or spread out over time?
- How big of a difference for each response is considered practically important?
- Do you think we are looking for tiny differences in big variability (hard to do because lots of replication is needed) or big differences in small variability (easy)?
- If more than one response needs to be characterized for your process, what is their relative importance?
- Are you interested in identifying the best trade-off in performance of several responses?
- Are you more interested in identifying important control factors or in ending up with a model that can predict your responses?
- How many trials can be run in a day?
- Are there any hard-to-change factors?
- How many devices do you have of each type?
- How hard is it to come back at a later time to run checkpoint trials?
- What is your budget?
- What is your deadline?

Summary Part 1 – Introduction and Response Surface Methods:

- Five steps to optimize a process:
- Think about process – see list of 20 (some) questions above
 - Do some work – not just any work will do - design is the set of trials run to support the proposed model
 - Analyze data – model first – even if it doesn’t fit the pictures of the process
 - Optimize Process – look at the pictures – minimum/maximum/target!
 - Verify results – checkpoints, checkpoints, checkpoints
- Expensive or time consuming trials? Use a sequence of designs to successively increase the complexity of the model supported.

Summary Part 2 – Multiple Response Optimization:

Determine the best model in performance among several responses. Be careful with subjective weighting or relative importance. Always verify the optimum with checkpoints.



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Kaiser Fung's Language to describe what you like

Make it Thick: data ink

Make it Sufficient

Make it Easy

Make it Scream

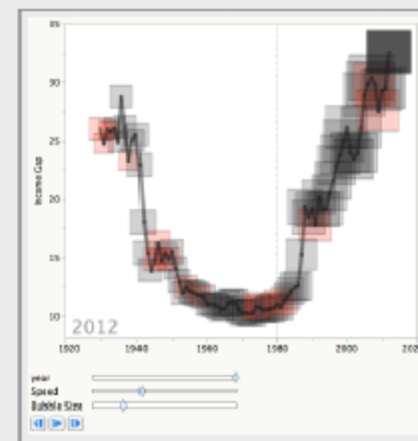
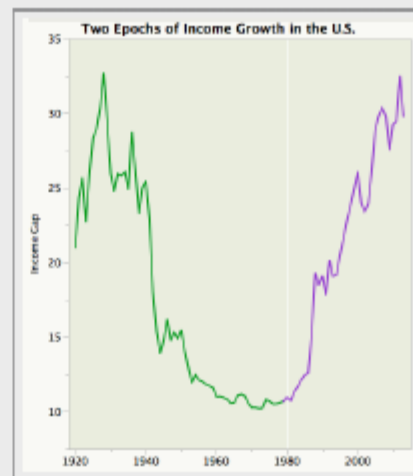
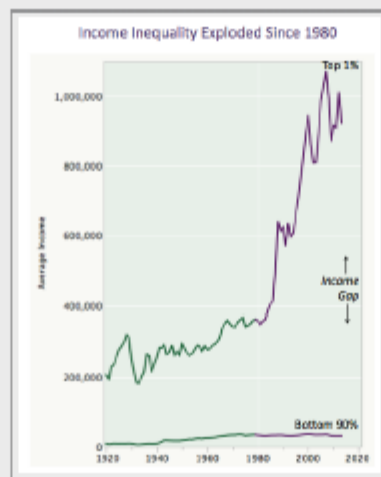
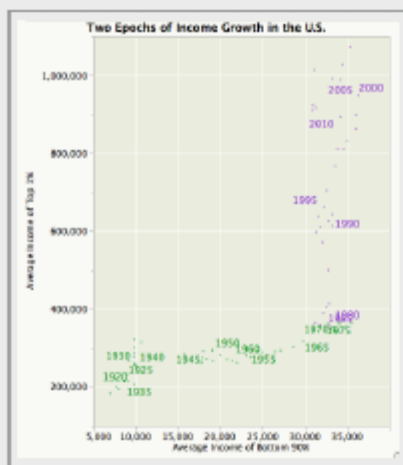
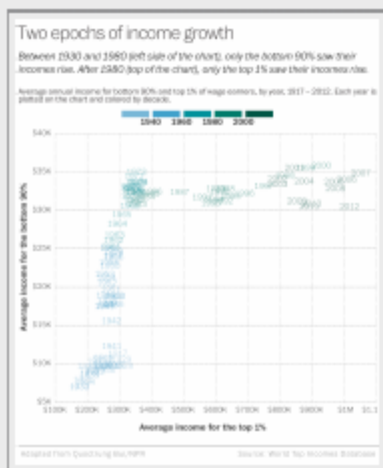
Speak Directly

Consider knowledge in the head

Make it Whole

Make it Interactive*

How has Income Inequality changed?



Create Color
and Label
indicators

Formula
Value color

Swap axes

Modulo
Value color
Background
Gridlines

Plot multiple
time series

Add reference
line
Add text

Transform
data to Ratio

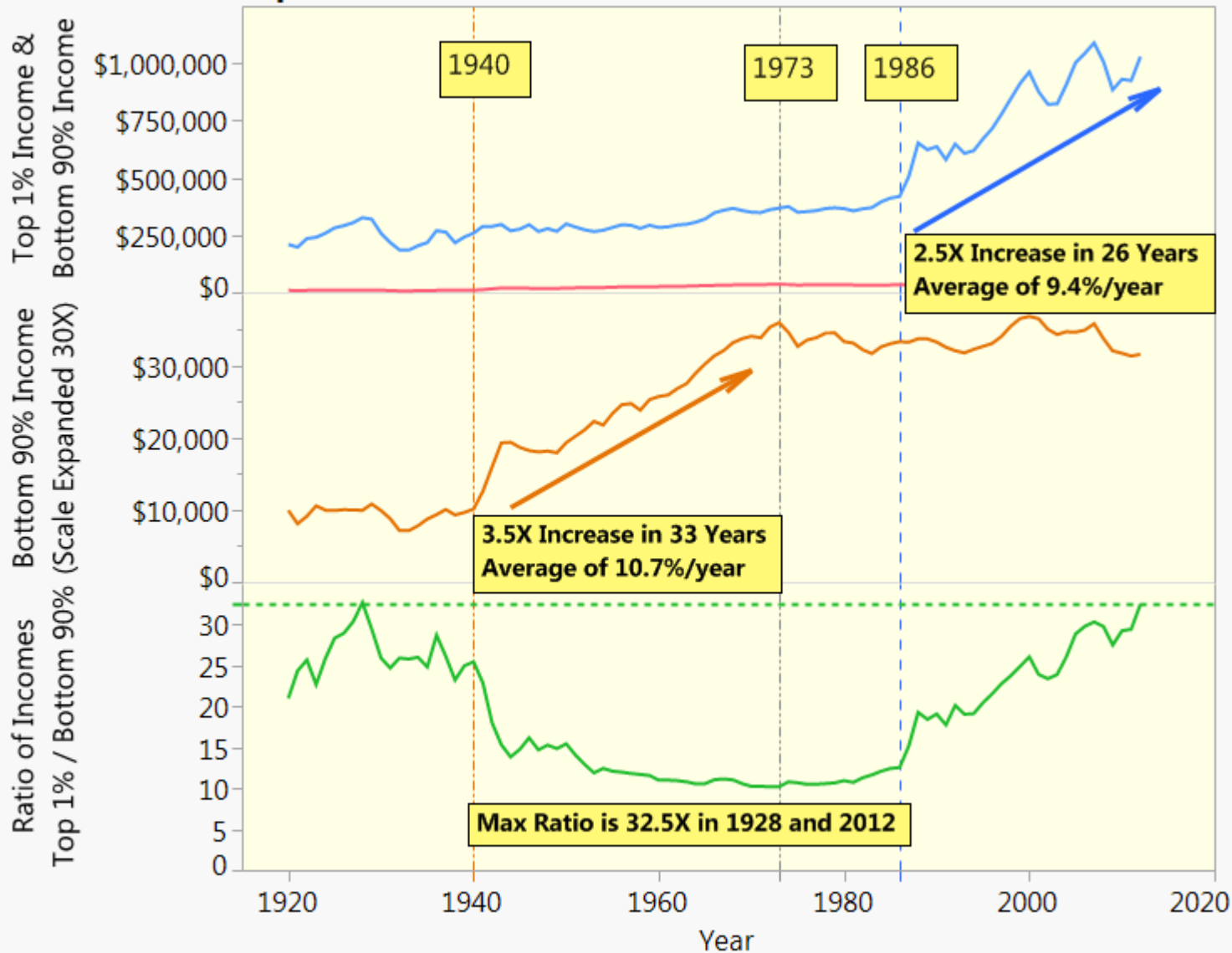
Formula

Merge GDP data
Explore &
Categorize
Bubble Plot

Join
Formula
Value color

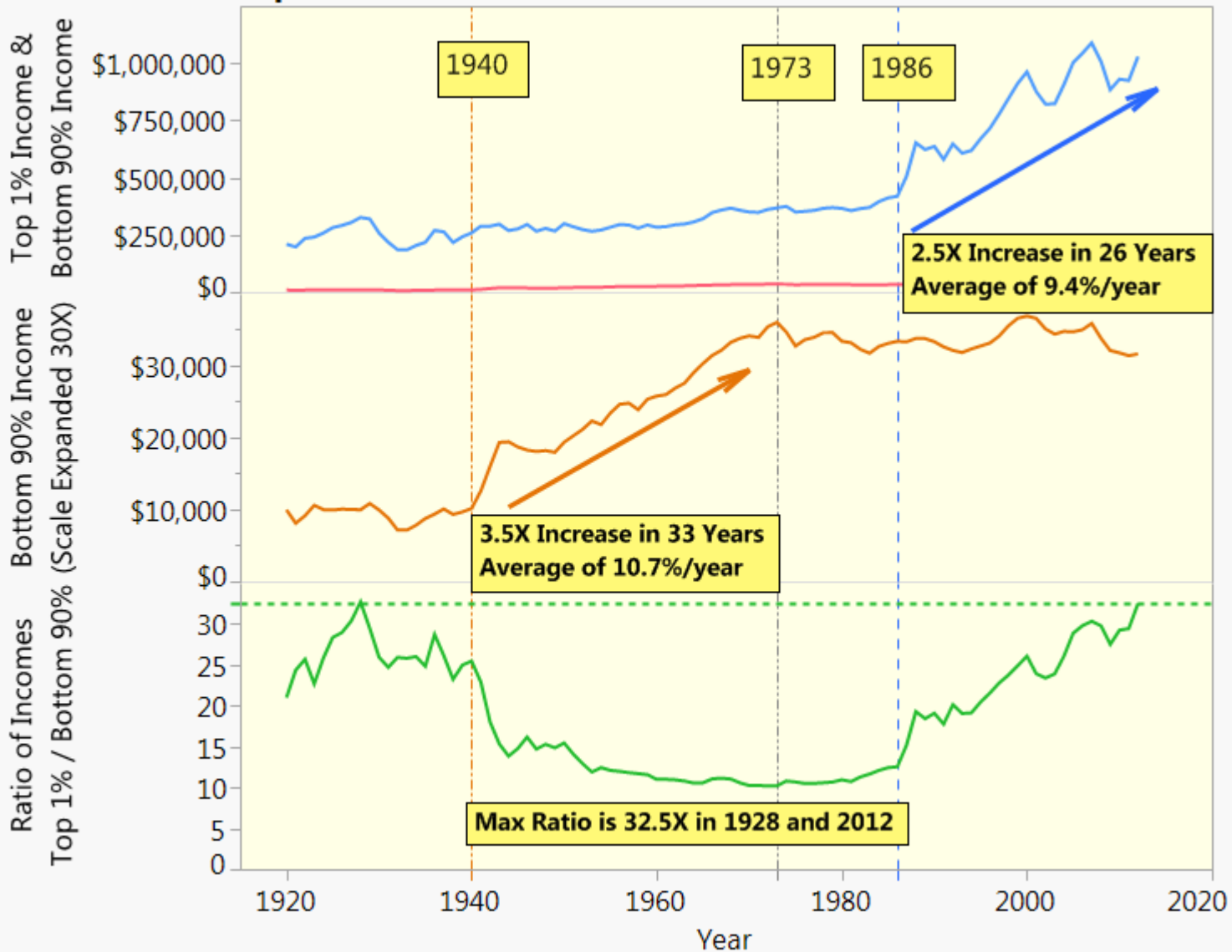
KAISER FUNG @JUNKCHARTS

Top 1% Income & Bottom 90% Income vs. Year



Where(2 rows excluded)

