An introduction to statistical inference

Francisco Rodríguez-Sánchez

https://frodriguezsanchez.net

Why statistics?

To answer questions like...

- what's the probability that something occurs?

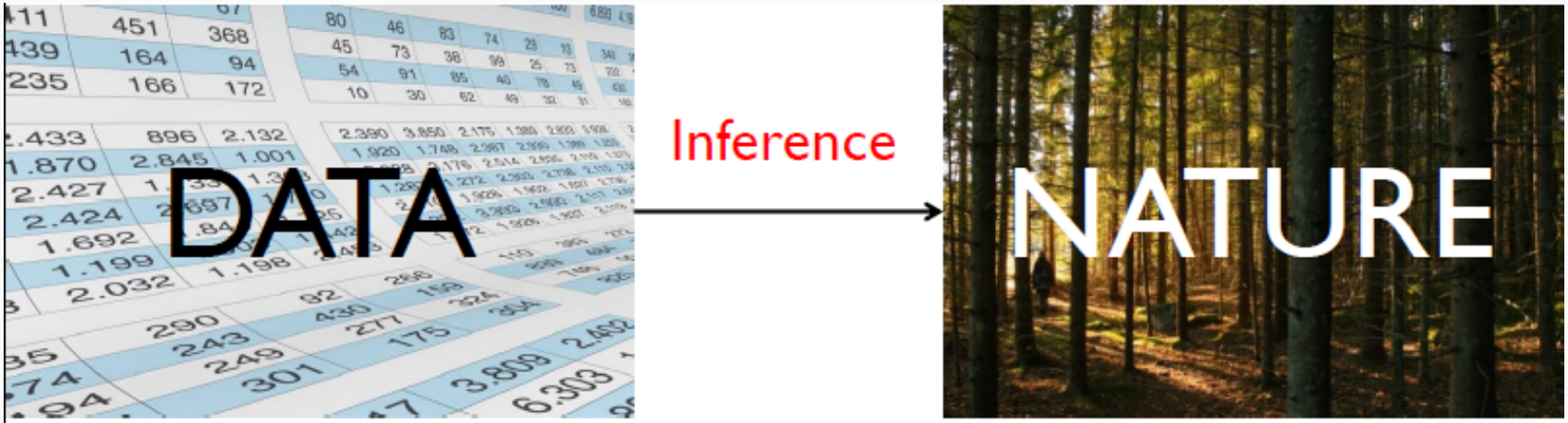
To answer questions like...

- what's the probability that something occurs?
- does X influence Y? How much?

To answer questions like...

- what's the probability that something occurs?
- does X influence Y? How much?
- can we predict Y knowing X, Z... How well?

To ensure correct inferences



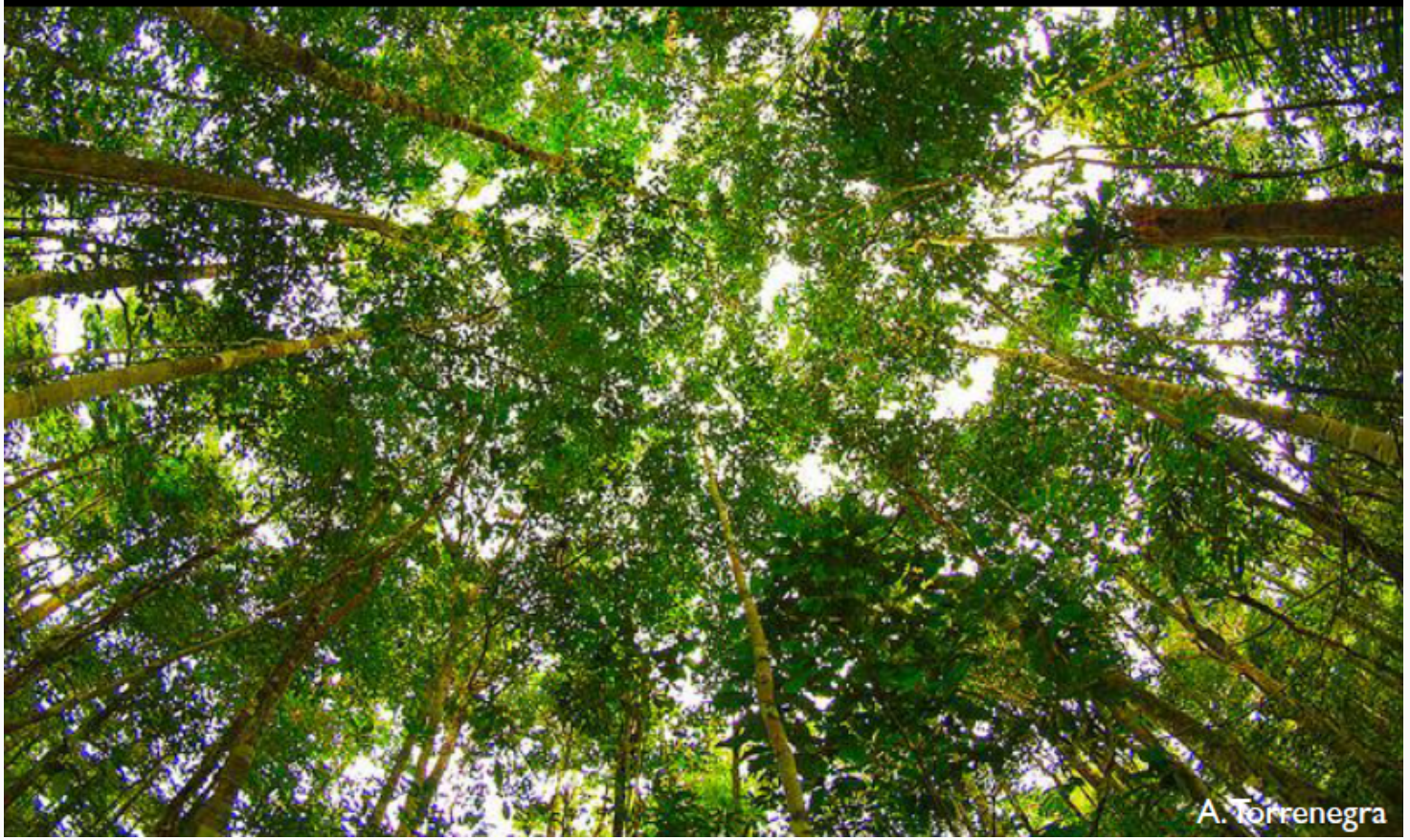
Bolker et al 2009 TREE:

'311 out of 537 GLMM analyses (58%) used these tools inappropriately'

