

# BIOMED SCI 552:

# STATISTICAL THINKING

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LECTURE 7: EXPLORATORY DATA ANALYSIS

# QUESTIONS FROM THURSDAY?

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# THE PROBLEM SET

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- People found this one a little more challenging
- That's a good thing
  - There is, on occasion, virtue in being a little stuck
- Remember: If you show your work and I can follow your logic, partial credit can be had



# PROBLEM I

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- This is just an extension of the Bayes' Theorem problem we covered in class

$$P(Disease|Test = Positive) = \frac{P(Test = Positive|Disease)P(Disease)}{P(Test = Positive)}$$

$$P(Disease|Test = Positive) = \frac{0.98 * 0.0133}{((1 - 0.0133) * 0.05) + (0.0133 * 0.98)}$$

$$P(Disease|Test = Positive) = 0.209$$



## QUESTION 2

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# MY TAKE ON QUESTION 2

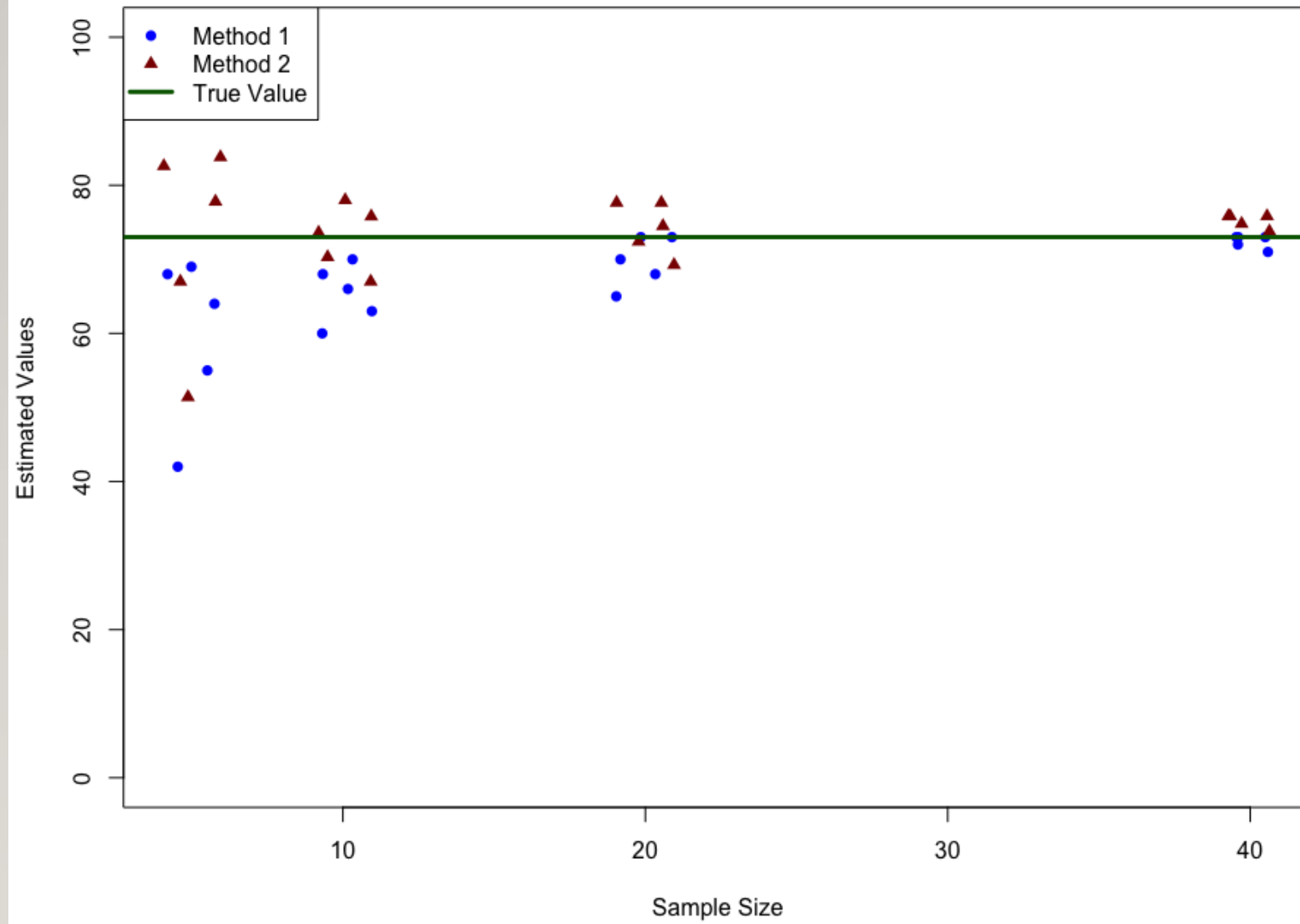
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- What is the cost of the test?
- What is the consequence of not knowing vs. knowing?
- What interventions are the result of the test, and are these themselves harmful or expensive?

# QUESTION 3

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- This was mostly an opportunity to explore this
- There's not necessarily *a* way to answer this question





# QUESTION 4

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- I've been given a problem with a probability of success ( $1/6$ ) and a number of trials (20) – this feels like a binomial distribution problem to me
- It's 6 *or more* times, so I don't just need the probability of 6, but of 6 to 20
- This seems laborious to me
- The probability of 0, 1, 2, 3, 4 and 5 is one minus the probability I want, and involves way less calculation

# CALCULATIONS

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$$f(s) = \frac{n!}{s!(n-s)!} p^s (1-p)^{n-s}$$