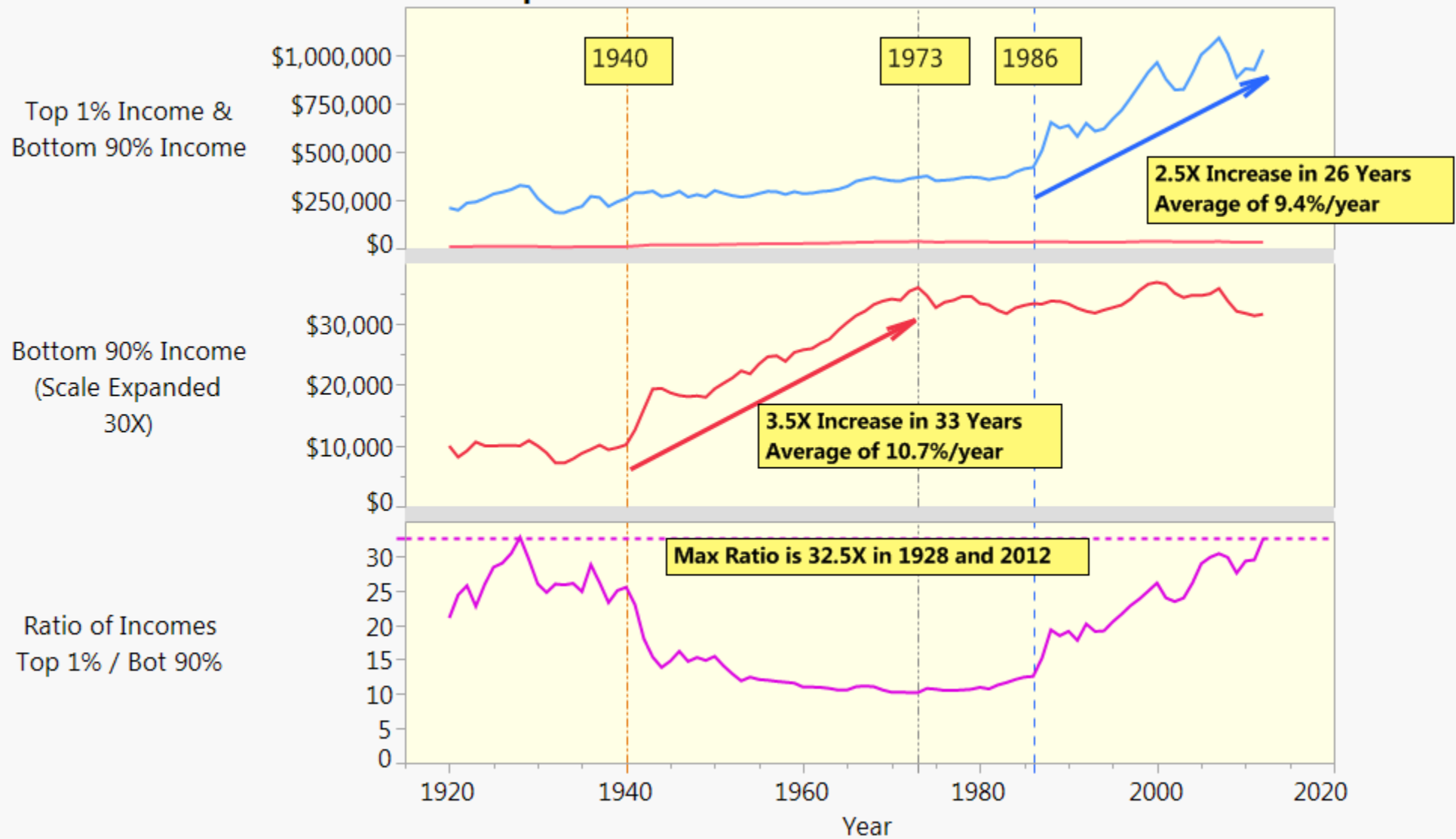
Top 1% Income & Bottom 90% Income vs. Year



Where(2 rows excluded)

1. Plot on same scale
2. Add gaps between plots
3. Make middle graph line color red too
4. Make bottom graph line color purple
5. Make Y-axes labels horizontal
6. Screen grid confusing
7. Plot more bins than average bottom 90% (e.g. 0-19, 20-39, 40-59, 60-79...)

Top 1% Income & Bottom 90% Income vs. Year





Xan Gregg @xangregg · Mar 28

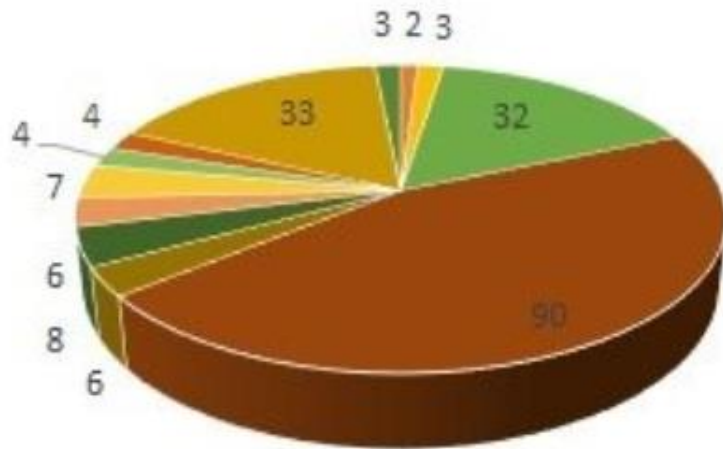


Remaking a 3D pie chart on Wikipedia for Pi Day, two weeks late. @junkcharts

#onelesspie

community.jmp.com/t5/JMP-Blog/Be...

Occupation of Woodmancote, 1881



ment Professional Domestic Agricu
 welfare Furniture making Food and Lodging Clothe
 Street Seller Non-specified Unknoc

Occupations of Woodmancote, 1888

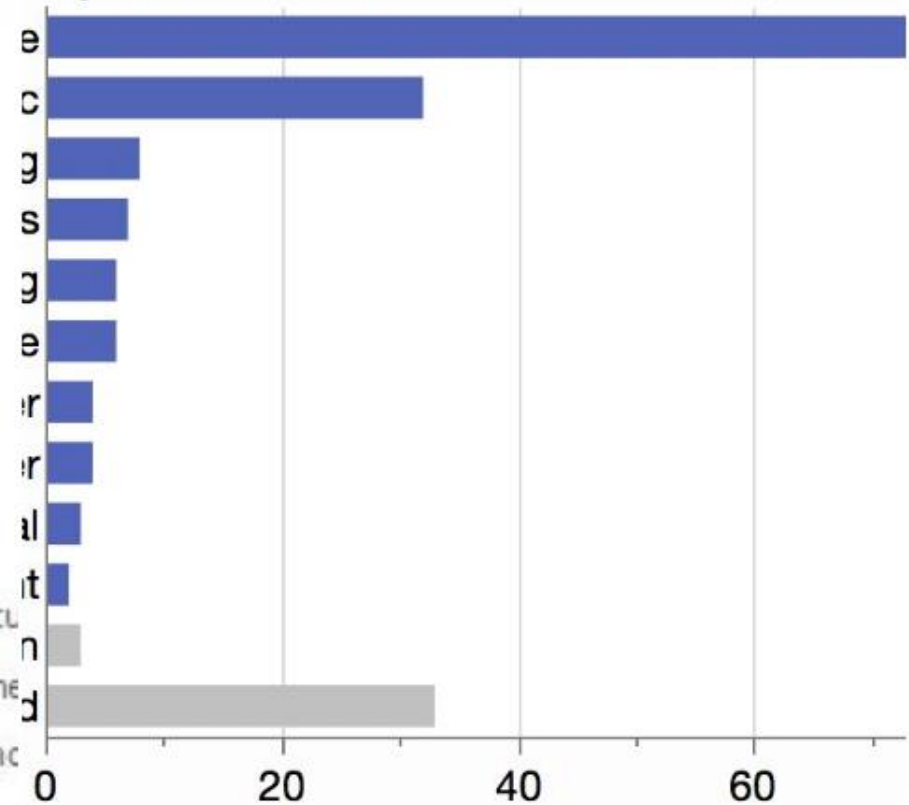


Table 86. Active dentists, by state: United States, selected years 2001–2015

[Data are based on reporting by dentists]

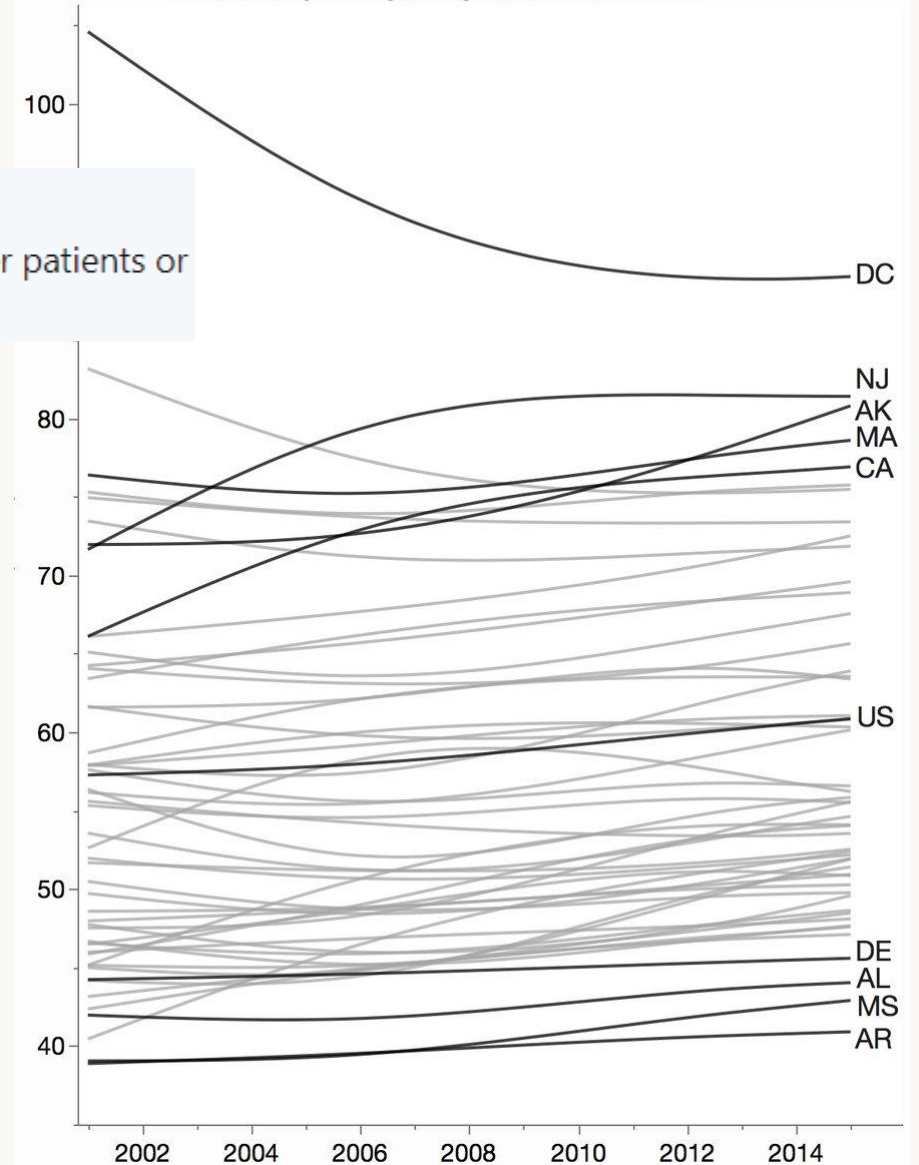
State	2001	2006	2013	2014	2015	2001	2006	2013	2014	2015
	Number of dentists					Number of dentists per 100,000 civilian population				
United States	163,345	172,603	191,347	192,313	195,722	57.32	57.85	60.47	60.30	60.89
Alabama	1,880	1,921	2,128	2,125	2,130	42.08	41.50	44.05	43.85	43.84
Alaska	457	489	577	588	597	72.11	72.41	78.24	79.78	80.85
Arizona										
Arkansas										
California										
Colorado										
Connecticut										
Delaware										
District of Columbia										
Florida										
Georgia	3,614	4,115	4,701	4,731	4,805	43.14	44.94	47.05	46.85	47.04
Hawaii	1,022	1,009	1,060	1,069	1,083	83.36	77.04	75.24	75.27	75.65
Idaho	690	864	932	907	939	52.27	58.83	57.79	55.48	56.74
Illinois	8,154	7,994	8,599	8,593	8,697	65.29	63.22	66.71	66.70	67.63
Indiana	2,870	2,842	3,116	3,104	3,157	46.84	44.88	47.42	47.05	47.69
Iowa	1,516	1,526	1,604	1,611	1,652	51.71	51.16	51.87	51.81	52.88
Kansas	1,314	1,347	1,461	1,471	1,482	48.63	48.75	50.47	50.68	50.90
Kentucky	2,256	2,287	2,488	2,441	2,445	55.46	54.20	56.56	55.32	55.25
Louisiana	2,058	2,017	2,221	2,199	2,262	45.96	46.88	48.00	47.30	48.43
Maine	598	642	693	669	674	46.51	48.50	52.15	50.29	50.70
Maryland	3,955	3,989	4,268	4,260	4,322	73.59	70.89	71.90	71.29	71.96
Massachusetts	4,898	4,797	5,232	5,303	5,319	76.56	74.84	77.99	78.50	78.28
Michigan	5,783	5,928	6,075	6,010	6,056	57.88	59.07	61.36	60.61	61.03
Minnesota	2,880	3,105	3,284	3,288	3,312	57.80	60.13	60.58	60.25	60.33
Mississippi	1,117	1,140	1,275	1,264	1,284	39.15	39.24	42.63	42.23	42.91
Missouri	2,634	2,666	2,900	2,952	2,943	46.69	45.63	47.98	48.68	48.38
Montana	511	525	598	612	619	56.34	55.11	58.95	59.81	59.93
Nebraska	1,103	1,117	1,203	1,223	1,250	64.13	63.01	64.36	64.95	65.92
Nevada	846	1,177	1,448	1,446	1,525	40.32	46.66	51.89	50.95	52.75
New Hampshire	735	815	847	830	851	58.54	62.29	64.04	62.50	63.96
New Jersey	6,054	6,922	7,238	7,256	7,303	71.28	79.92	81.26	81.17	81.52
New Mexico	814	861	1,062	1,065	1,060	44.44	43.88	50.89	51.07	50.84
New York	14,309	14,062	14,468	14,428	14,560	74.98	73.61	73.48	73.06	73.55
North Carolina	3,474	4,016	4,719	4,791	5,038	42.31	45.04	47.93	48.20	50.17
North Dakota	305	311	394	405	419	47.73	47.89	54.45	54.73	55.36
Ohio	5,929	5,797	6,003	5,978	6,078	52.07	50.49	51.87	51.55	52.34
Oklahoma	1,664	1,749	1,943	1,937	1,966	47.99	48.66	50.42	49.93	50.26
Oregon	2,197	2,431	2,708	2,700	2,785	63.35	66.22	68.94	67.99	69.12
Pennsylvania	7,595	7,454	7,698	7,783	7,774	61.75	59.58	60.22	60.83	60.72
Rhode Island	588	576	566	553	572	55.62	54.18	53.76	52.42	54.15
South Carolina	1,839	1,958	2,288	2,229	2,350	45.24	44.93	47.98	46.16	48.00
South Dakota	348	382	457	460	460	45.91	48.78	54.07	53.91	53.58
Tennessee	2,912	2,947	3,246	3,252	3,273	50.64	48.40	49.97	49.67	49.59
Texas	9,642	10,365	13,391	13,692	14,268	45.23	44.37	50.53	50.75	51.94
Utah	1,409	1,559	1,892	1,864	1,885	61.70	61.73	65.16	63.30	62.92
Vermont	354	343	365	347	355	57.82	55.07	58.20	55.36	56.71
Virginia	4,189	4,367	5,194	5,277	5,329	58.19	56.91	62.82	63.36	63.57
Washington	3,957	4,312	4,951	5,050	5,219	66.11	67.68	71.00	71.50	72.79
West Virginia	863	835	890	881	897	47.91	45.68	48.03	47.65	48.64
Wisconsin	3,069	2,860	3,215	3,202	3,193	56.76	51.28	55.97	55.60	55.33
Wyoming	266	266	309	323	317	53.77	50.89	52.99	55.28	54.09