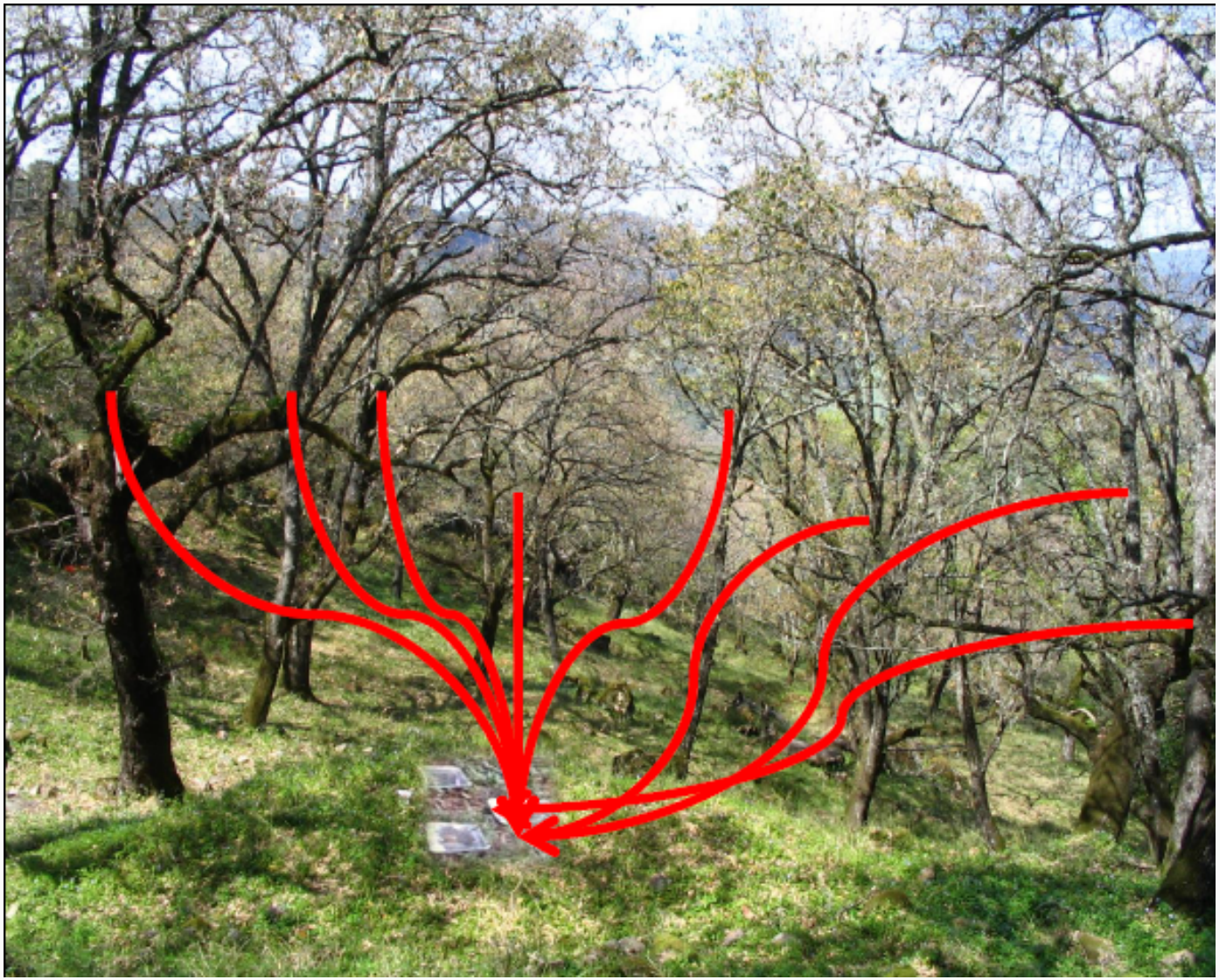
To get answers to tough problems

For example...

How many seeds do trees produce?



Inferring tree fecundity



Course goals

- **Understand** statistical inference

Course goals

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- Avoid **misconceptions**

Course goals

- **Understand** statistical inference
- Avoid **misconceptions**
- Promote **good practices**

The purpose of models is not to fit data but to sharpen thinking

Sam Karlin

Topics

- Descriptive statistics

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- Graphics

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- Descriptive statistics
- Graphics
- Sampling

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- Experimental design

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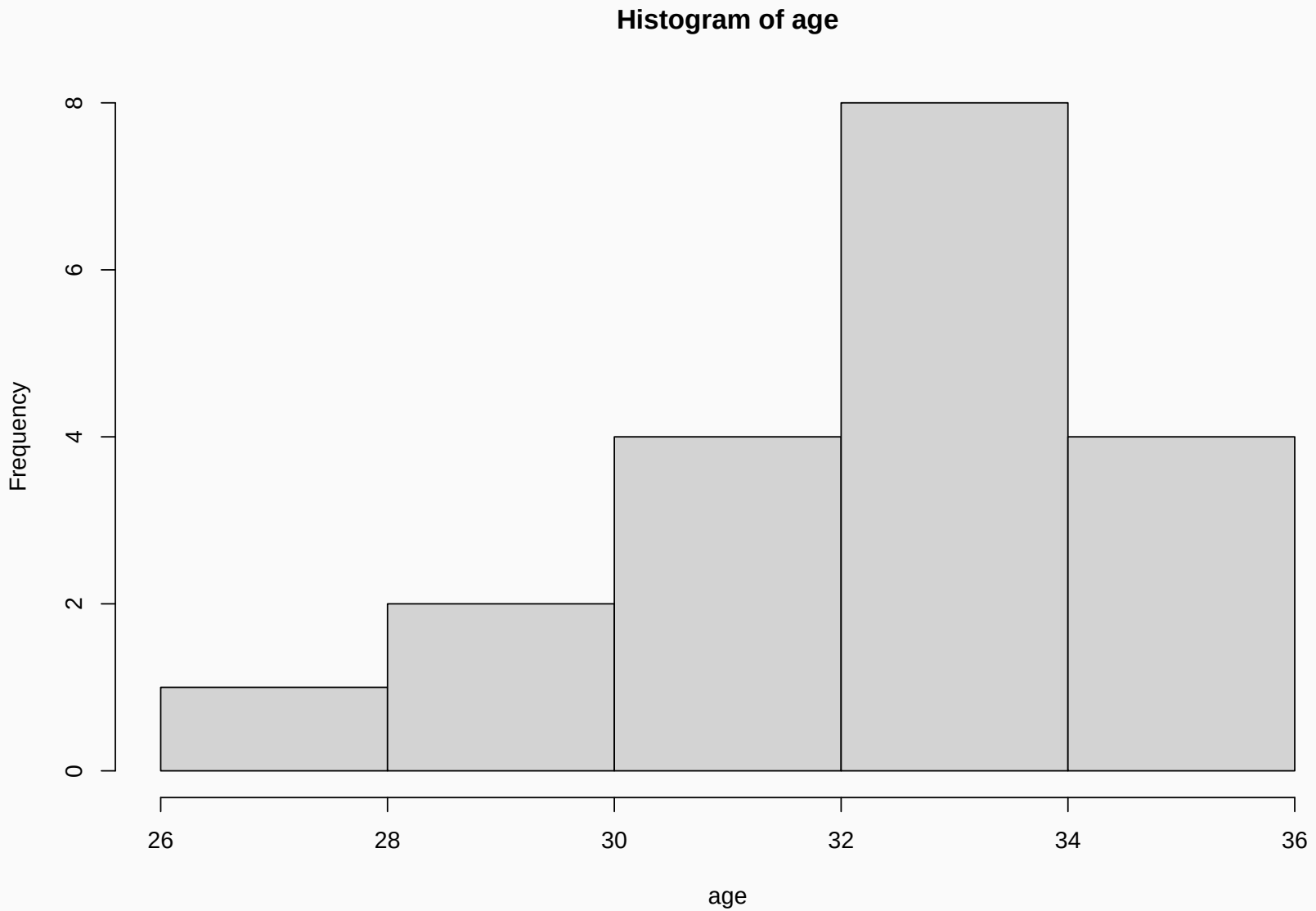
- Model selection

Descriptive statistics

Guess my age

Graph your estimates



Do you think these data are good estimates of my age?