Or...

```
dbinom(s, size, prob, log=FALSE)
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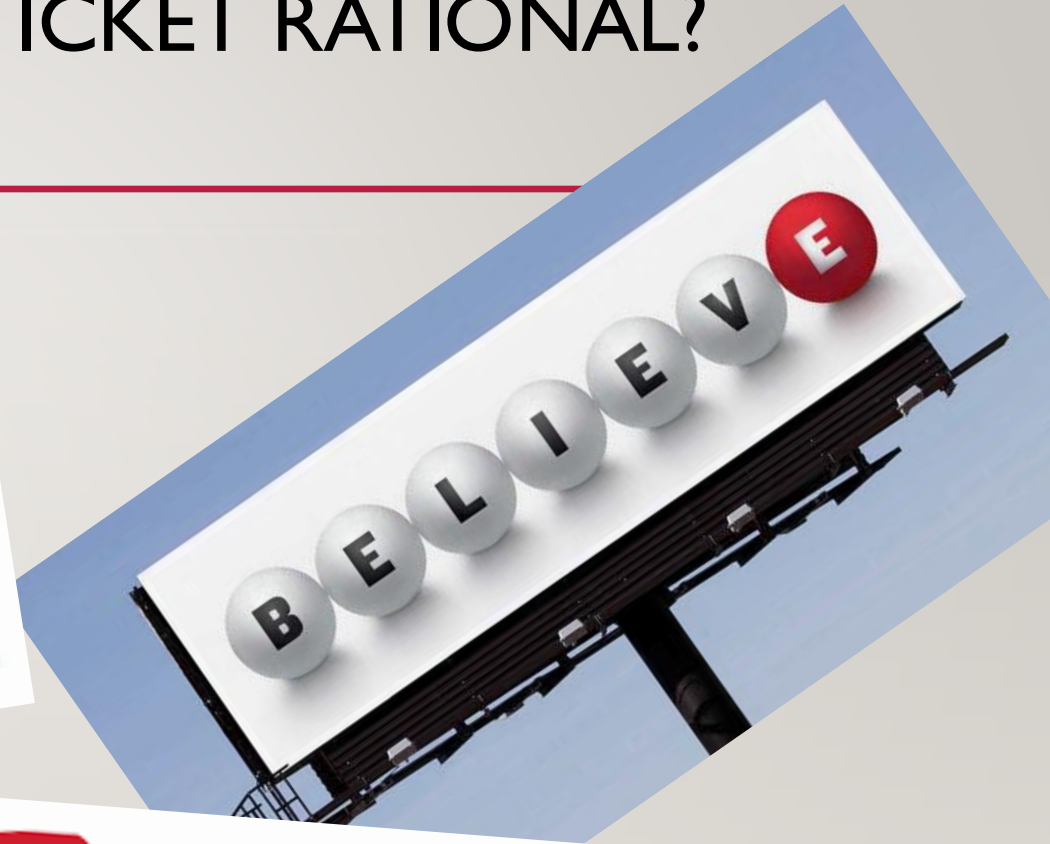
S	P(S)	Cumulative Probability
0	0.02606	0.02606
1	0.10428	0.13034
2	0.19818	0.32852
3	0.23787	0.56638
4	0.20224	0.76862
5	0.12946	0.89808

# TAKE THE BET?

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- $P(\text{Winning}) = 1 - 0.89808 = 0.10192$
- That's an unlikely victory. But the payout is decent. On average, we expect to make  $\$100 * 0.10192 = \$10.192$  on the bet. Let's round that to \$10.19
- On the other hand, on average, we expect to lose  $0.89808 * \$20$  or \$17.96 on the bet
- Maybe find some other activity to occupy your time

# IS BUYING A SINGLE LOTTERY TICKET RATIONAL?





# MAYBE...

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- One lottery ticket is a rational purchase *if* the entertainment value of the fantasy of winning exceeds the cost of the ticket
- Expected Value of a Lottery Ticket:
- Cost = Ticket Price
- Value = Fantasy + A Potentially Large Number \* Basically Zero = Fantasy
- **Two** lottery tickets doubles the price, for no increased value (you haven't increased the value of the fantasy, and the expected monetary reward is still, essentially, zero)

# QUESTIONS?

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# EXPLORATORY DATA ANALYSIS

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# WHAT IS EXPLORATORY DATA ANALYSIS