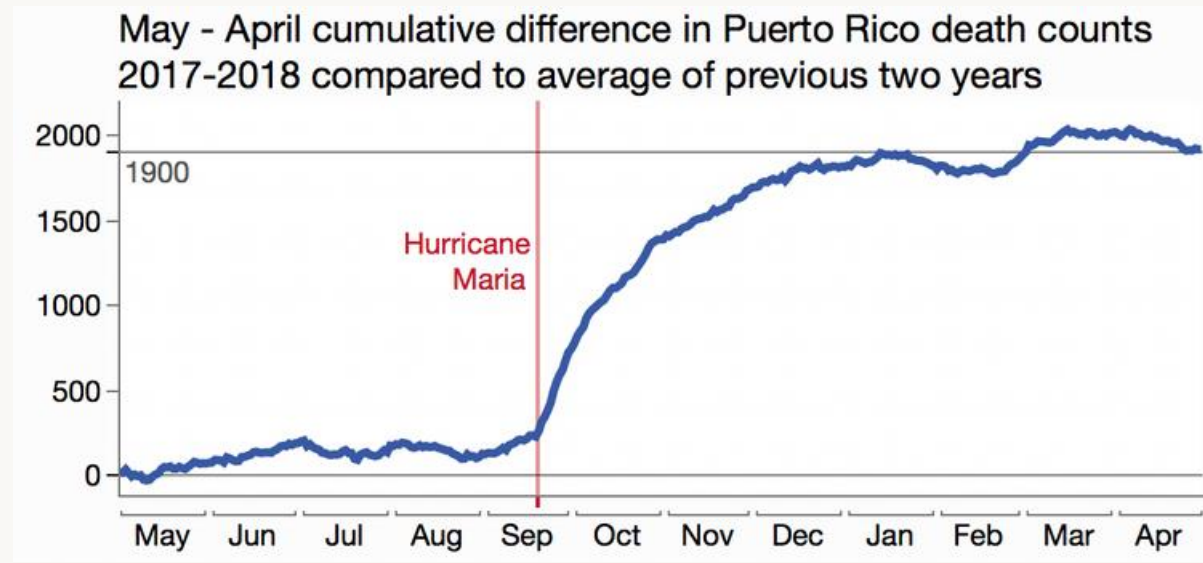
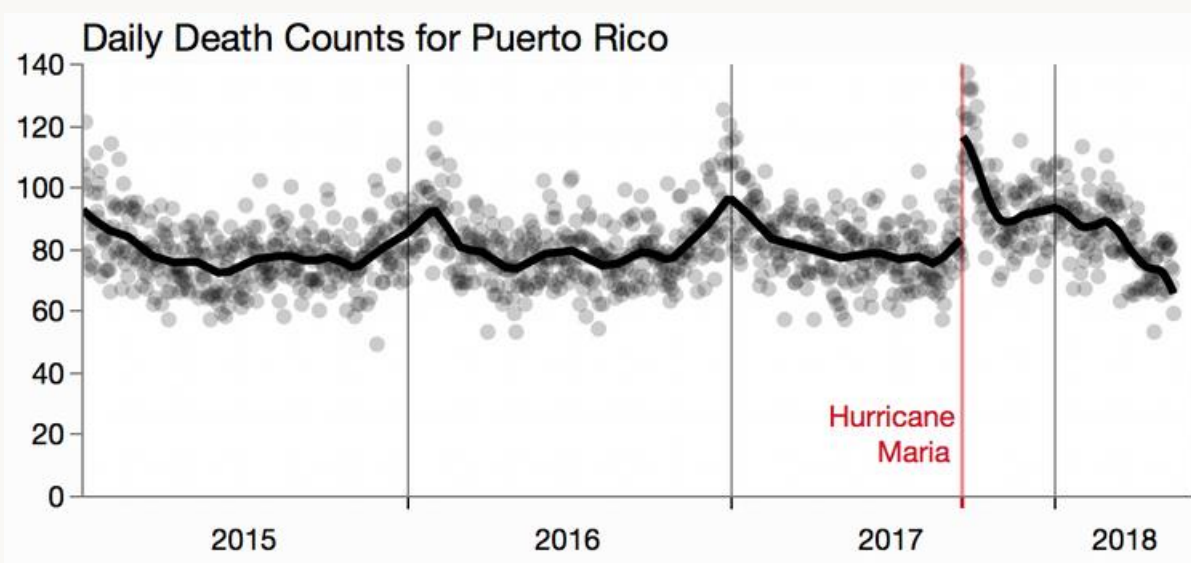
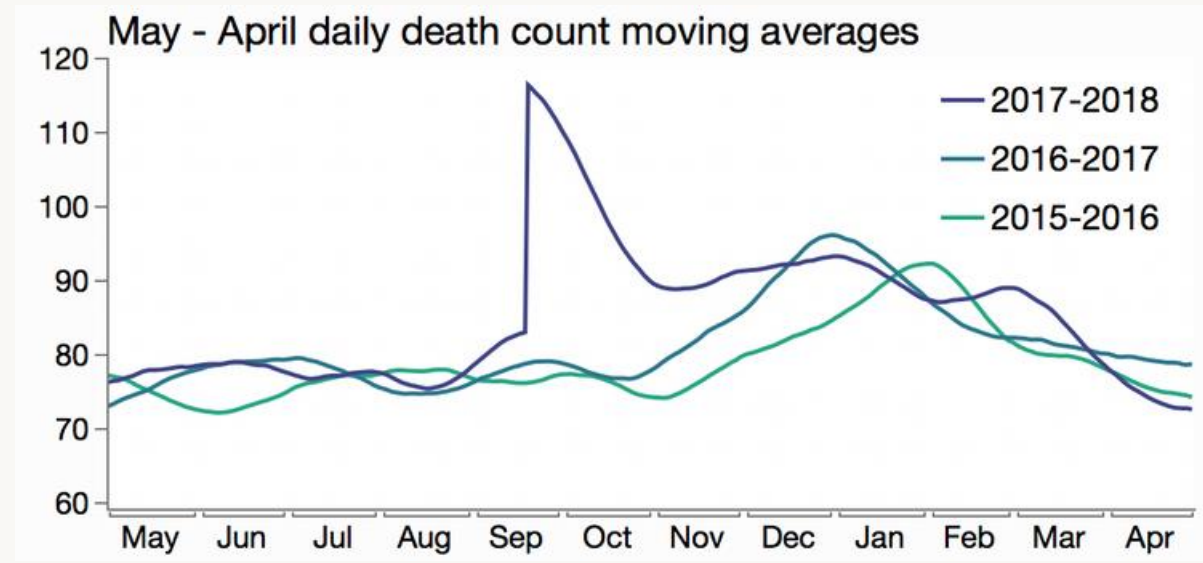
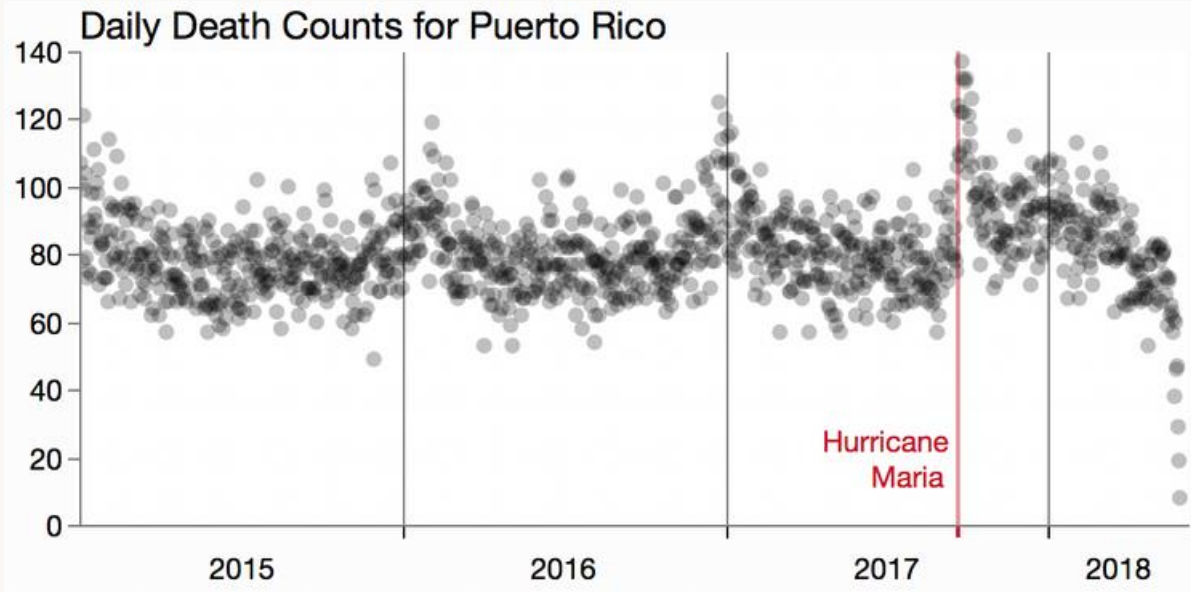
Xan Gregg @xangregg · May 27

Dentists per capita in US states. What going on with DC? Commuter patients or extra teeth grinding...?

Dentists per capita by state since 2001



<https://www.cdc.gov/nchs/data/hus/2016/086.pdf>



<https://community.jmp.com/t5/JMP-Blog/Visualizing-Puerto-Rico-s-Hurricane-Maria-daily-mortality/ba-p/60243>

All Graphs Are Wrong, but Some Are Useful

Back to Xan's Talk...

View Xan's Original Presentation at <https://community.jmp.com/docs/DOC-8270>

All models are wrong, but some are useful.

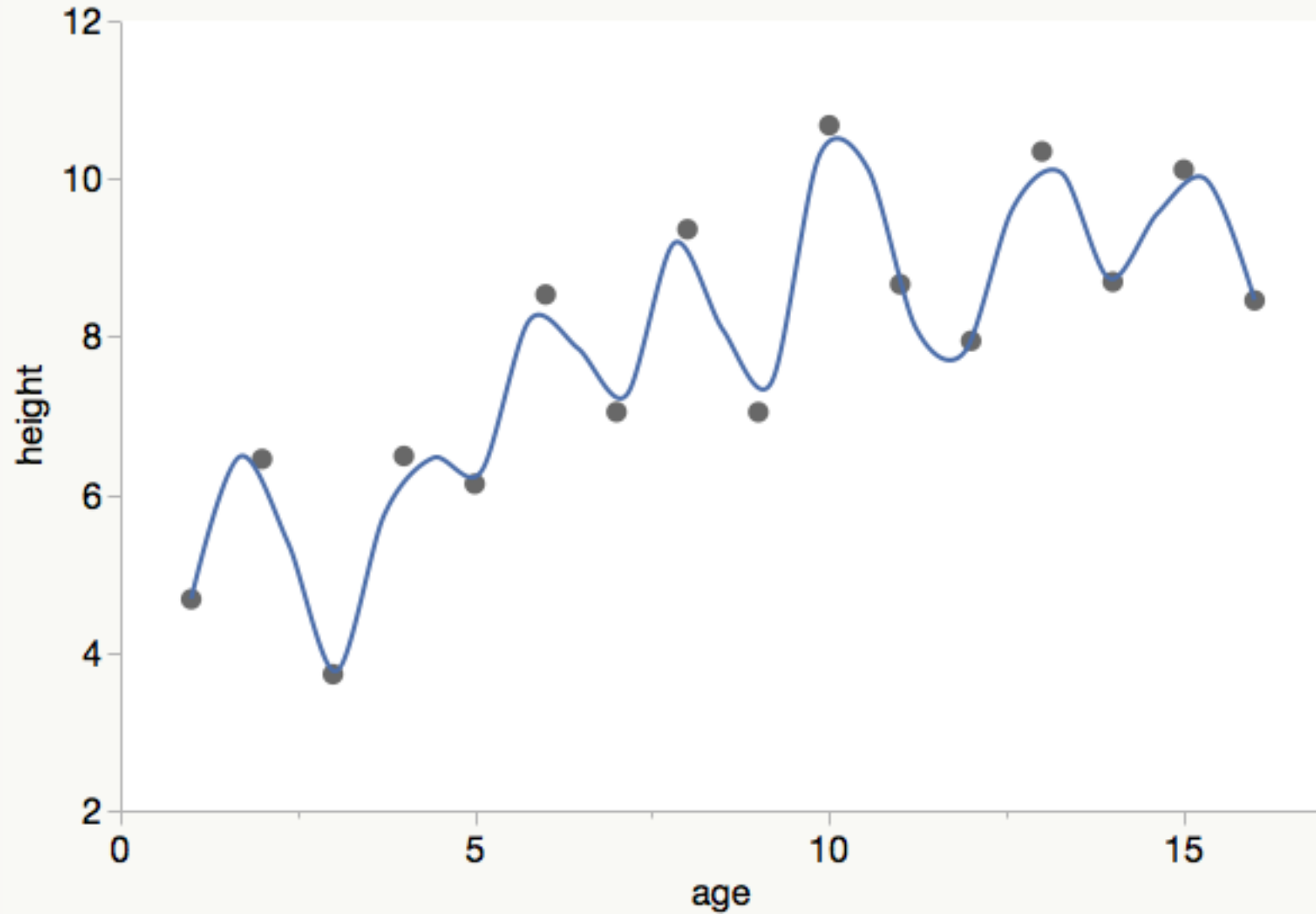
George E. P. Box (1979)