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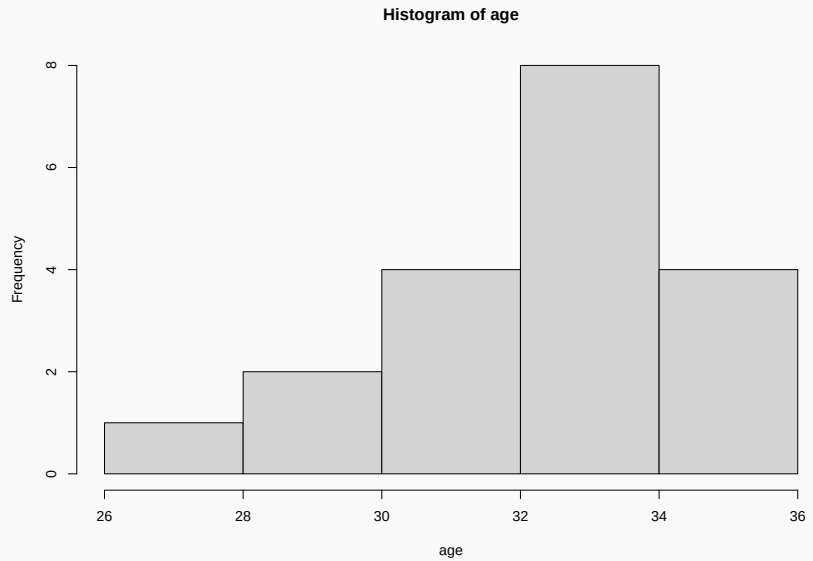


Why / Why not?

Data are hardly ever objective.

We decide **what to measure, when, where, and how**.

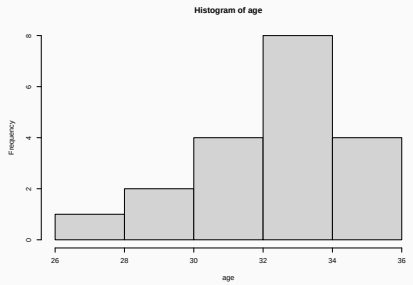
Always consider:

How well do these numbers reflect what we are trying to measure?

Summarise that distribution

Central tendency / location

- mean: $\frac{a_1 + a_2 + a_3}{n}$



Variation / Spread

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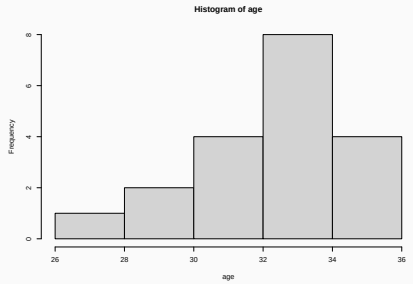
- median (50% percentile)



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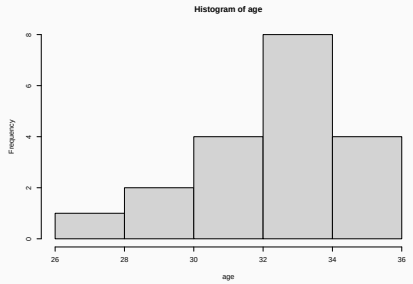

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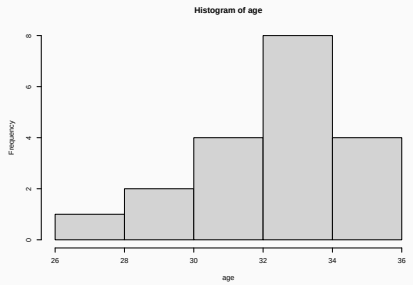

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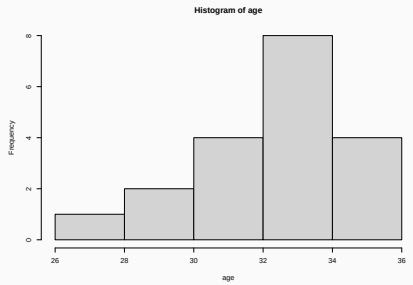

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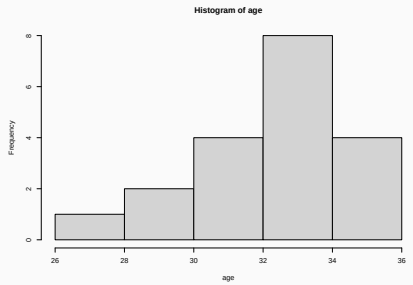

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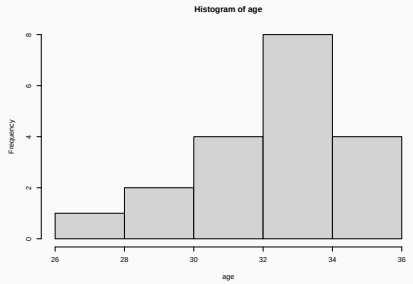

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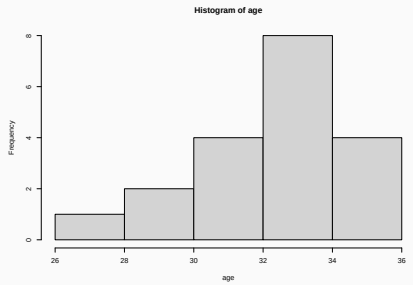

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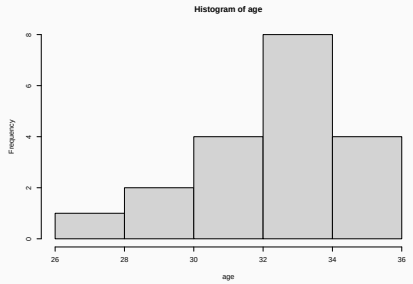