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- First, we're going to call it EDA for now to keep things short
- EDA is the process of...well...exploring your data
- EDA is an exploration of the characteristics of your data, often using data visualization, to help you identify patterns, spot errors, and suggest directions to take an analysis in
- It's very helpful for assessing your assumptions
- Essentially invented by John Tukey in 1970



# ELEMENTS OF EDA

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- Univariate, non-graphical techniques
- Univariate graphical techniques
- Multivariate, non-graphical techniques
- Multivariate, graphical techniques

# UNIVARIATE TECHNIQUES

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- These techniques are primarily about simply describing a single variable, to help you understand it
- What sort of distribution might it follow?
- Are there outliers or extreme values?
  - Are these in error, or are they simply extreme values?
  - I once found a 2000-year-old man in what was theoretically a clean data set
  - I also found some test data accidentally left in, because it looked funny

# FIVE NUMBER SUMMARY OF A VARIABLE

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- Two Extremes:
  - Minimum and Maximum
- The Median
- The Quartiles (aka the 25<sup>th</sup> and 75<sup>th</sup> percentiles)
- Why these and not the mean and standard deviation?

# AN EXPERIMENT

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- I give you two samples with the following information:

Sample 1 Mean	Sample 1 SD	Sample 2 Mean	Sample 2 SD
30.095	4.99	30.1202	8.99

- Are these different samples? What's wrong? It's fairly hard to tell...
- Lets look at a five number summary, using the `fivenum()` function in R...



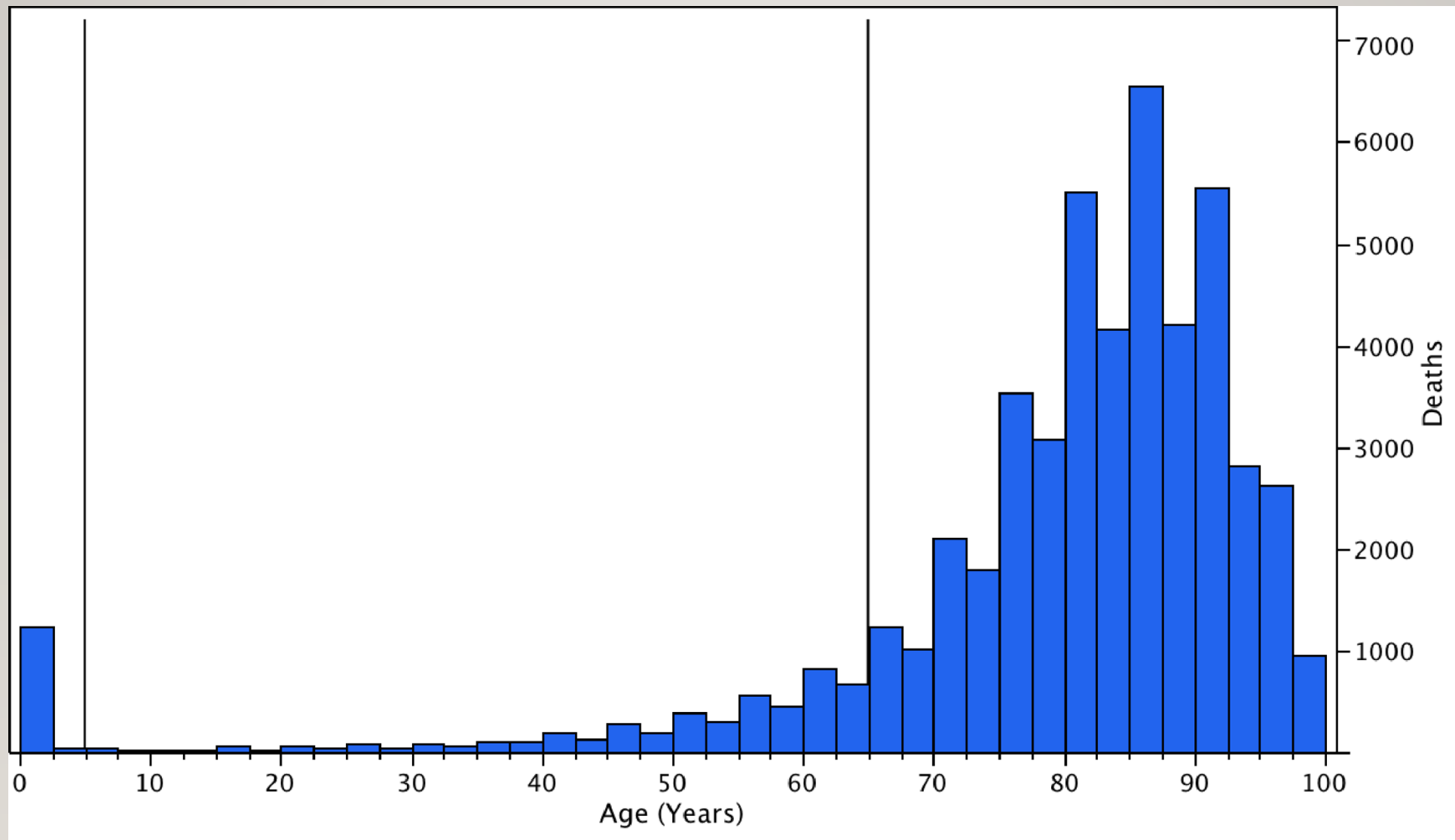
Sample	Min	25 <sup>th</sup> Percentile	Median	75 <sup>th</sup> Percentile	Max
1	10.87	26.68	30.11	33.42	49.22
2	11.60	26.65	30.03	33.45	778.0

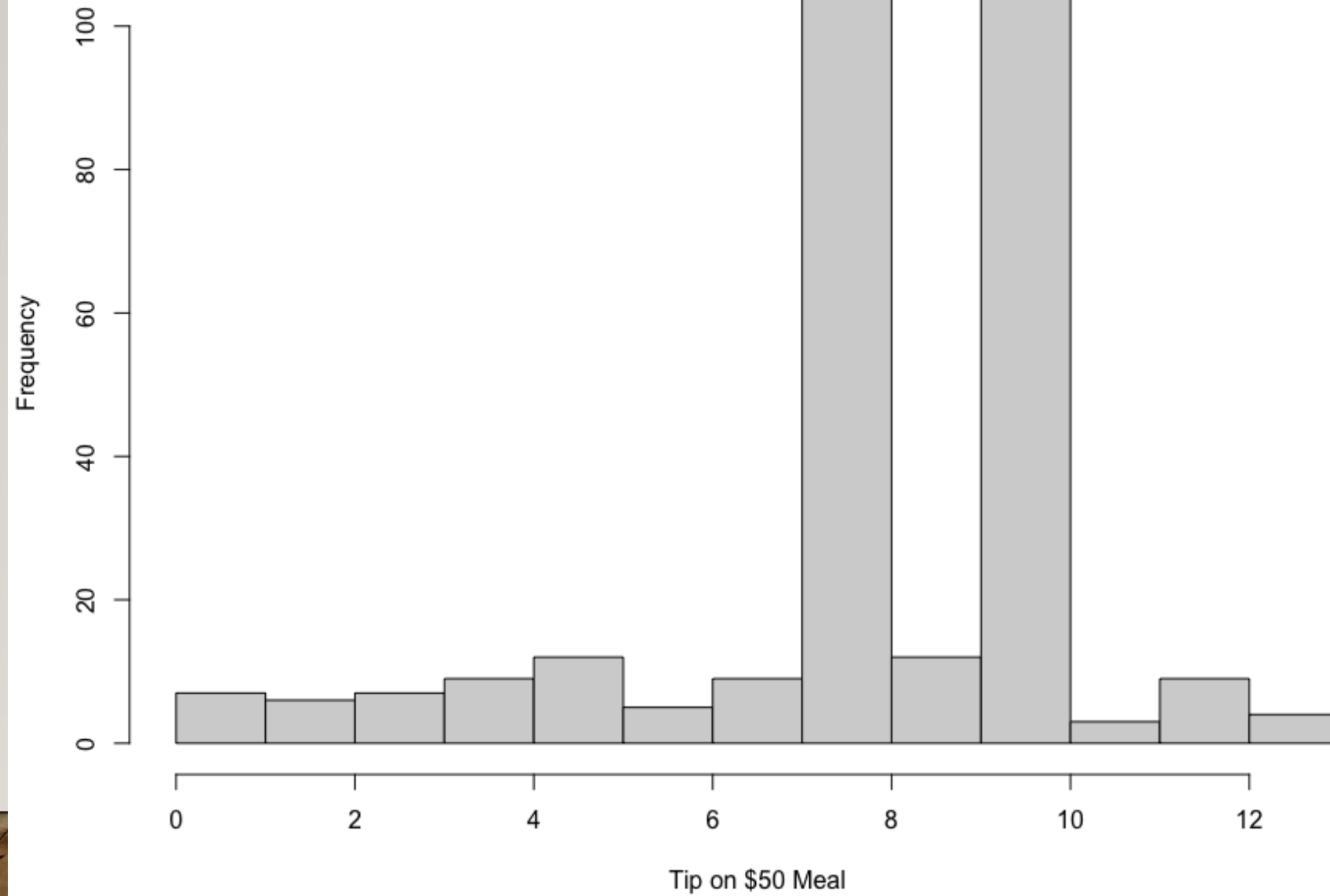
The problem is now obvious

# VISUALIZING A SINGLE VARIABLE

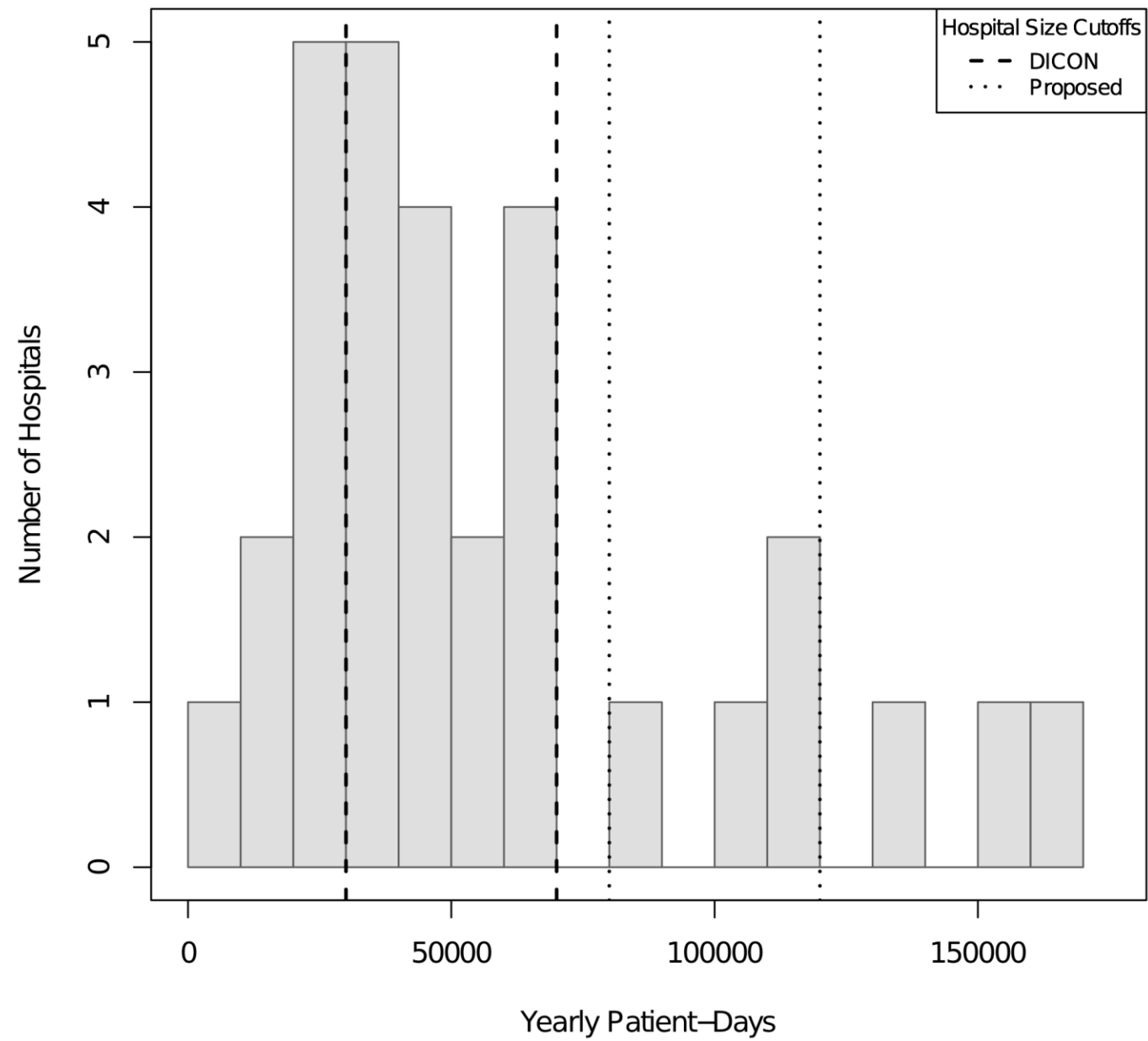
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- You can also visualize a variable using a histogram, density plot, or other methods
- This can show you things like break points in your data, natural cut offs, etc.
  - This is often very important if you want to categorize a continuous variable – it's often helpful to make sure you're not cutting a logical grouping in half
- This can also help you detect if there are thresholds in your data you were (or were not) expecting
  - Do values of a lab assay suddenly truncate?
  - Do you not enroll anyone of a particular value or lower (or higher) even though you know they exist?





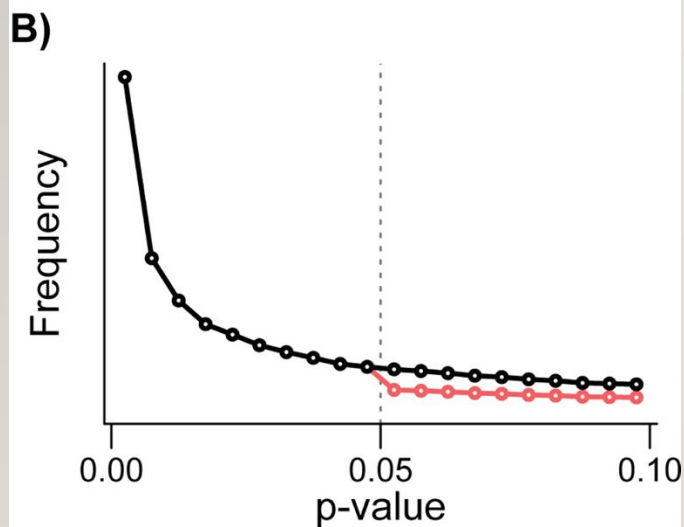
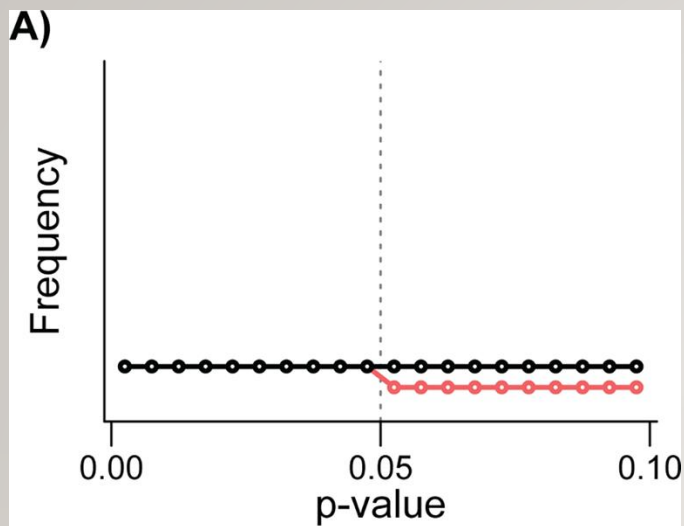




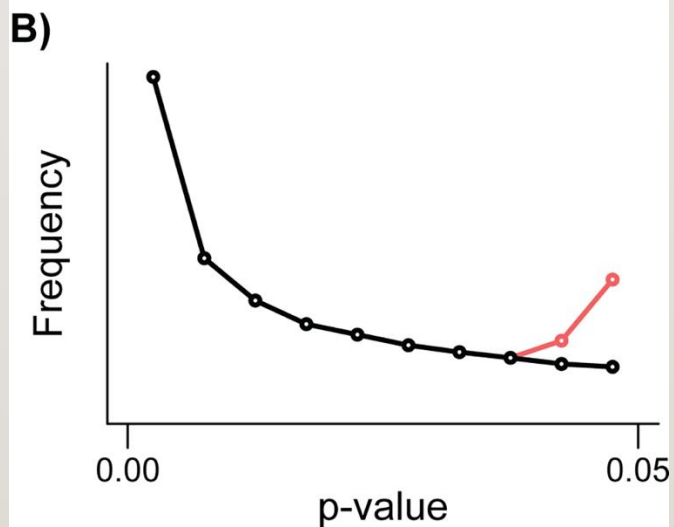