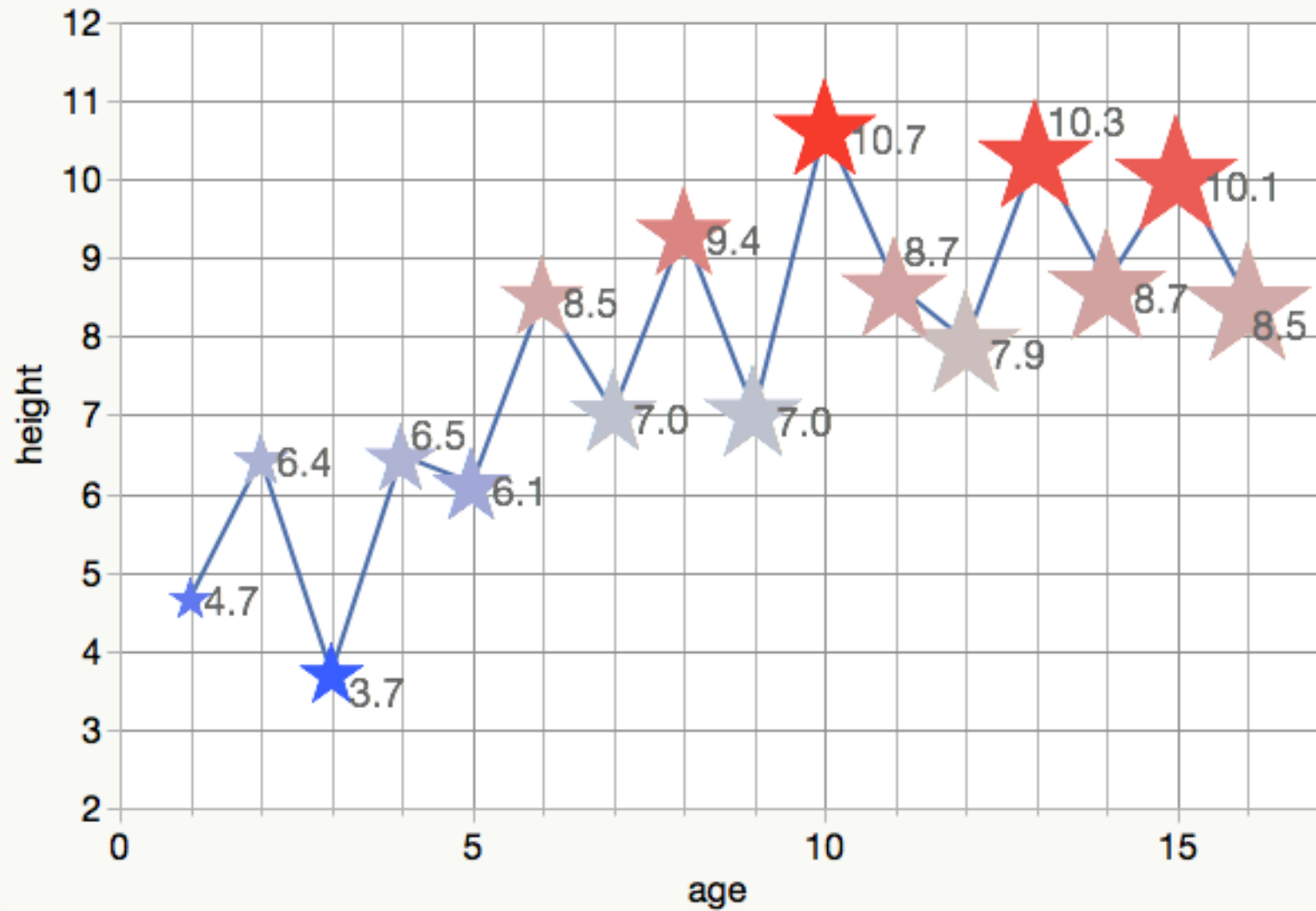
Since all models are wrong the scientist cannot obtain a “correct” one by excessive elaboration. ... overelaboration and overparameterization is often the mark of mediocrity.

George E. P. Box (1976)

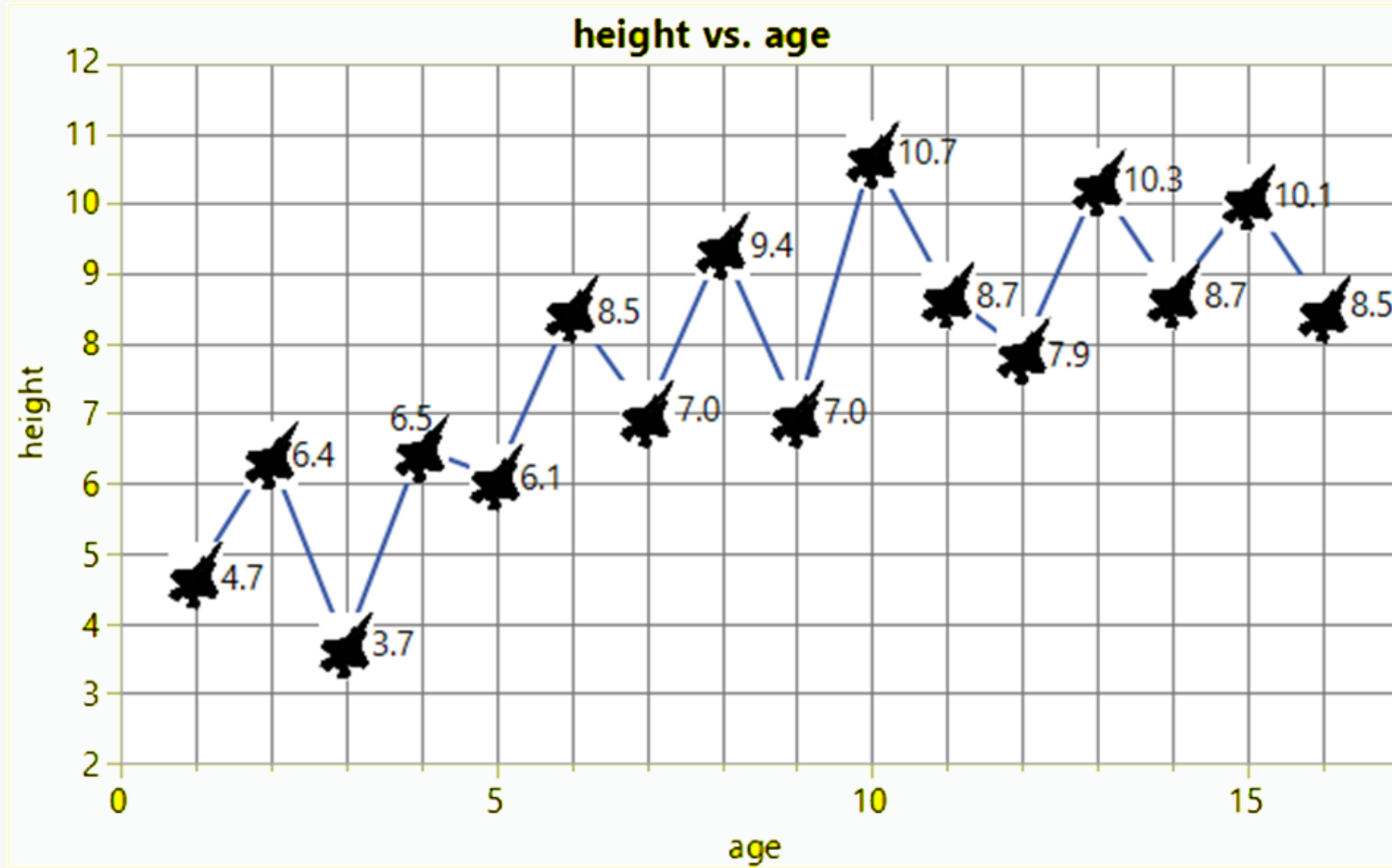
Overelaboration in Modeling



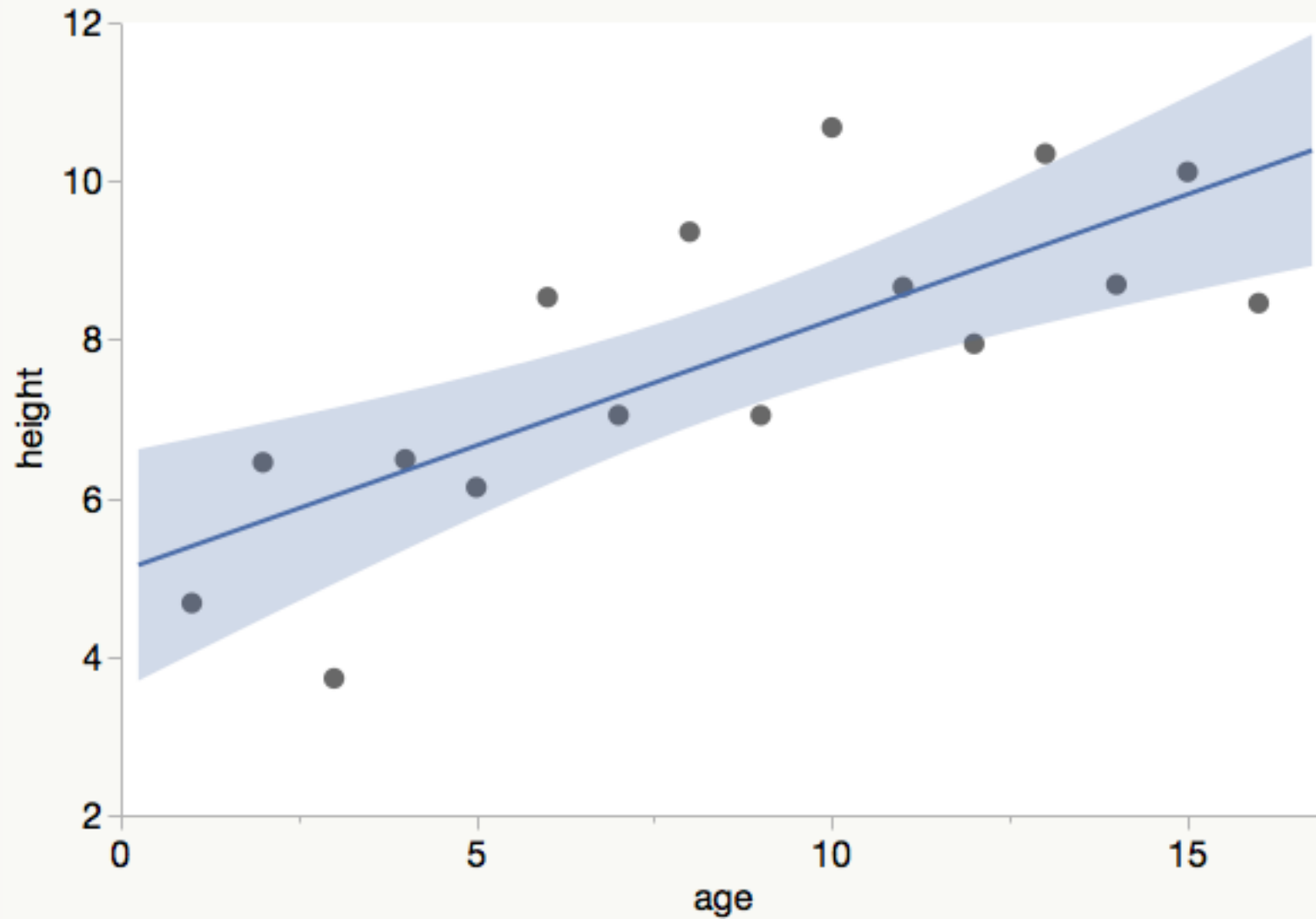
Overelaboration in Graphing



Overelaboration in Graphing



Information rather than Data



Admiral James “Sandy” Winnefeld Jr.