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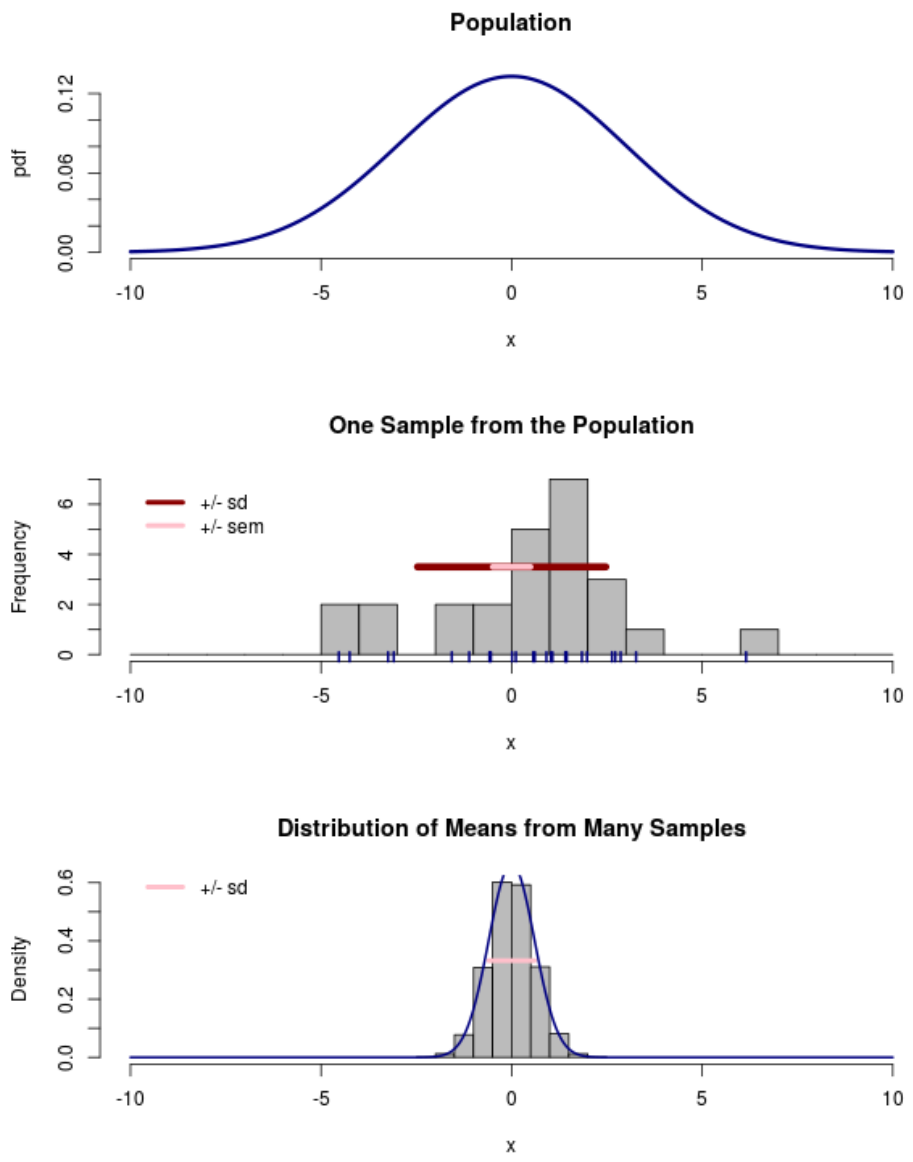
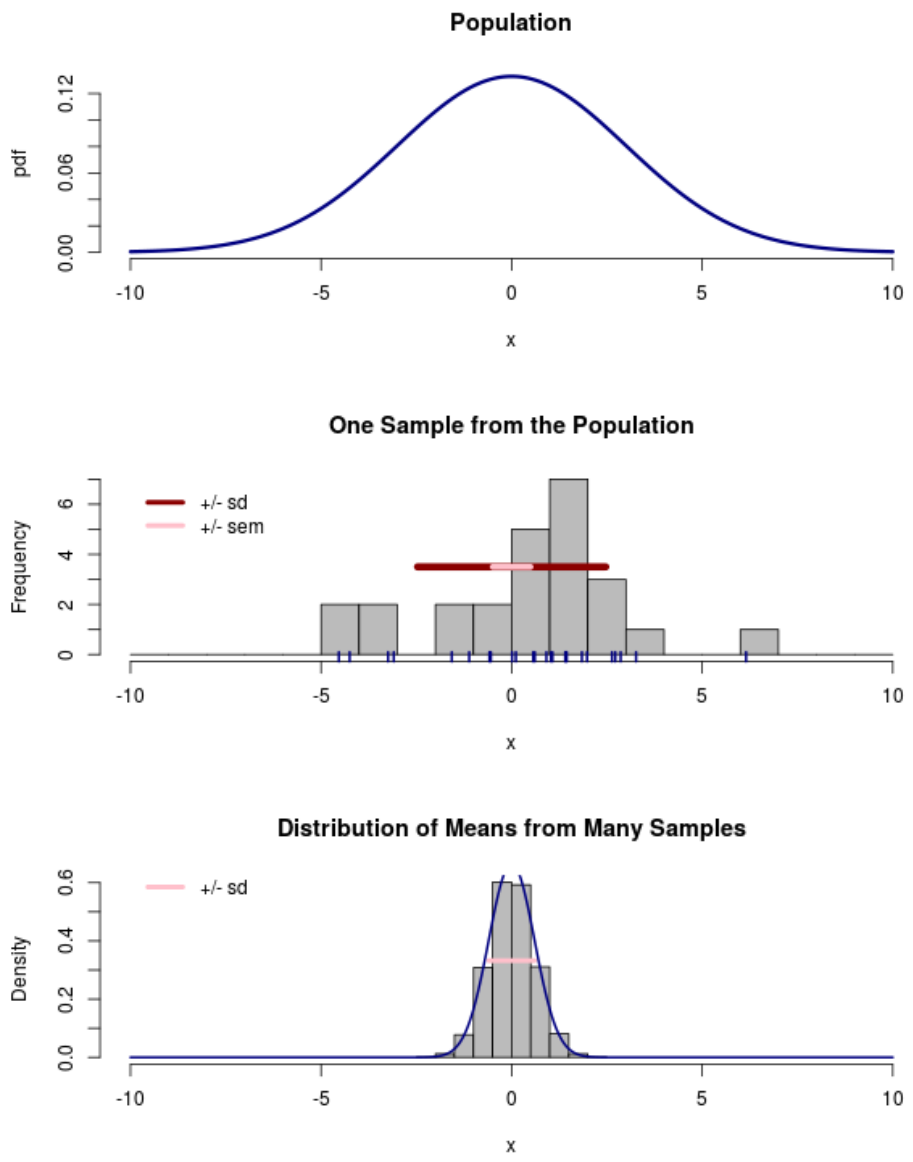
- confidence intervals

Relationship between SD and SEM



- SD quantifies scatter in population

Relationship between SD and SEM



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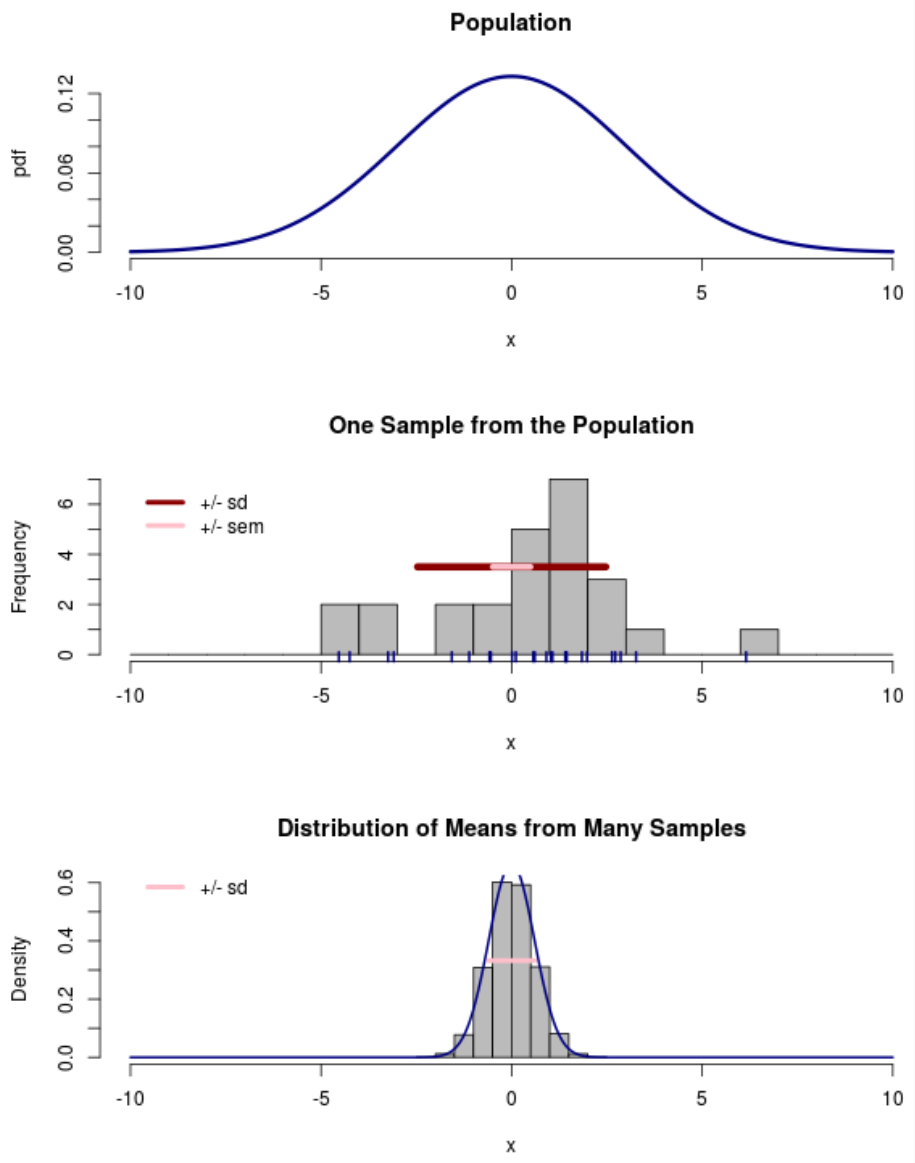