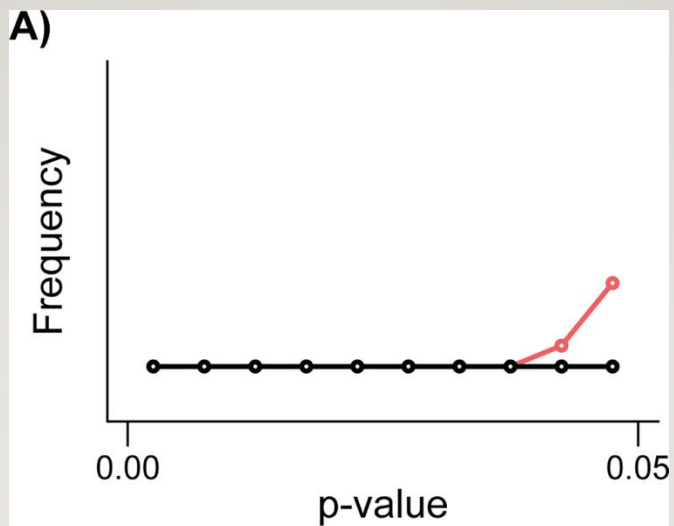
# P-HACKING AND PUBLICATION BIAS

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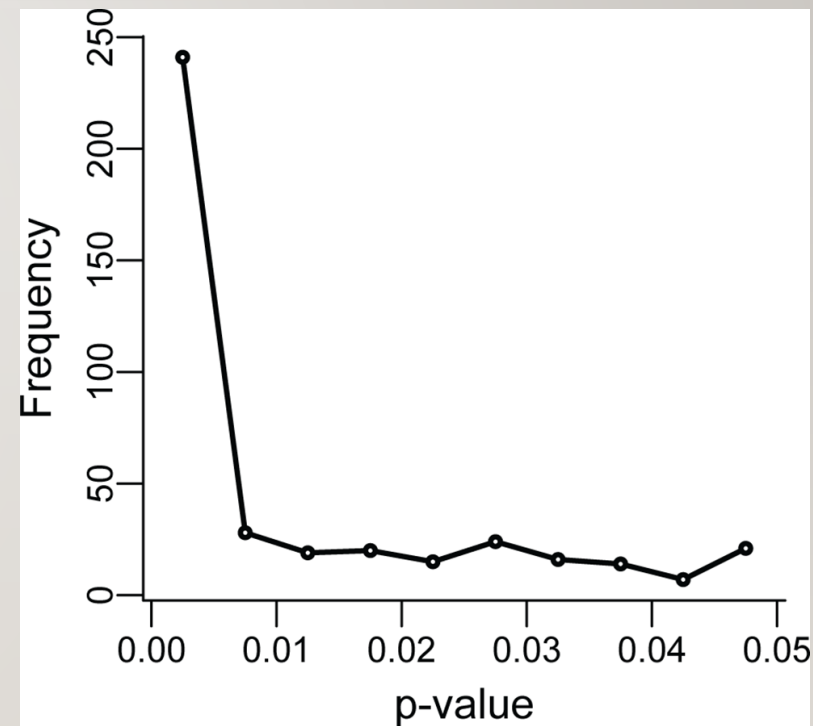
- One application of this type of visualization is detecting things like p-hacking and publication bias in a meta-analysis
- P-values should follow a theoretical distribution if they're not being influenced by researcher or publisher judgement
- But do they?
- Head ML, Holman L, Lanfear R, Kahn AT, Jennions MD (2015) The Extent and Consequences of P-Hacking in Science. *PLoS Biol* 13(3): e1002106.  
<https://doi.org/10.1371/journal.pbio.1002106>



Publication Bias



P-Hacking



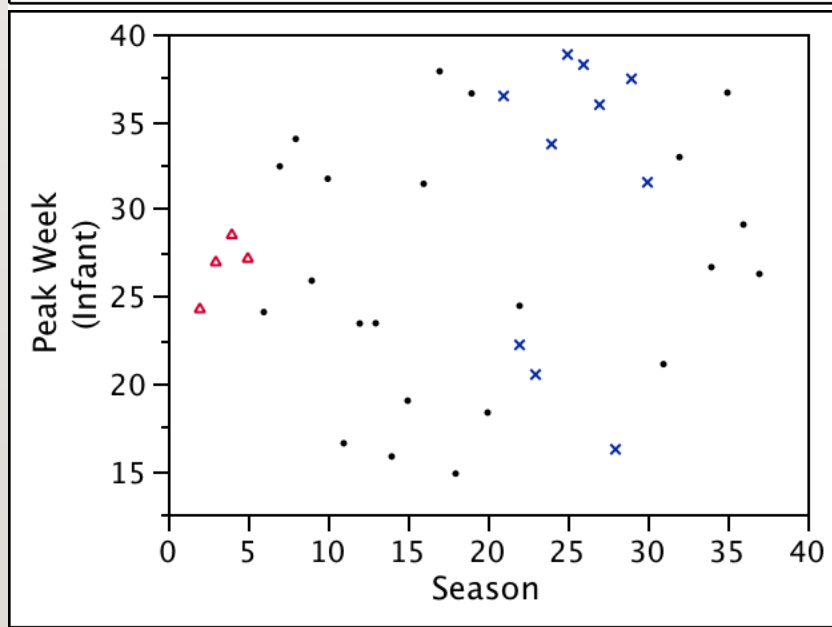
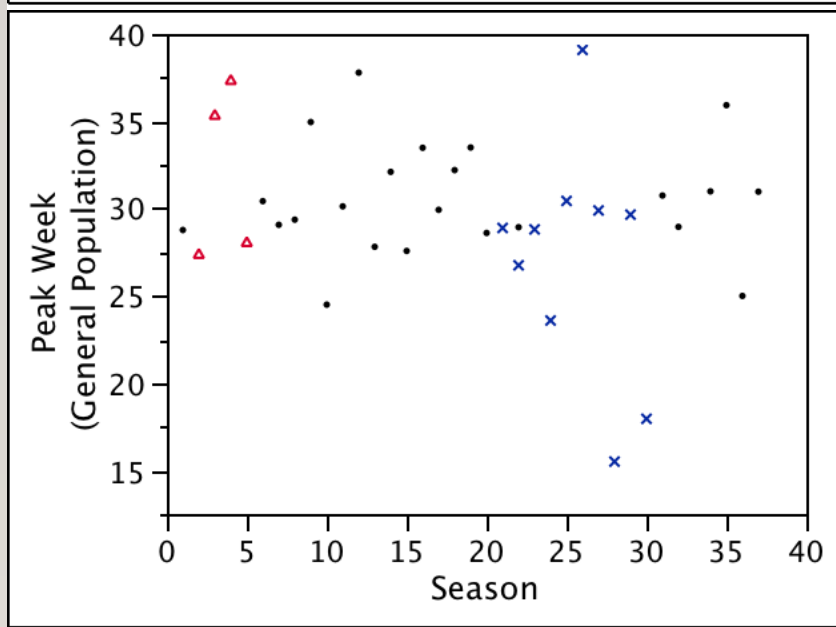
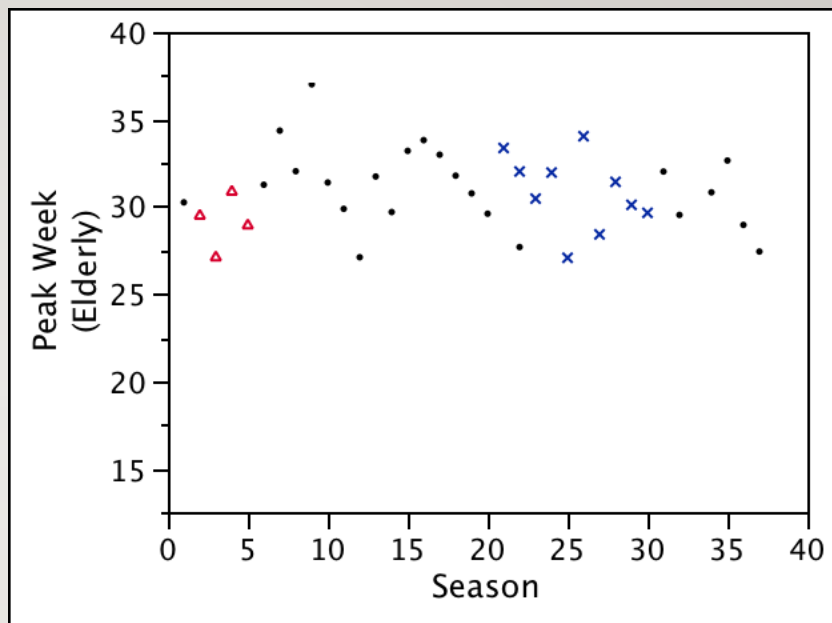
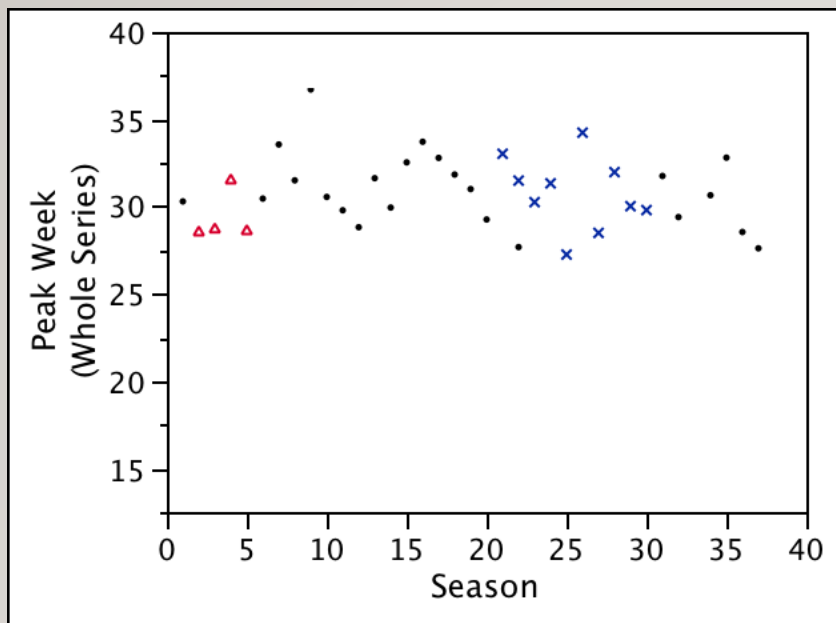
A Meta-Analysis

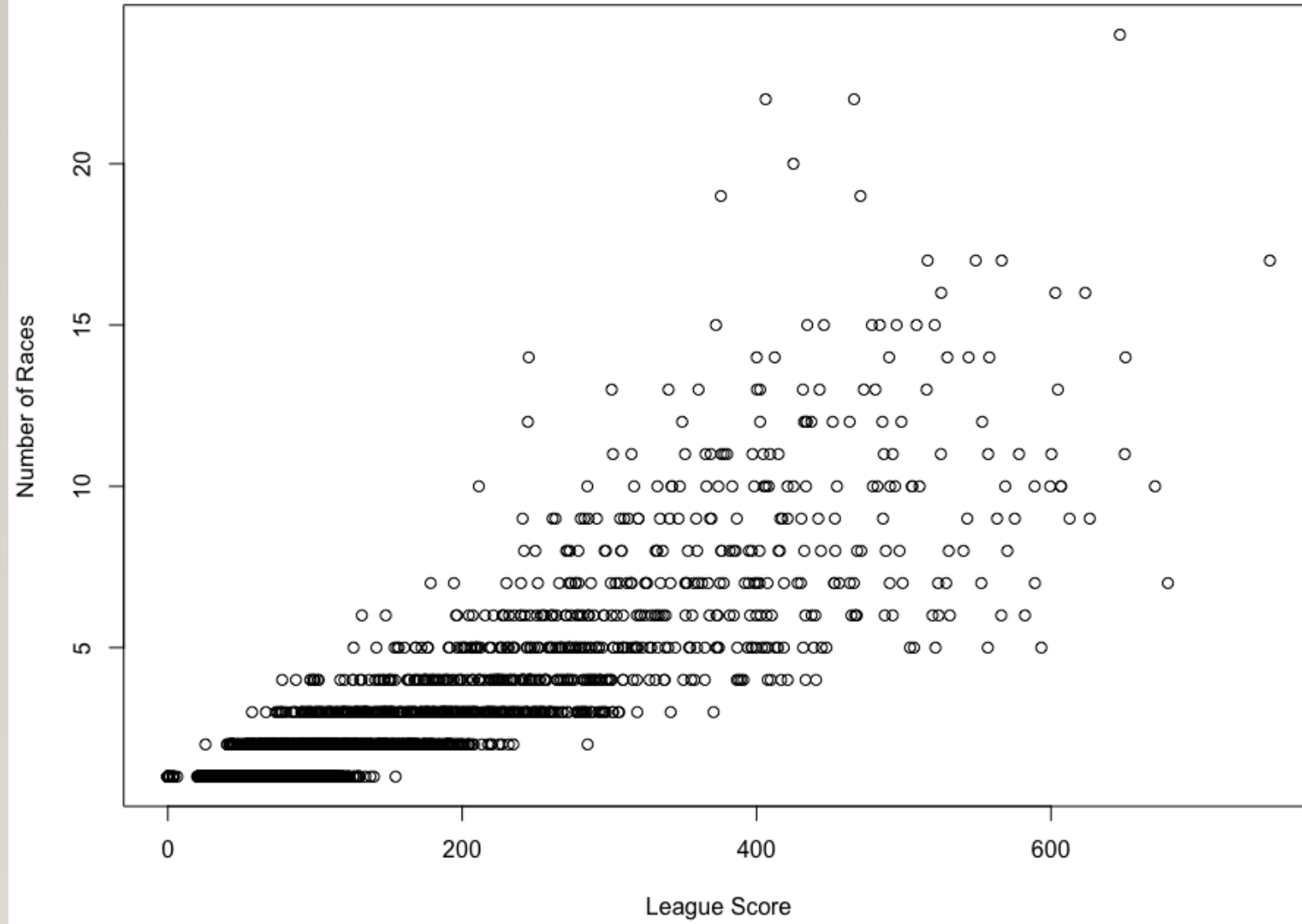
# MULTIVARIATE ANALYSIS

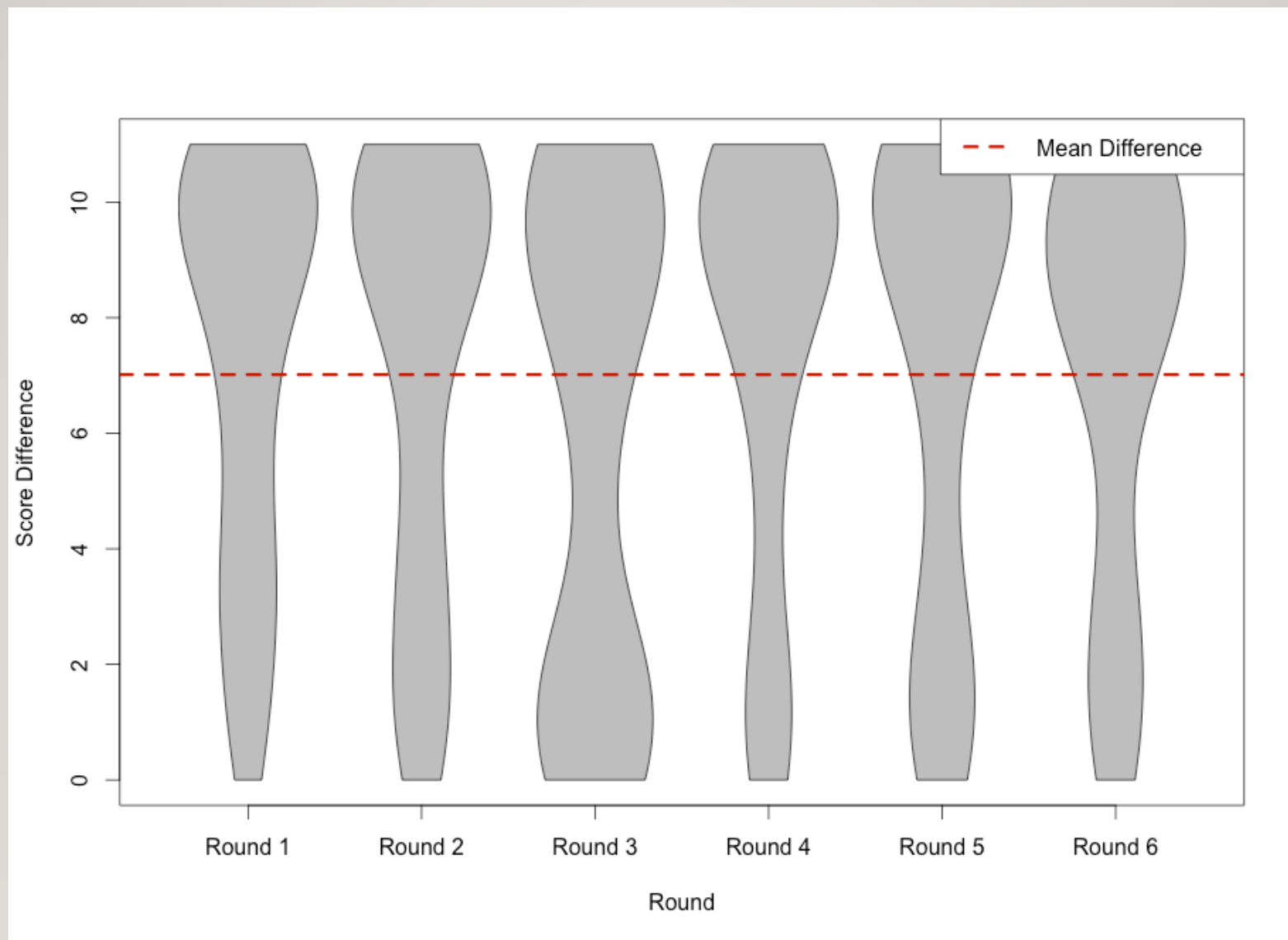
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- Much of EDA is concerned with understanding the relationship between two or more variables, for a number of reasons
- These can be visualized with scatter plots, box or violin plots, and a number of other methods
- There's also quantitative methods such as correlation coefficients, or linear models of the relationships
  - Once again, to be covered in a future module









# THE IMPORTANCE OF VISUALIZATION

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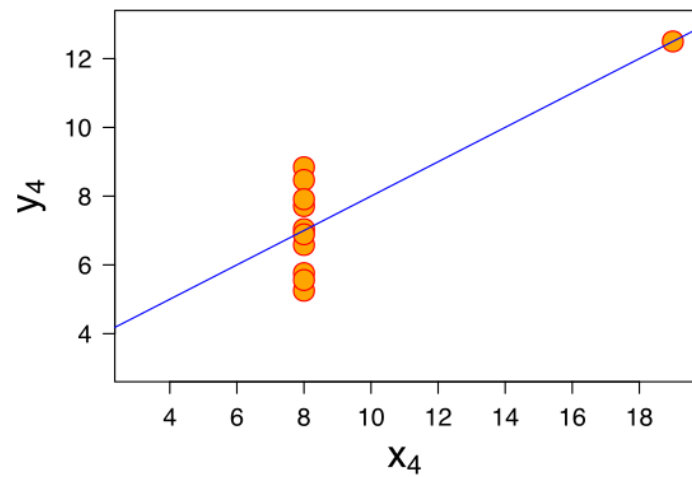