Vice Chairman of the Joint Chiefs of Staff (2011-2015)

May 2011, MORS MDA Workshop, Point Loma, CA

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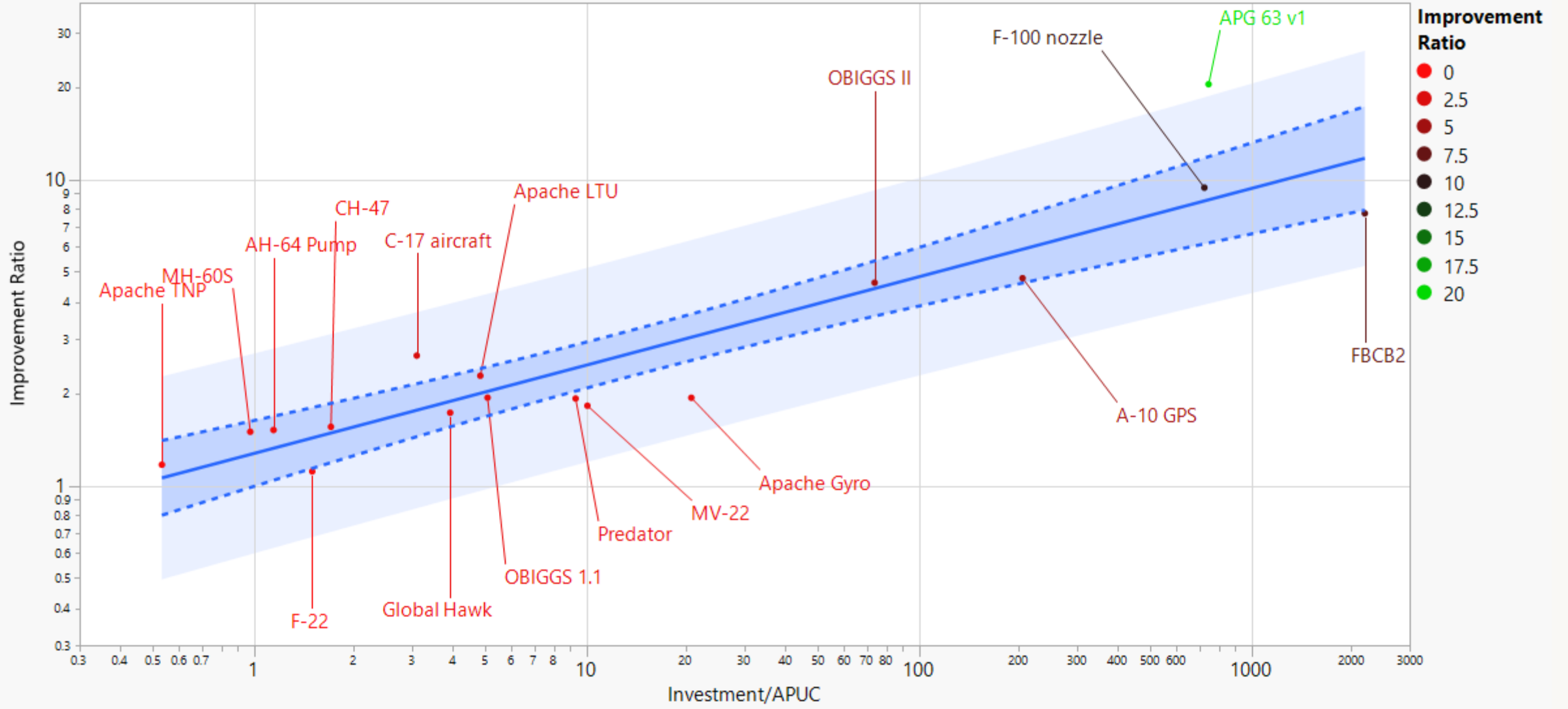
“I’ve got data.

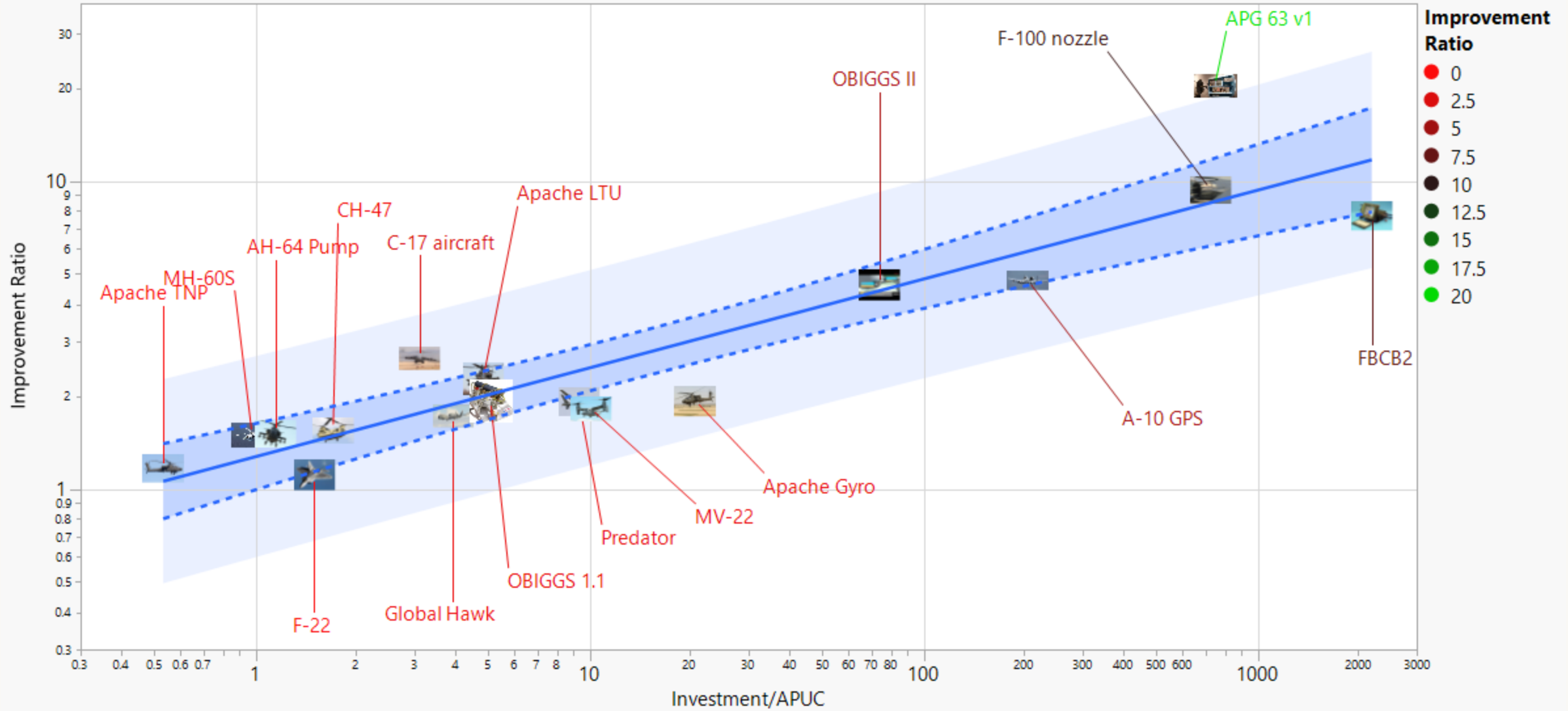
What I need is information.

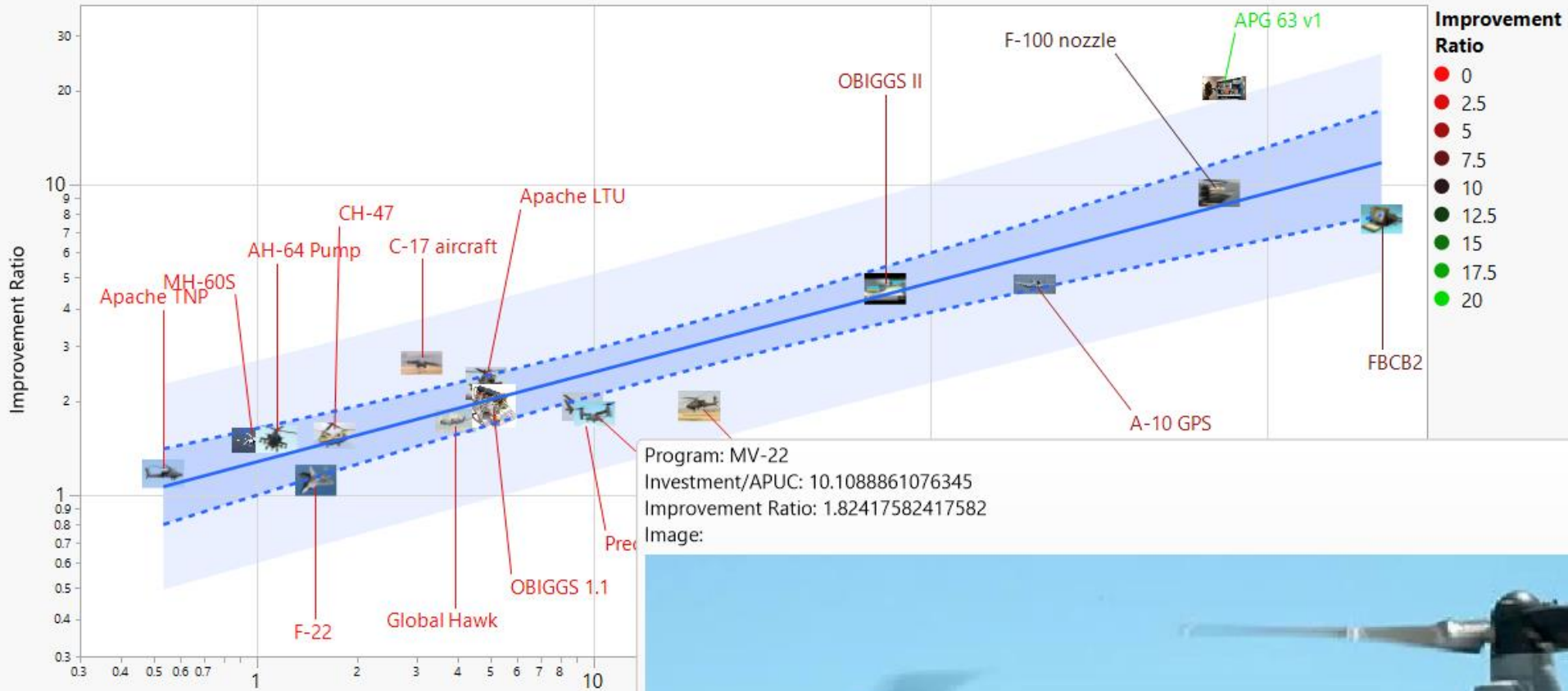
More than that I need knowledge.

And, more than that I need understanding.

So, I can take action.”





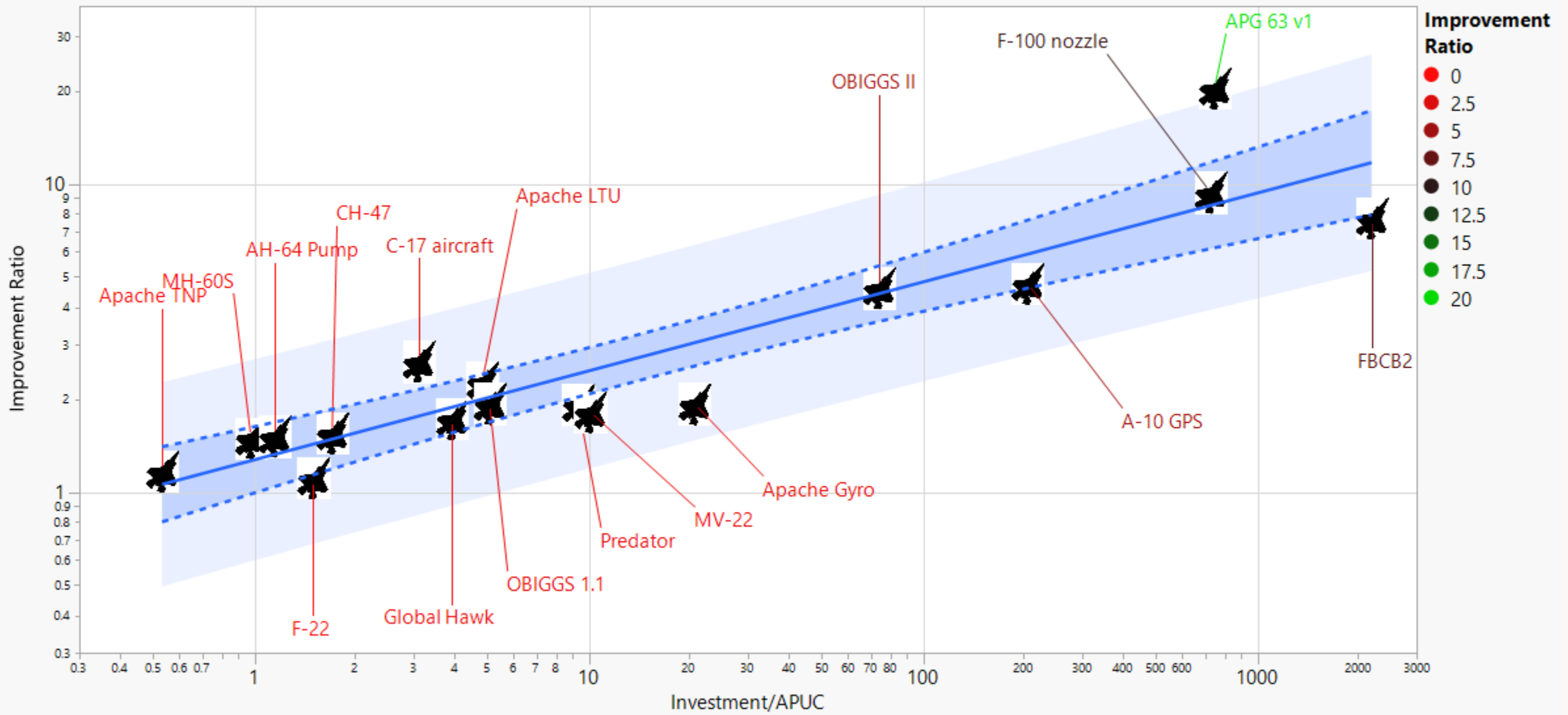


Program: MV-22
Investment/APUC: 10.1088861076345
Improvement Ratio: 1.82417582417582
Image:



“Never underestimate impressing the commander.”