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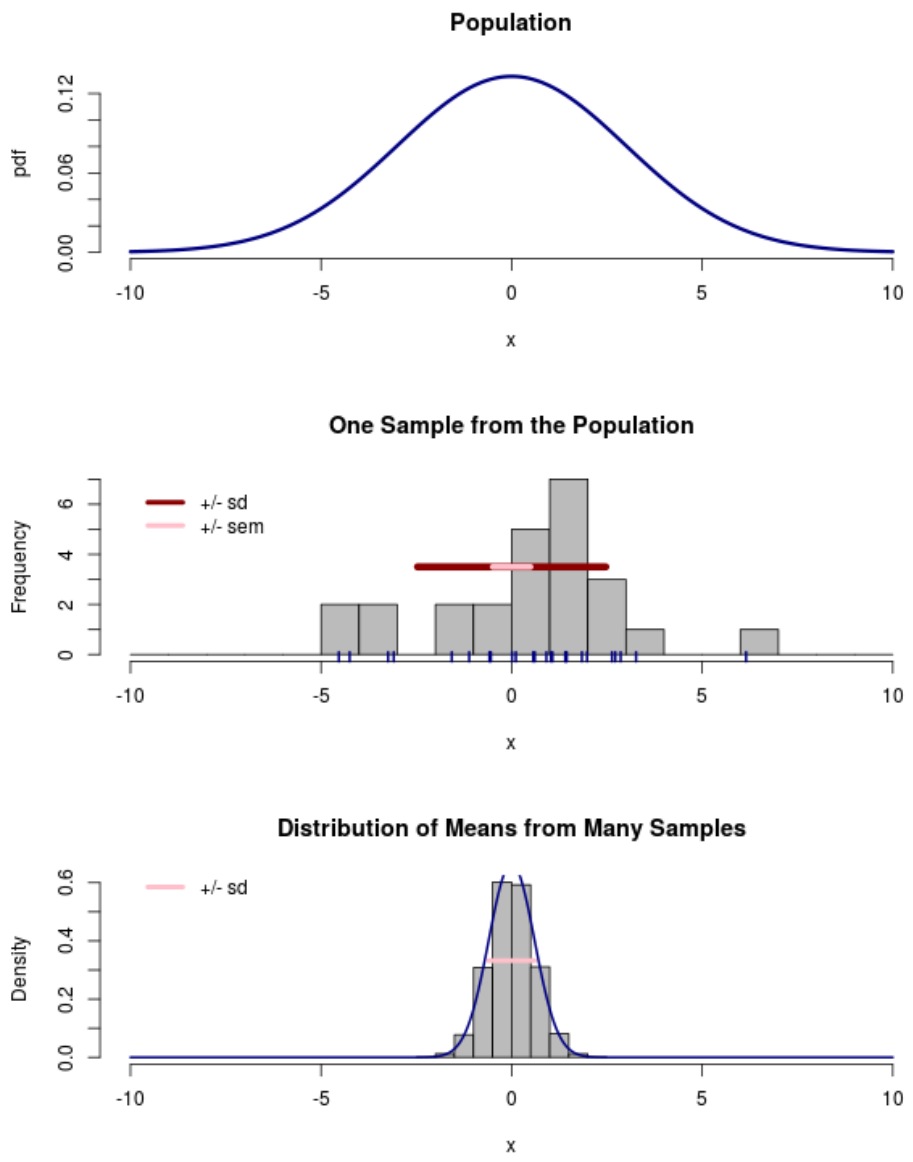

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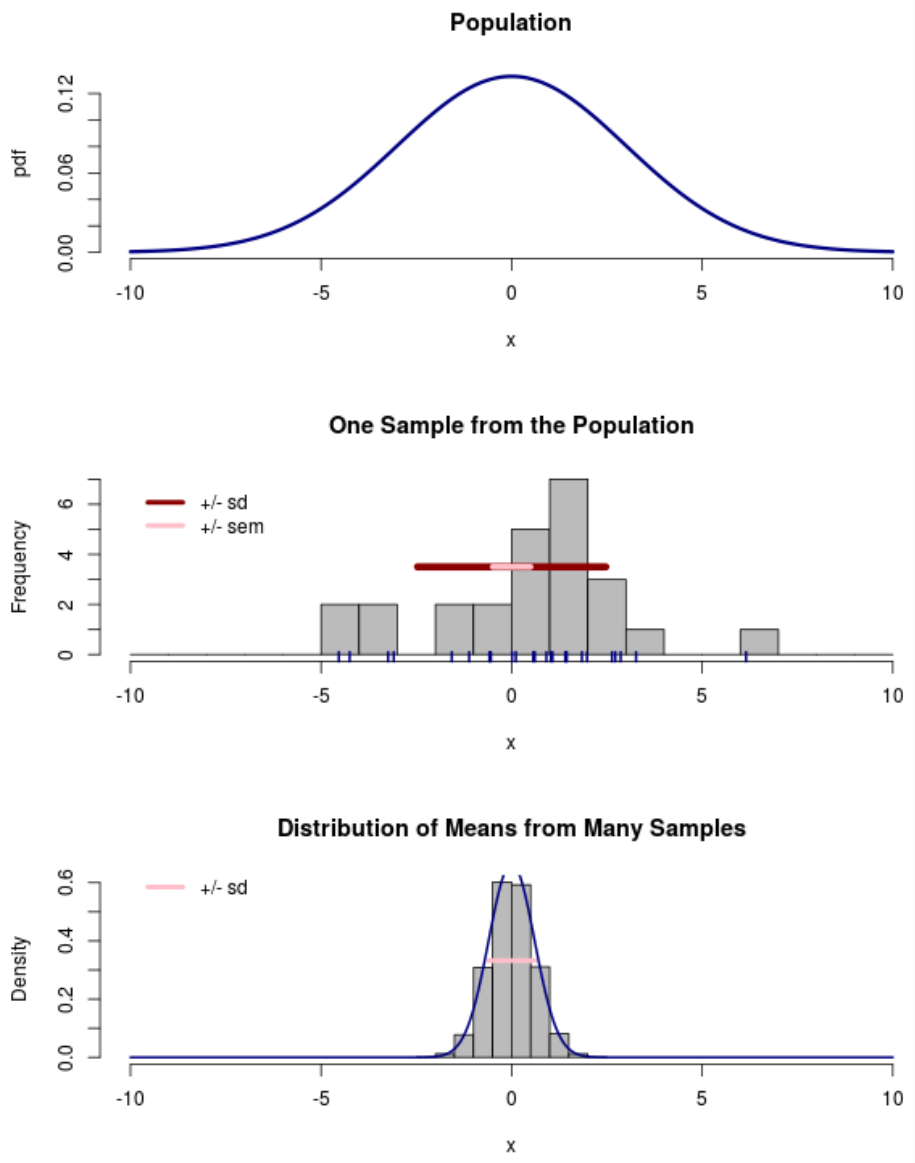