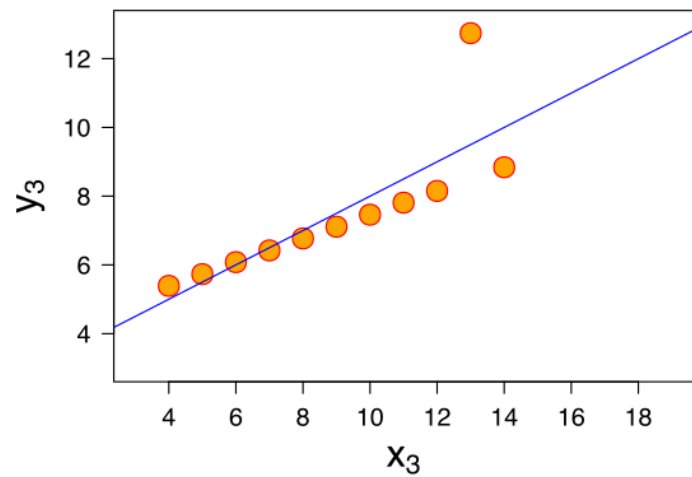
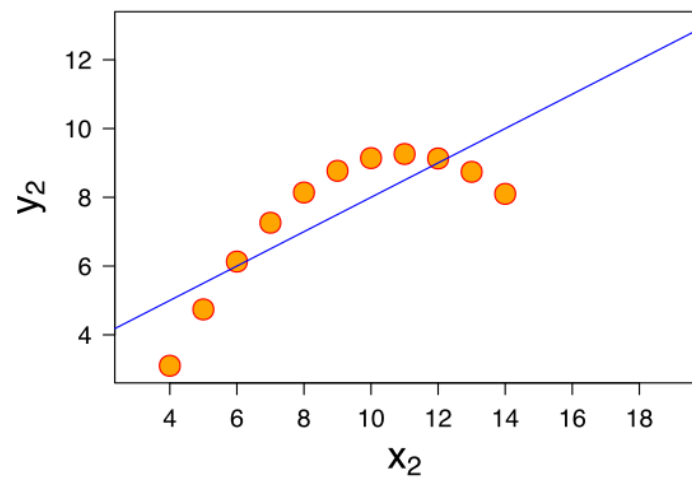
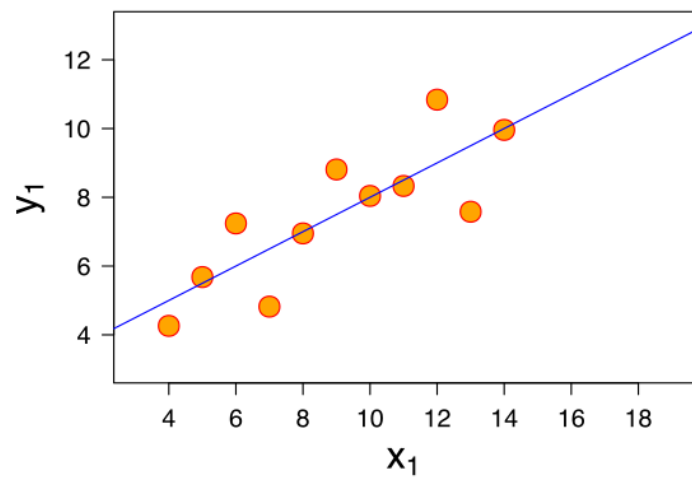
- There is often a perception that numerical measures – means, medians, correlation coefficients, etc. are cold and precise and preferable to the fuzzy business of looking at a graph and going “That’s odd...”
- Human pattern recognition is a double edged sword – it’s very good, but it’s also overtuned
- Francis Anscombe designed four datasets, each with 11 points, in 1973 to explore this phenomenon



# ANSCOMBE'S QUARTET

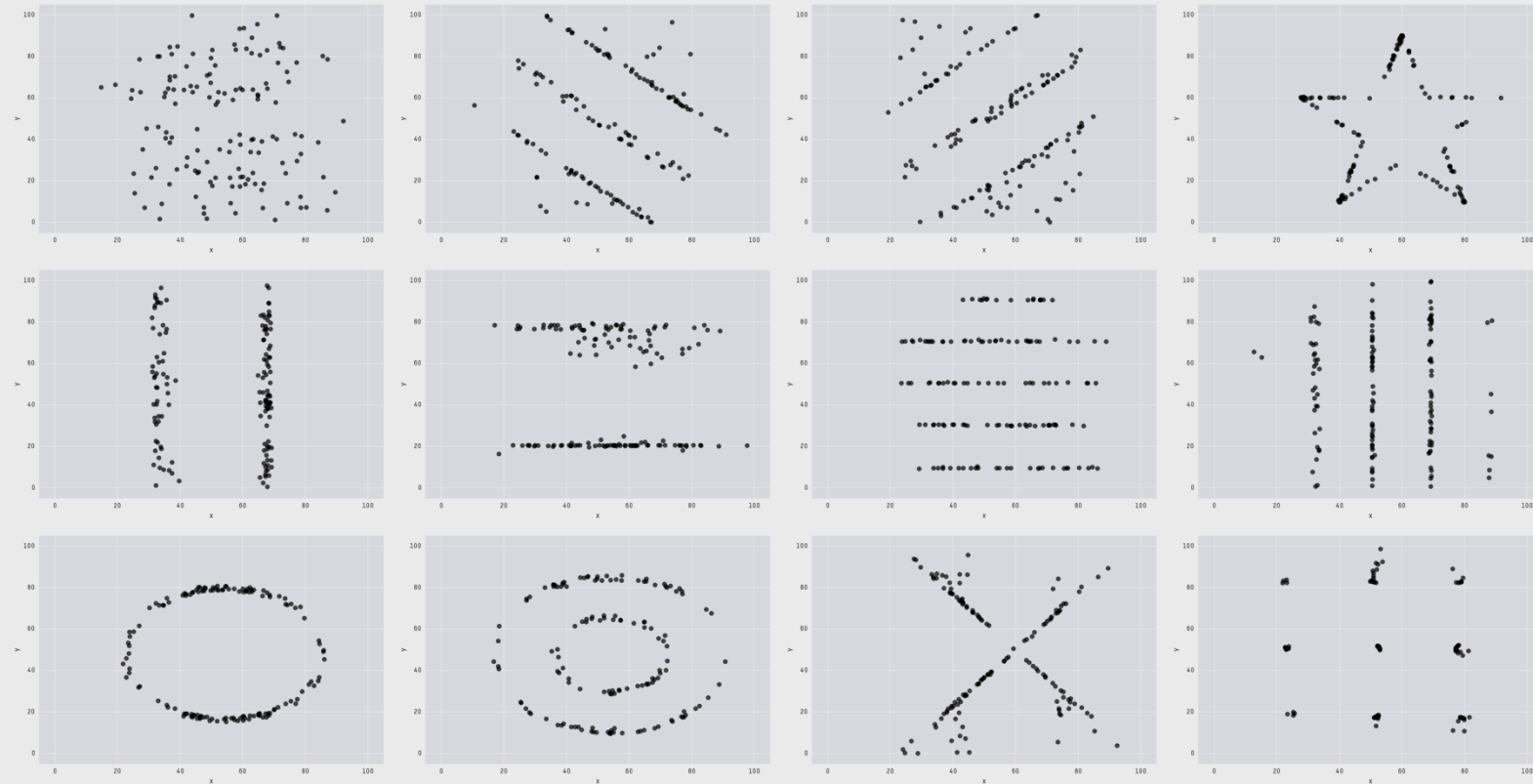
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- Each dataset has:
  - An exact mean of X (9)
  - An exact variance of X (11)
  - A mean of Y to two decimal places (7.50)
  - A variance of Y of  $4.125 \pm 0.003$
  - A correlation between X and Y of 0.816 to three decimal places
  - A linear regression line of  $y = 3.00 + 0.500x$  to two and three decimal places respectively
  - A coefficient of determination ( $R^2$ ) of 0.67 to two decimal places





X Mean: 54.26  
 Y Mean: 47.83  
 X SD : 16.76  
 Y SD : 26.93  
 Corr. : -0.06



Justin Matejka and George Fitzmaurice. 2017. Same Stats, Different Graphs: Generating Datasets with Varied Appearance and Identical Statistics through Simulated Annealing. In Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems (CHI '17). Association for Computing Machinery, New York, NY, USA, 1290–1294. <https://doi.org/10.1145/3025453.3025912>