- Transformed Fit Log to Log
- Transformed Fit Log to Log



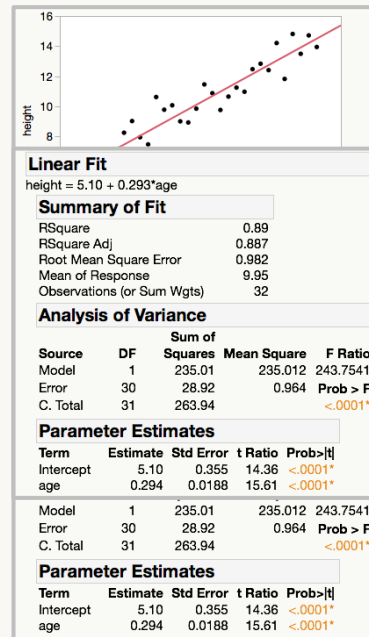
**“Never underestimate
impressing the commander.”**

Statistical Discovery

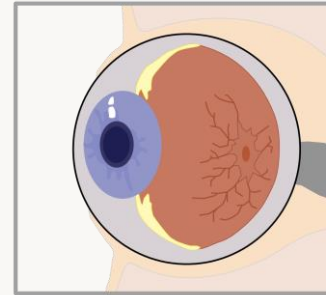
Collect

x	mid	y	lo	hi	sensor
84	2.60	3.43	1.60	3.60	A
990	-1.50	-2.47	-2.50	-0.50	A
203	3.46	4.52	2.46	4.46	A
290	1.08	0.39	0.08	2.08	A
742	3.28	2.41	2.28	4.28	A
379	-2.31	-2.05	-3.31	-1.31	A
646	1.05	2.10	0.05	2.05	A
178	4.22	3.28	3.22	5.22	A
272	1.27	2.18	0.27	2.27	A
670	2.00	1.21	1.00	3.00	A
689	2.41	2.15	1.41	3.41	A
233	3.09	2.07	2.09	4.09	A
593	-1.09	0.77	-2.09	-0.09	A
295	1.08	0.1	0.08	2.08	A
54	1.77	0.94	0.77	2.77	A
82	2.58	3.1	1.58	3.58	A
484	3.57	-4.6	-4.67	2.67	A
2	-1.02	0.2	-1.02	0.98	A
188	3.33	3.6	2.63	4.63	A
18	0.78	1.84	0.2	1.78	A
439	-3.86	-3.06	-4.86	-2.86	A
167	3.94	3.06	2.94	4.94	A
463	-3.59	-2.83	-4.59	-2.59	A
180	3.79	3.07	2.79	4.79	A
69	2.25	2.90	1.25	3.25	A
848	3.13	3.08	2.13	4.13	A
585	-1.49	-0.58	-2.49	-0.49	A
276	1.28	1.81	0.28	2.28	A
340	-0.71	-0.24	-1.71	0.29	A
379	-2.06	-1.82	-3.06	-1.06	A
546	-2.84	-3.78	-3.84	-1.84	A
969	-3.78	-3.37	-4.78	-2.78	B
226	-0.47	-0.99	-1.47	0.53	B

Analyze



See



Understand

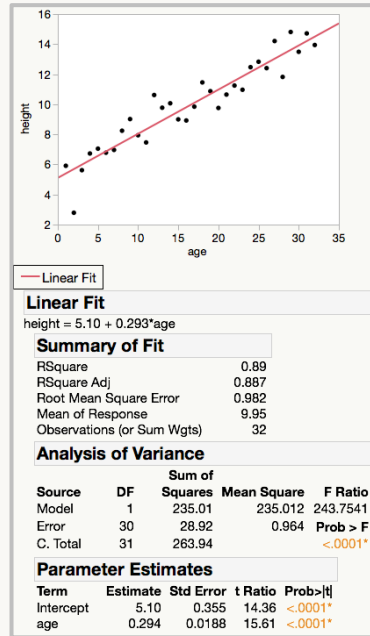


Statistical Discovery

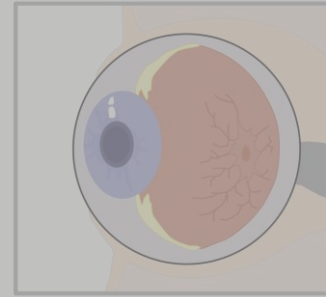
Collect

x	mid	y	lo	hi	sensor
84	2.60	3.43	1.60	3.60	A
990	-1.50	-2.47	-2.50	-0.50	A
203	3.46	4.52	2.46	4.46	A
290	1.08	0.39	0.08	2.08	A
742	3.28	2.41	2.28	4.28	A
379	-2.31	-2.05	-3.31	-1.31	A
646	1.05	2.10	0.05	2.05	A
178	4.22	3.28	3.22	5.22	A
272	1.27	2.18	0.27	2.27	A
670	2.00	1.21	1.00	3.00	A
689	2.41	2.15	1.41	3.41	A
233	3.09	2.07	2.09	4.09	A
593	-1.09	-0.77	-2.09	-0.09	A
295	1.08	0.21	0.08	2.08	A
54	1.77	0.94	0.77	2.77	A
82	2.58	3.52	1.58	3.58	A
484	-3.67	-4.69	-4.67	-2.67	A
2	-0.02	0.22	-1.02	0.98	A
188	3.63	3.62	2.63	4.63	A
18	0.78	1.84	-0.22	1.78	A
439	-3.86	-3.88	-4.86	-2.86	A
167	3.94	3.06	2.94	4.94	A
463	-3.59	-2.83	-4.59	-2.59	A
180	3.79	3.07	2.79	4.79	A
69	2.25	2.90	1.25	3.25	A
848	3.13	3.08	2.13	4.13	A
585	-1.49	-0.58	-2.49	-0.49	A
276	1.28	1.81	0.28	2.28	A
340	-0.71	-0.24	-1.71	0.29	A
379	-2.06	-1.82	-3.06	-1.06	A
546	-2.84	-3.78	-3.84	-1.84	A
969	-3.78	-3.37	-4.78	-2.78	B
226	-0.47	-0.99	-1.47	0.53	B

Analyze



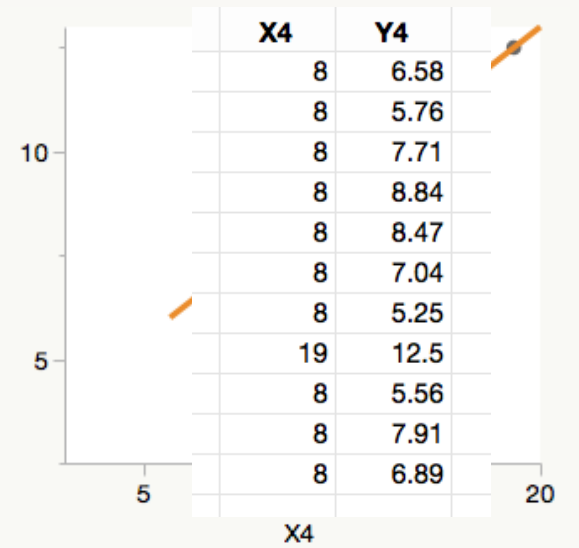
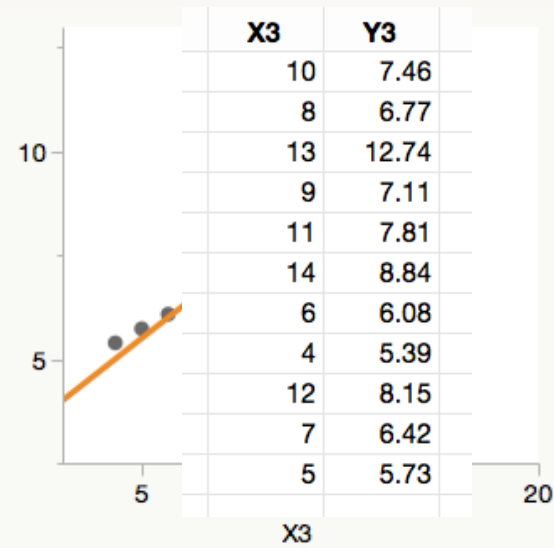
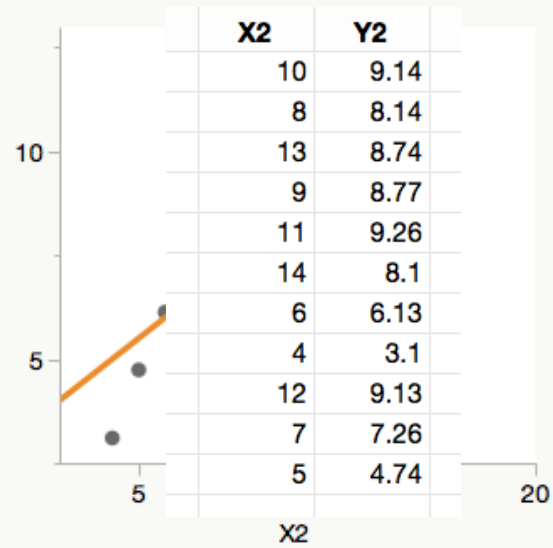
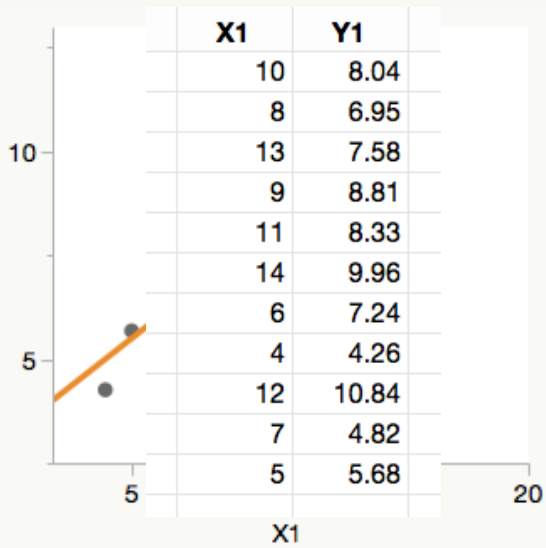
See



Understand



Why graph? Anscombe's Quartet



RSquare	0.67
RSquare Adj	0.63
Root Mean Square Error	1.2
Mean of Response	7.5
Observations (or Sum Wgts)	11

RSquare	0.67
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RSquare Adj	0.63
Root Mean Square Error	1.2
Mean of Response	7.5
Observations (or Sum Wgts)	11

Term	Estimate	Std Error	Prob> t
Intercept	3.00	1.125	0.0257*
X1	0.50	0.118	0.0022*

Term	Estimate	Std Error	Prob> t
Intercept	3.00	1.125	0.0258*
X2	0.50	0.118	0.0022*

Term	Estimate	Std Error	Prob> t
Intercept	3.00	1.124	0.0256*
X3	0.50	0.118	0.0022*

Term	Estimate	Std Error	Prob> t
Intercept	3.00	1.124	0.0256*
X4	0.50	0.118	0.0022*

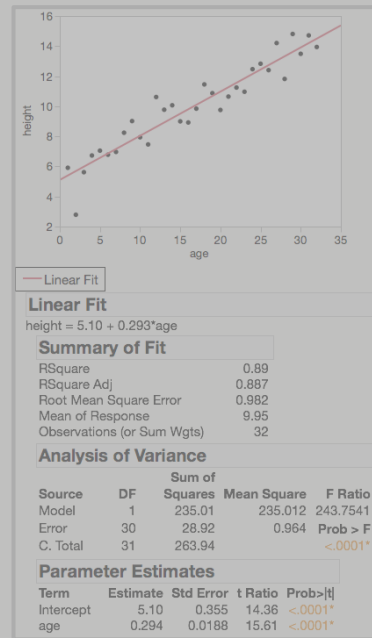
Statistical Discovery

Collect

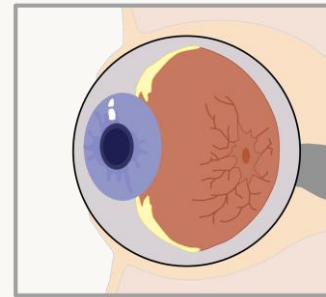
x	mid	y	lo	hi	sensor
84	2.60	3.43	1.60	3.60	A
990	-1.50	-2.47	-2.50	-0.50	A
203	3.46	4.52	2.46	4.46	A
290	1.08	0.39	0.08	2.08	A
742	3.28	2.41	2.28	4.28	A
379	-2.31	-2.05	-3.31	-1.31	A
646	1.05	2.10	0.05	2.05	A
178	4.22	3.28	3.22	5.22	A
272	1.27	2.18	0.27	2.27	A
670	2.00	1.21	1.00	3.00	A
689	2.41	2.15	1.41	3.41	A
233	3.09	2.07	2.09	4.09	A
593	-1.09	-0.77	-2.09	-0.09	A
295	1.08	0.21	0.08	2.08	A
54	1.77	0.94	0.77	2.77	A
82	2.58	3.52	1.58	3.58	A
484	-3.67	-4.69	-4.67	-2.67	A
2	-0.02	0.22	-1.02	0.98	A
188	3.63	3.62	2.63	4.63	A
18	0.78	1.84	-0.22	1.78	A
439	-3.86	-3.88	-4.86	-2.86	A
167	3.94	3.06	2.94	4.94	A
463	-3.59	-2.83	-4.59	-2.59	A
180	3.79	3.07	2.79	4.79	A
69	2.25	2.90	1.25	3.25	A
848	3.13	3.08	2.13	4.13	A
585	-1.49	-0.58	-2.49	-0.49	A
276	1.28	1.81	0.28	2.28	A
340	-0.71	-0.24	-1.71	0.29	A
379	-2.06	-1.82	-3.06	-1.06	A
546	-2.84	-3.78	-3.84	-1.84	A
969	-3.78	-3.37	-4.78	-2.78	B
226	-0.47	-0.99	-1.47	0.53	B