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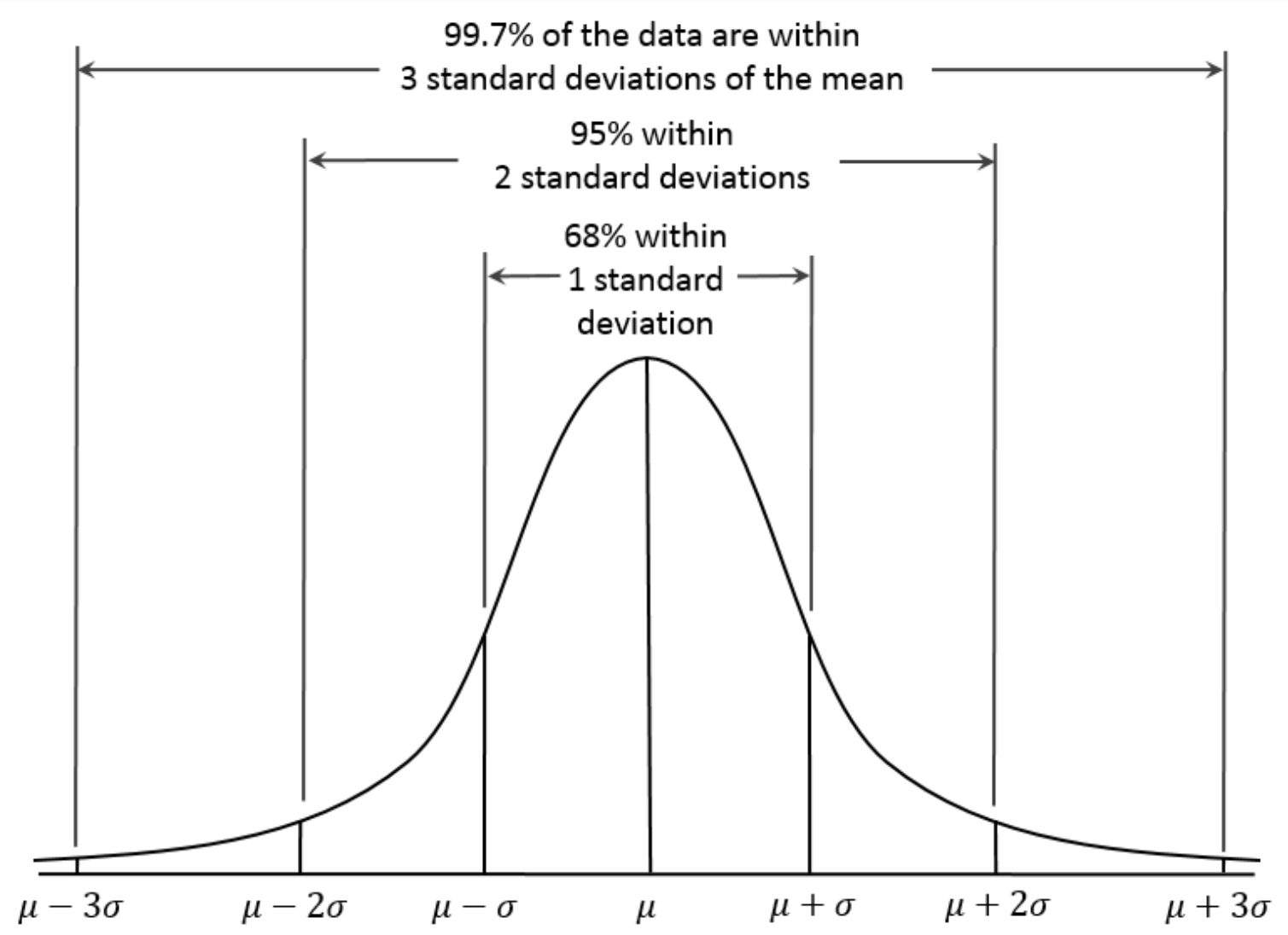
- https://gallery.shinyapps.io/sampling_and_stderr/

In a Normal distribution



What statistical descriptors are best? (and why)

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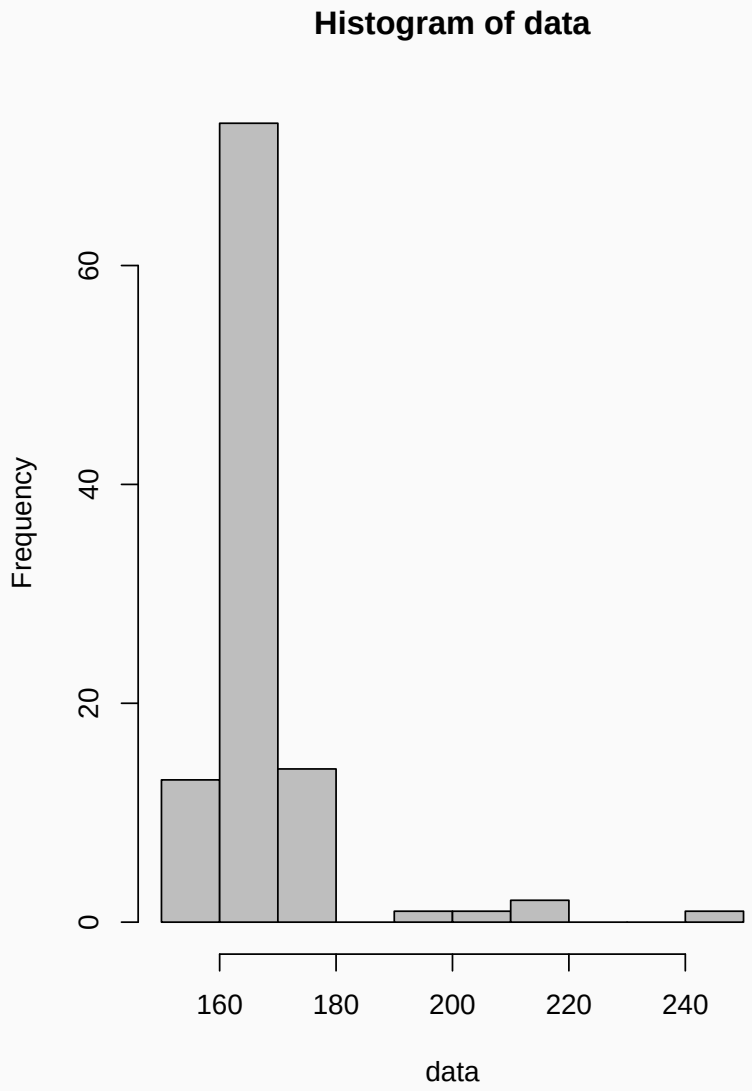