# SPECIAL THINGS TO LOOK OUT FOR

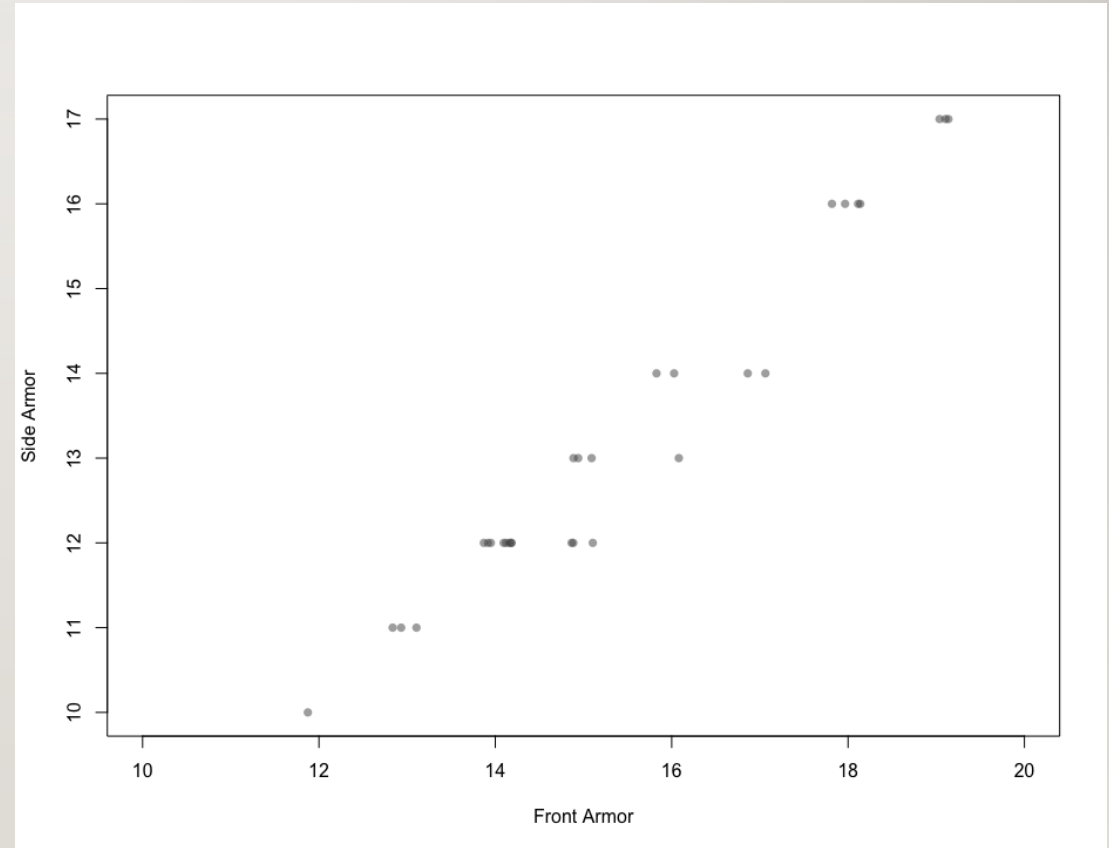
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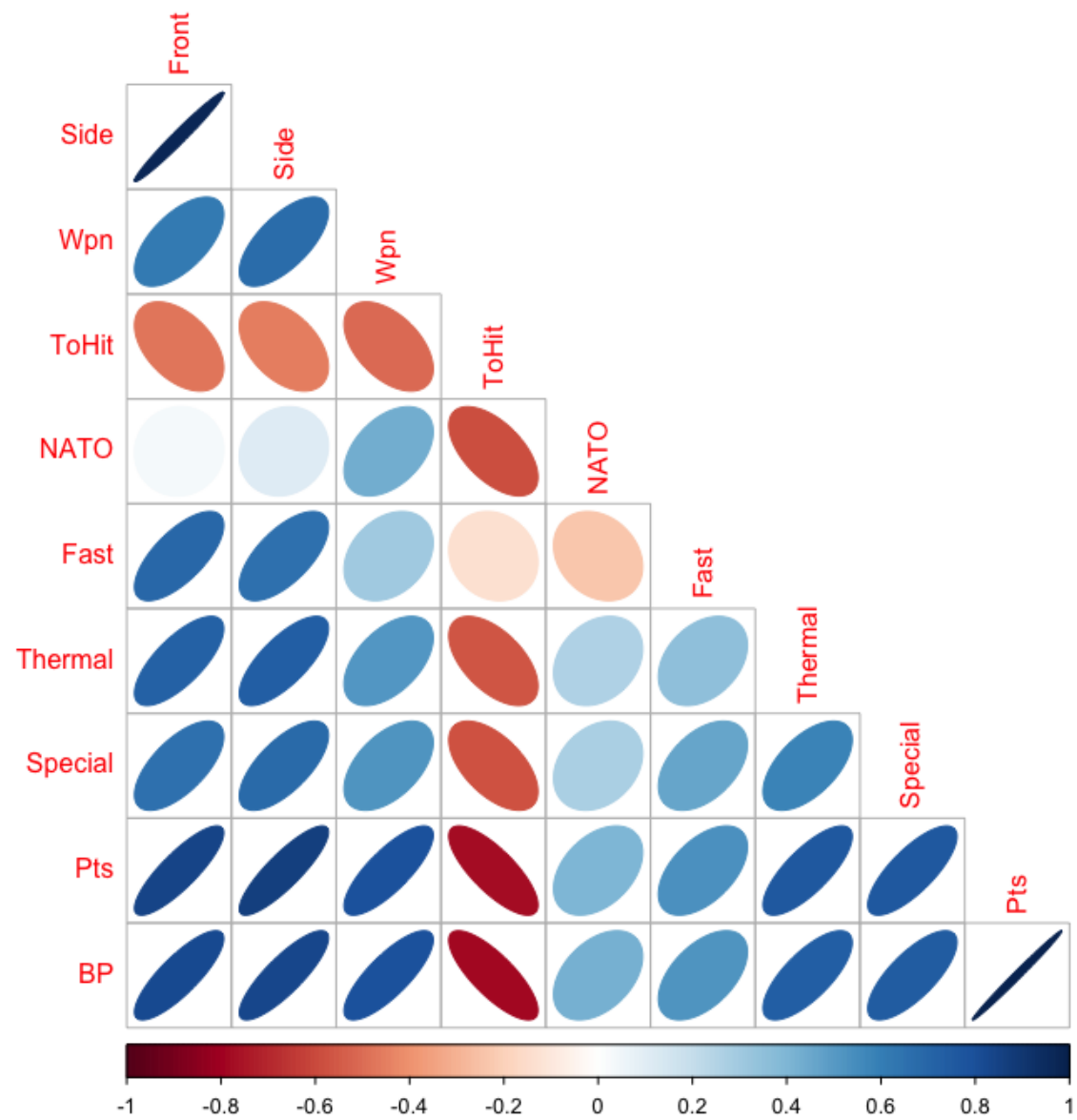
- Very strong correlations
- Missing data patterns
  - Especially missing data patterns associated with another variable
- Areas of empty data
  - i.e. “empty cells”



# VERY STRONG CORRELATIONS

- Very strong correlations suggest that one variable very well predicts another
- If this is what *you want*, good
- If you think you're going to include both of these variables in an analysis, this is bad, as you're going to add variance for no gain in information





# COMPLETE SEPARATION

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- What can happen in this case is that one variable completely and perfectly predicts another
- This is called “complete separation”
  - There’s also quasi-complete separation, which is you’re dangerously close to this
- This is a problem, because you’re likely not explaining something, but rather statistically representing a tautology

# MISSING DATA PATTERNS

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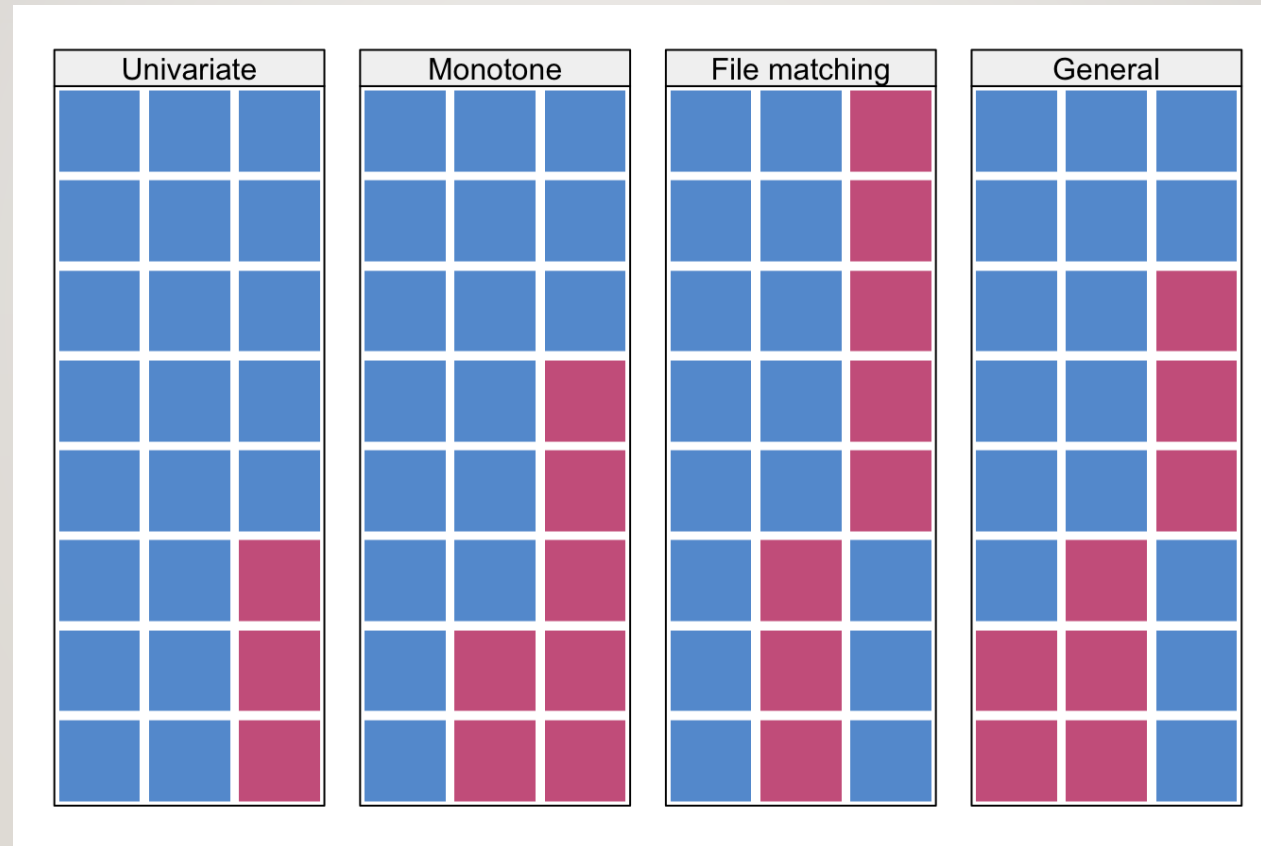


Figure by Stefan van Burren



# EMPTY CELLS

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- One of the underlying assumption of many of the methods we use is called “Positivity”
- In the observed data, there must be a non-zero probability of every individual or unit receiving any level of the treatment or exposure variable
- You take a sample of students in Pullman, and one of the variables you ask about is whether or not they drive a stick shift car
- Zero students say yes
- Is this a violation of the positivity assumption?

# AN EXAMPLE

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- You have been hired by the United States Navy to study non-combat related injuries in sailors
- You have data from 1967 to 2010 (the next 14 years remain classified)
- You have been given a number of variables: Age, what type of ship the sailor serves on, their rank and job, gender, physical fitness scores, height, weight, etc.
- Can anyone guess the problem?

# POSITIVITY PROBLEMS

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- Merely not having someone in a cell is not a problem
  - Again, think stochastically – how did someone end up in your sample, and what alternative samples might there be
  - Rare is not impossible
  - But impossible is bad
- These questions come up a lot in social epidemiology and related fields, and can get somewhat philosophical
  - Is a minoritized population that is not found in the highest income neighborhoods, while the majority population is not found in the lowest income neighborhoods (with overlap in the middle) a positivity violation or not?