Analyze



See



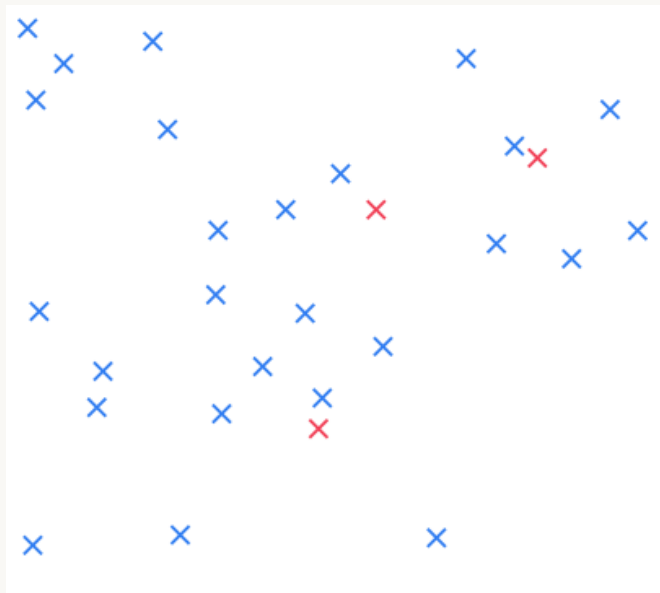
Understand



Pre-attentive Processing



Pre-attentive Processing



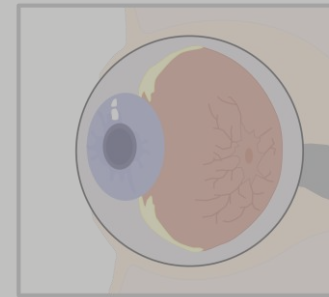
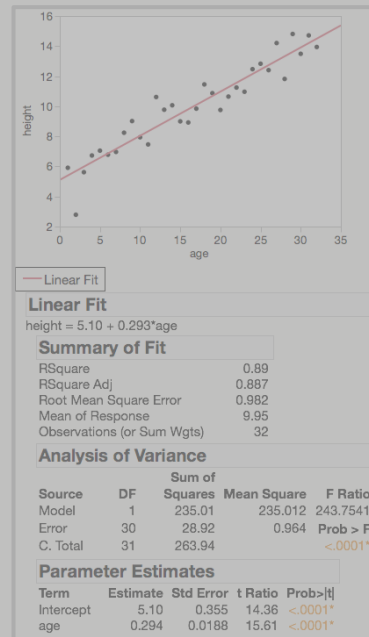
Statistical Discovery

Collect

x	mid	y	lo	hi	sensor
84	2.60	3.43	1.60	3.60	A
990	-1.50	-2.47	-2.50	-0.50	A
203	3.46	4.52	2.46	4.46	A
290	1.08	0.39	0.08	2.08	A
742	3.28	2.41	2.28	4.28	A
379	-2.31	-2.05	-3.31	-1.31	A
646	1.05	2.10	0.05	2.05	A
178	4.22	3.28	3.22	5.22	A
272	1.27	2.18	0.27	2.27	A
670	2.00	1.21	1.00	3.00	A
689	2.41	2.15	1.41	3.41	A
233	3.09	2.07	2.09	4.09	A
593	-1.09	-0.77	-2.09	-0.09	A
295	1.08	0.21	0.08	2.08	A
54	1.77	0.94	0.77	2.77	A
82	2.58	3.52	1.58	3.58	A
484	-3.67	-4.69	-4.67	-2.67	A
2	-0.02	0.22	-1.02	0.98	A
188	3.63	3.62	2.63	4.63	A
18	0.78	1.84	-0.22	1.78	A
439	-3.86	-3.88	-4.86	-2.86	A
167	3.94	3.06	2.94	4.94	A
463	-3.59	-2.83	-4.59	-2.59	A
180	3.79	3.07	2.79	4.79	A
69	2.25	2.90	1.25	3.25	A
848	3.13	3.08	2.13	4.13	A
585	-1.49	-0.58	-2.49	-0.49	A
276	1.28	1.81	0.28	2.28	A
340	-0.71	-0.24	-1.71	0.29	A
379	-2.06	-1.82	-3.06	-1.06	A
546	-2.84	-3.78	-3.84	-1.84	A
969	-3.78	-3.37	-4.78	-2.78	B
226	-0.47	-0.99	-1.47	0.53	B