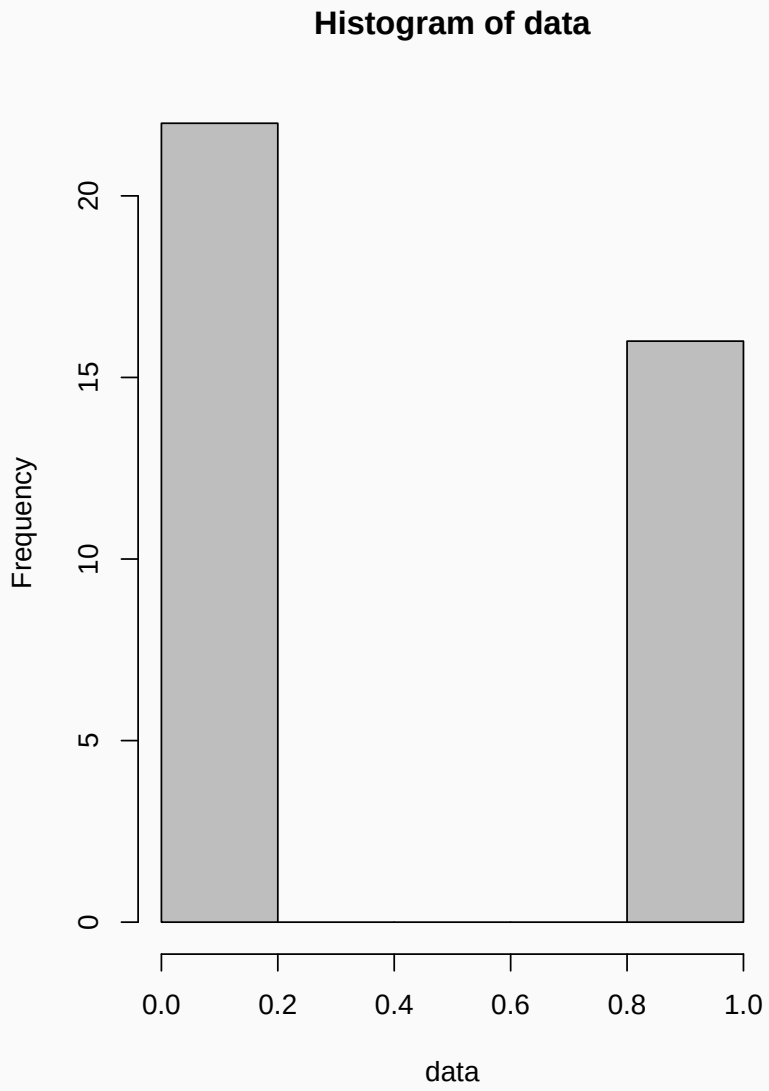

Sampling, confidence intervals, and Bayesian inference

Inference: from samples to population

We rarely measure the whole **population**, but take **samples** instead.

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5. Do all CIs contain true mean height?

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- The probability that X is greater than 0 is at least 95%
- The probability that X equals 0 is smaller than 5%

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Understanding confidence intervals

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- To read more: Morey et al (2015)

What happens if we increase sample size?

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- CI width *decreases*...

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- but still 5% of CIs will NOT contain true mean!

Bayesian credible intervals

- Bayesian **credible** intervals do give the probability that true parameter value is contained within them.

Bayesian credible intervals

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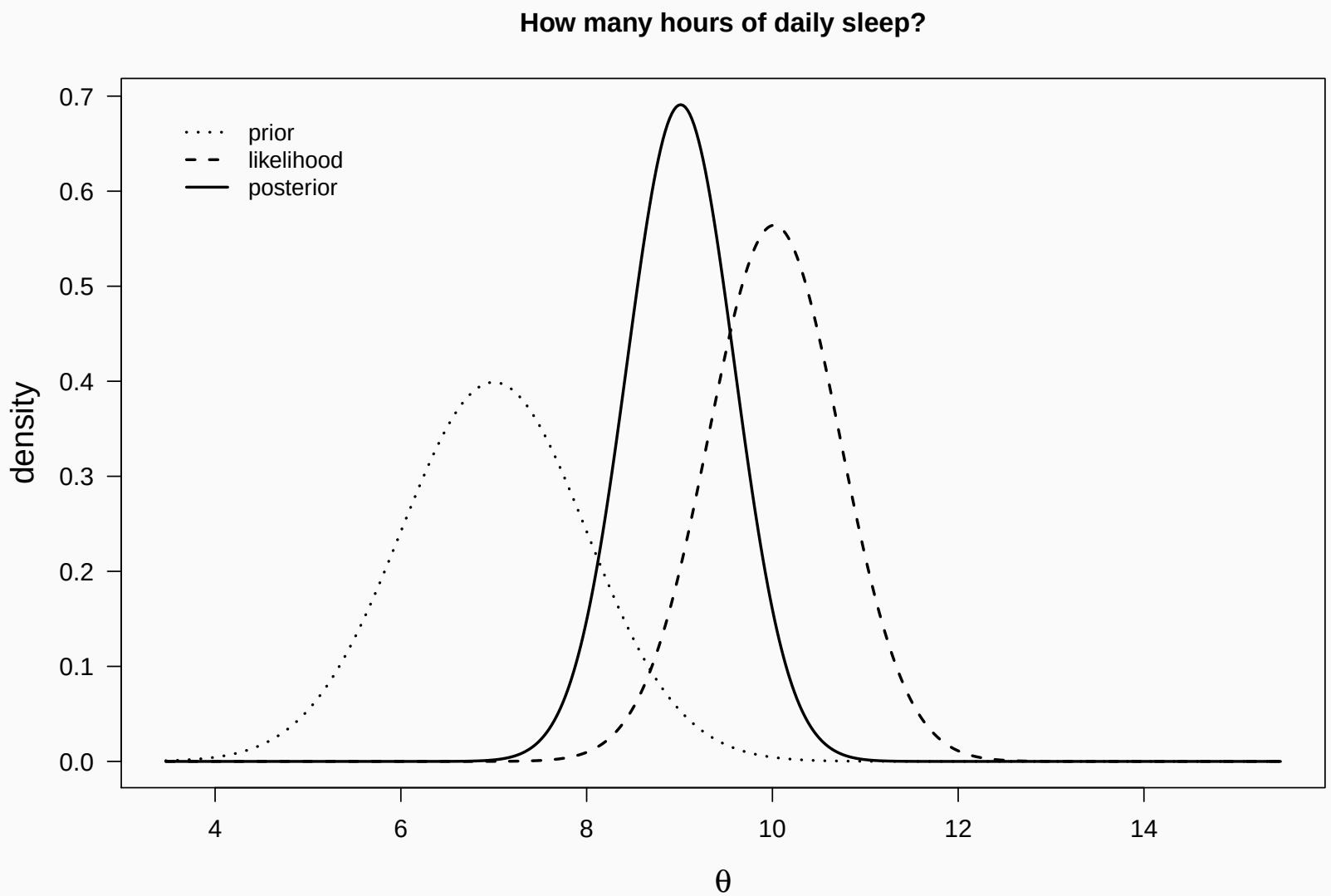
- Frequentist CIs and Bayesian credible intervals can be similar, but not always.