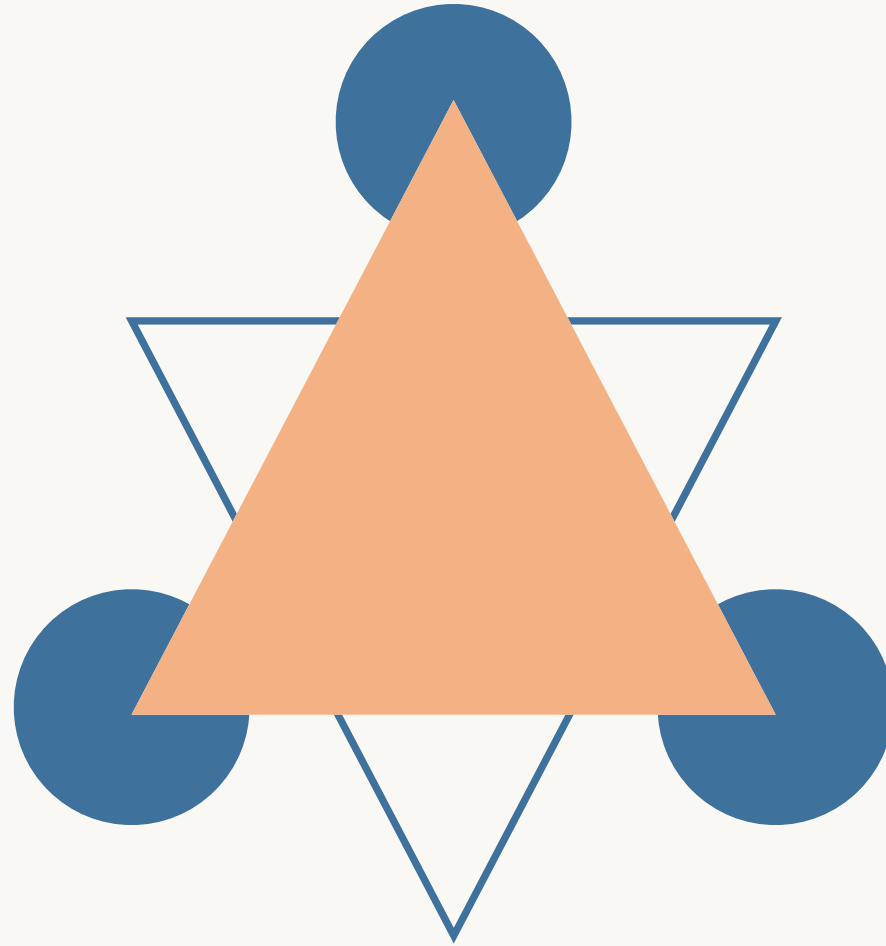
Analyze



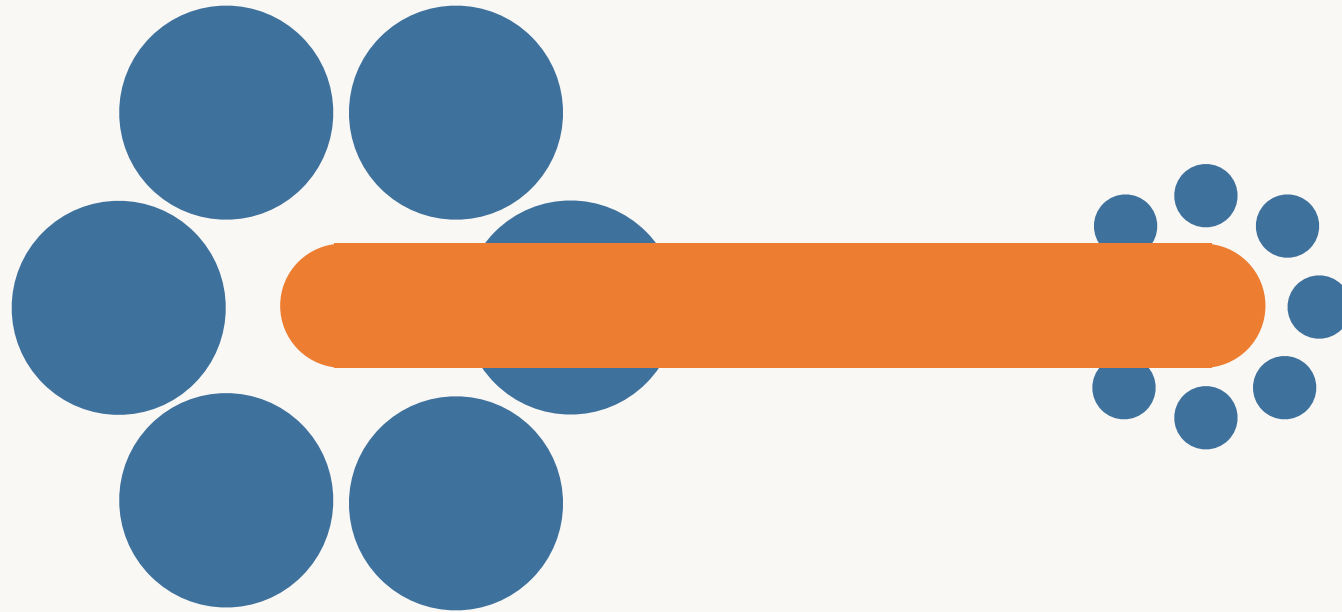
Understand



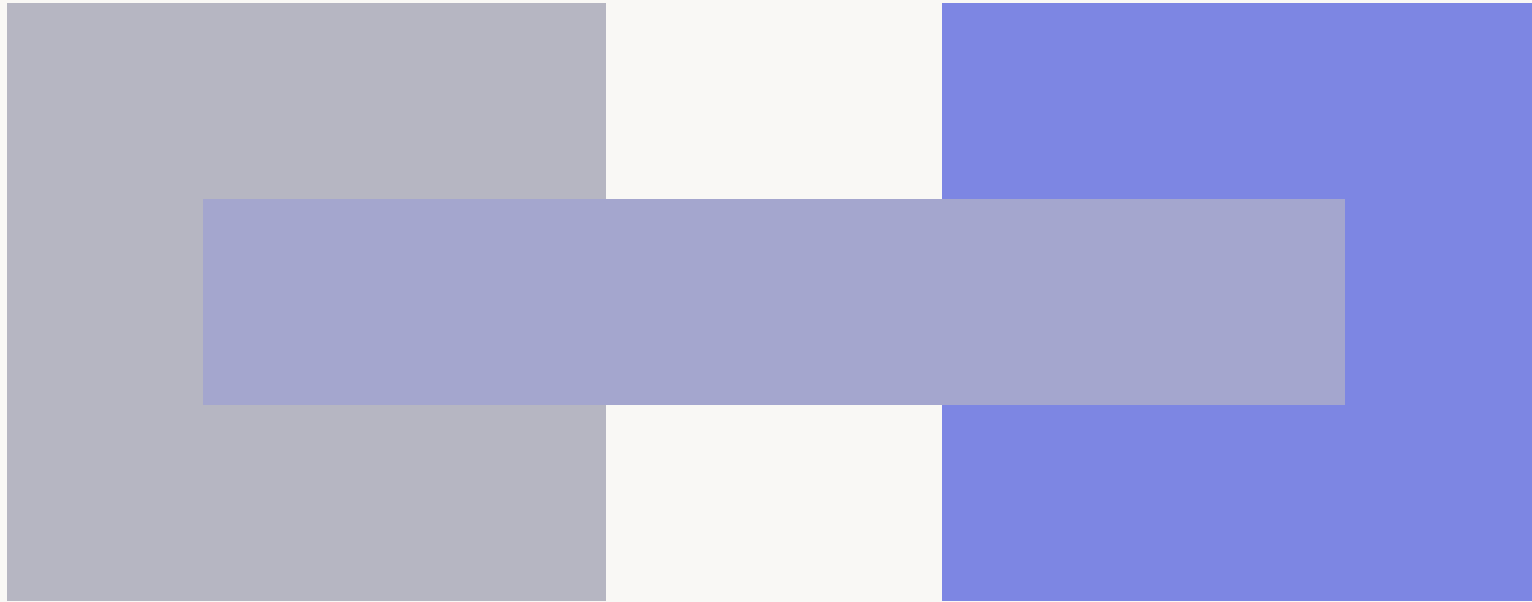
Kanizsa Triangle



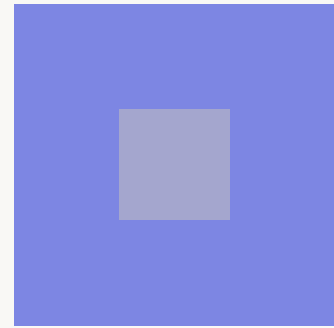
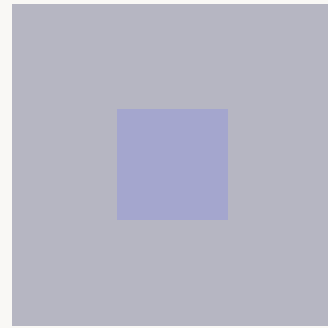
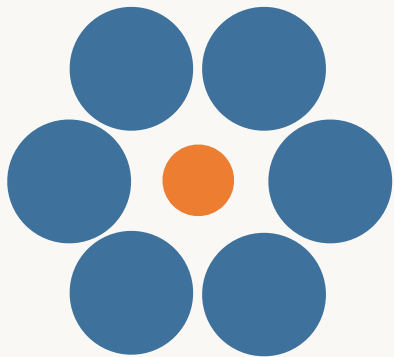
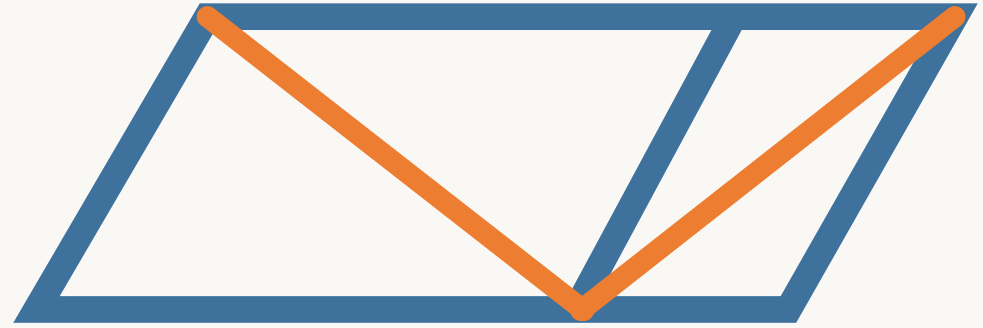
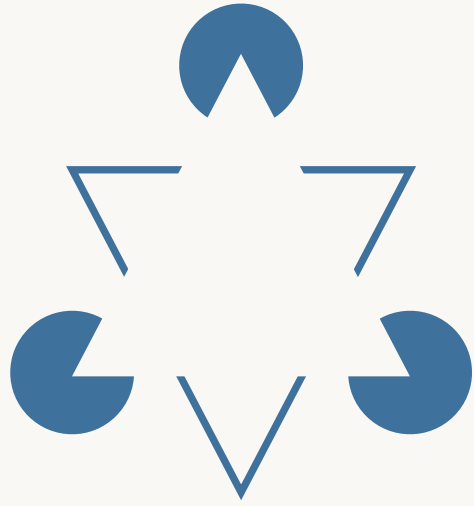
Ebbinghaus Illusion



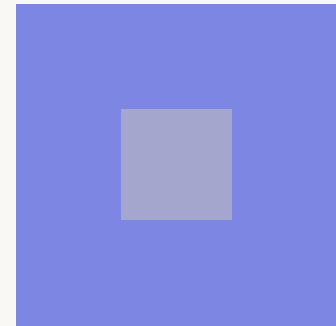
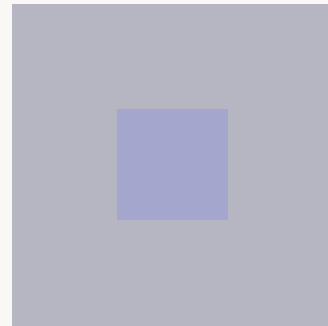
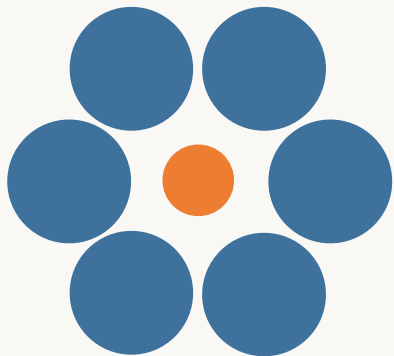
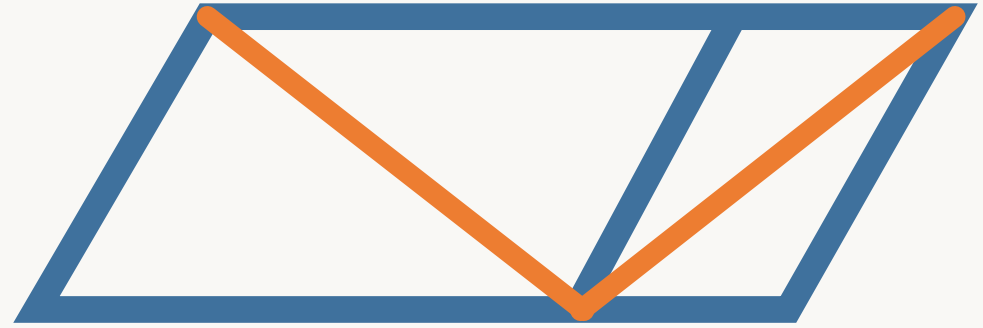
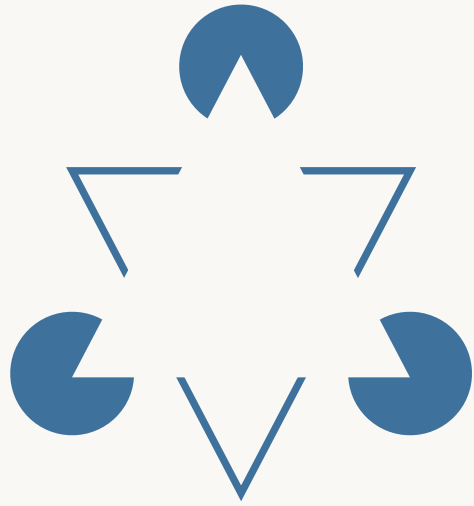
Chubb Illusion



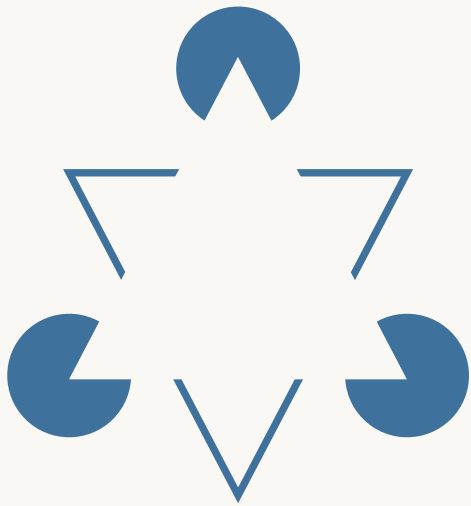
Features, not Flaws



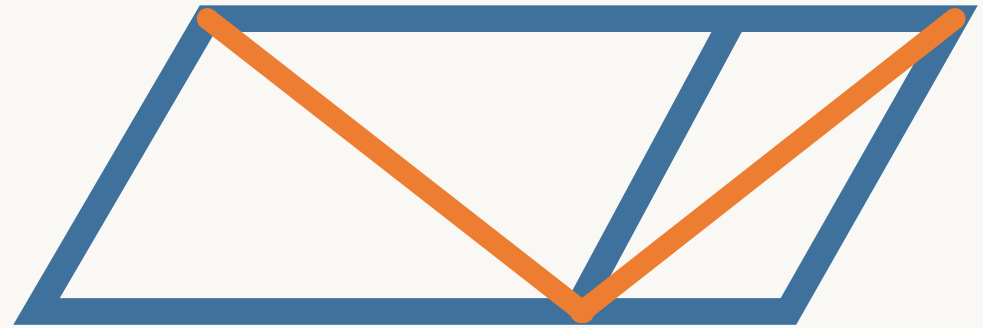
Resistance to Alternative Denotation



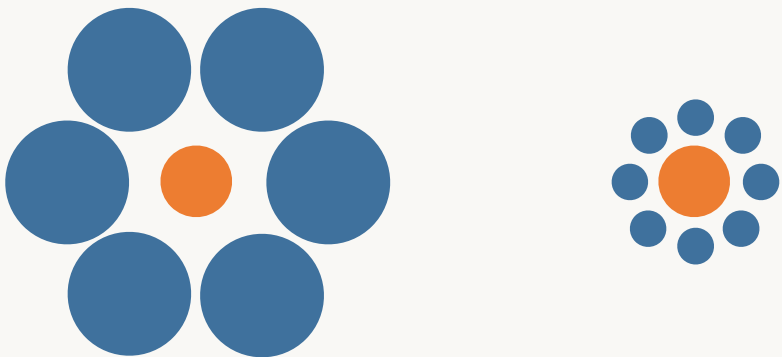
Shape



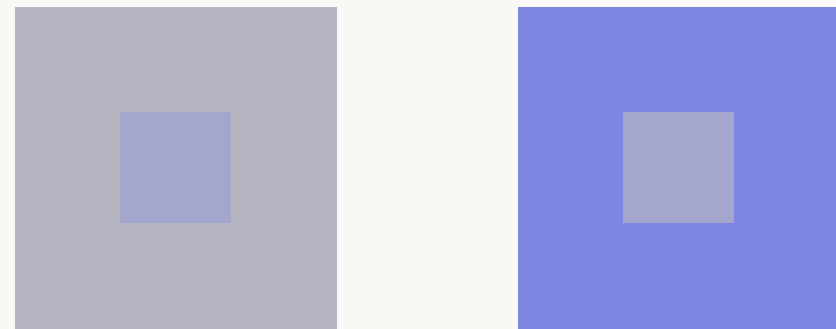
Length



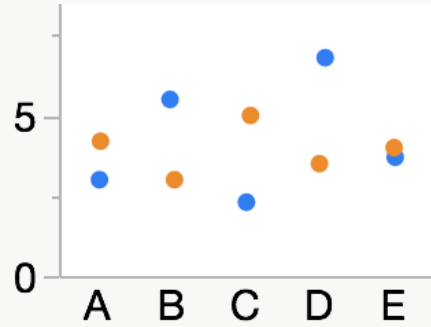
Size



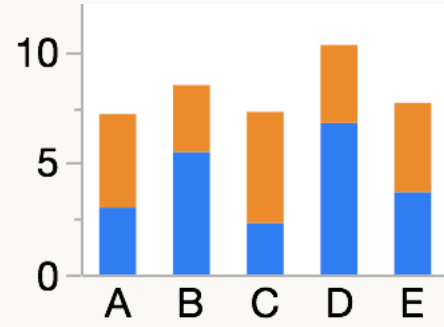
Color



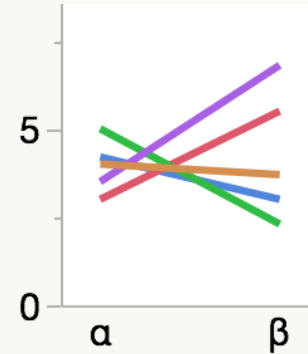
Graphic Attributes: Quantitative Scales



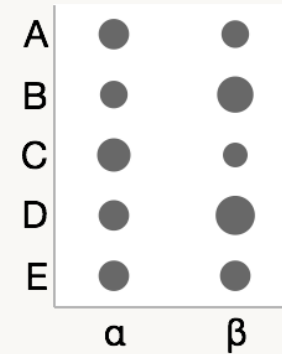
Position



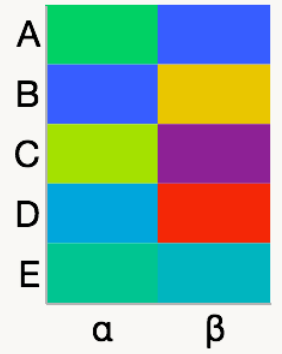
Length



Slope



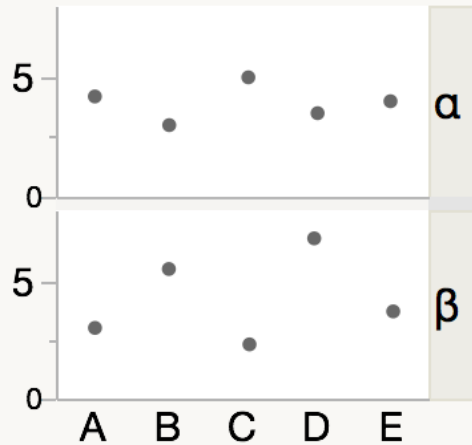
Area



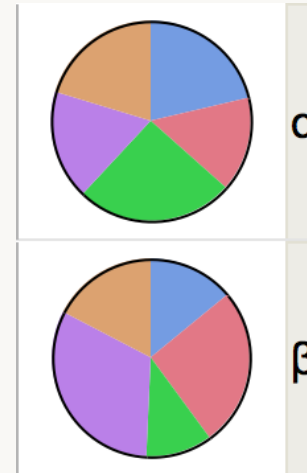
Color Hue



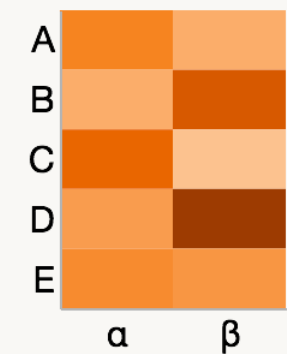
Position (unaligned)



Angle



Color Density



Putting Theory Into Practice



- Information vs. Data
- Distance perception
- Color perception

- Graph the information
- Use (don't abuse) pre-attentive processing
- Choose appropriate color scales
- Less is more

All Graphs Are Wrong,
but *Yours* Can Be Useful

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