Bayesian inference: prior, posterior, and likelihood

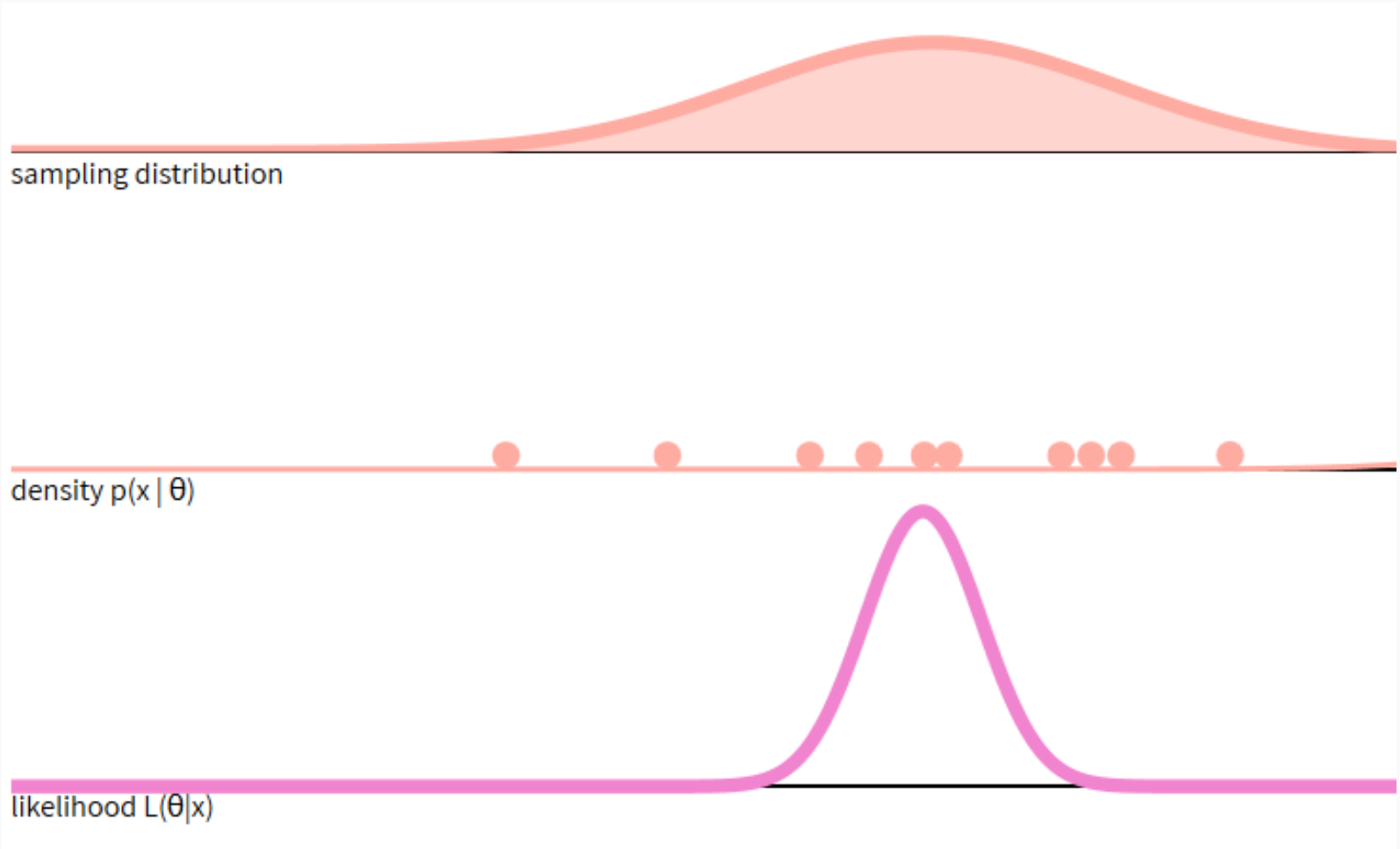
$P(H|D) \propto P(D|H) \cdot P(H)$

Posterior $\propto$ *Likelihood* $\cdot$ *Prior*



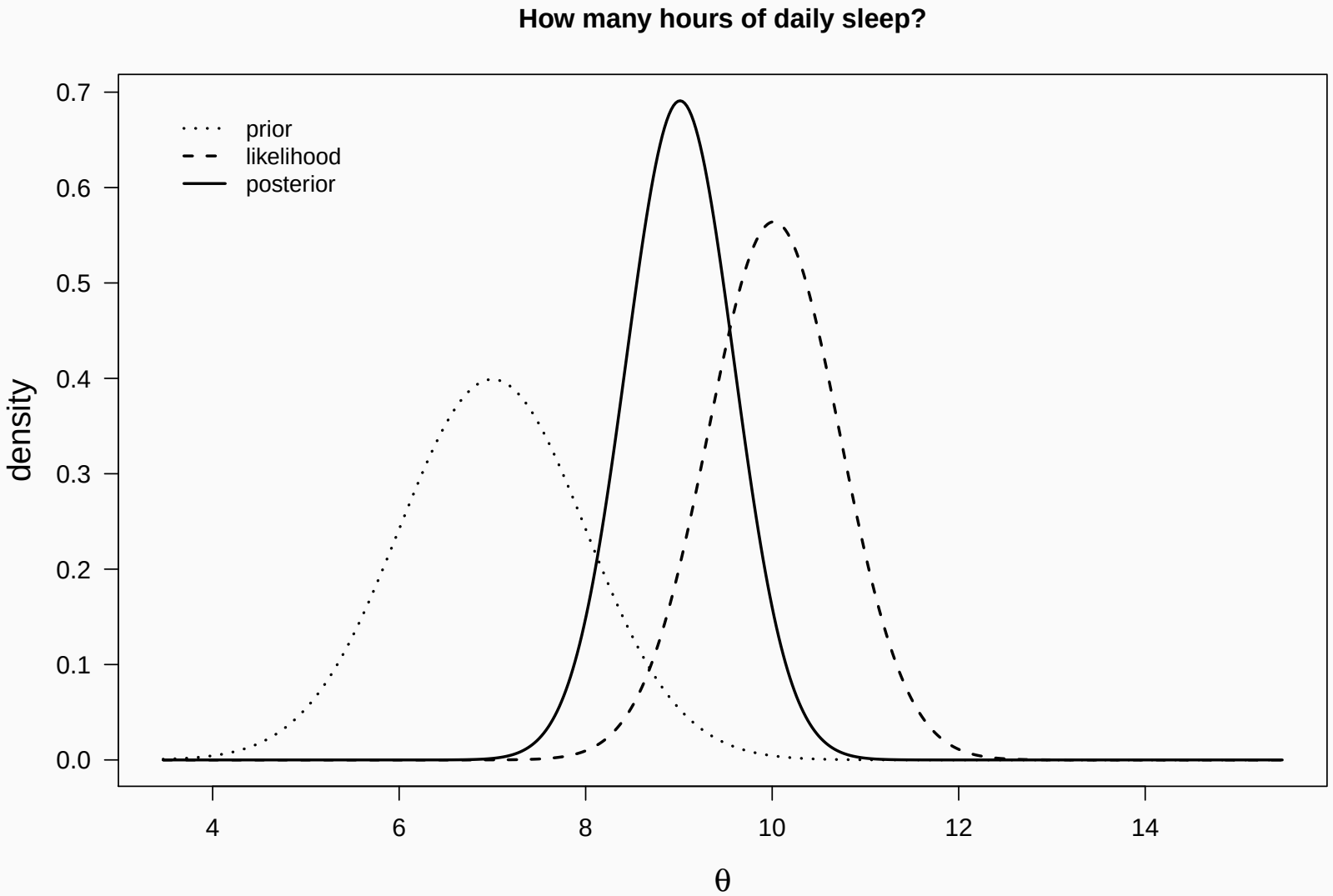
What is the likelihood?

$$L(\theta|x) = P(x|\theta)$$

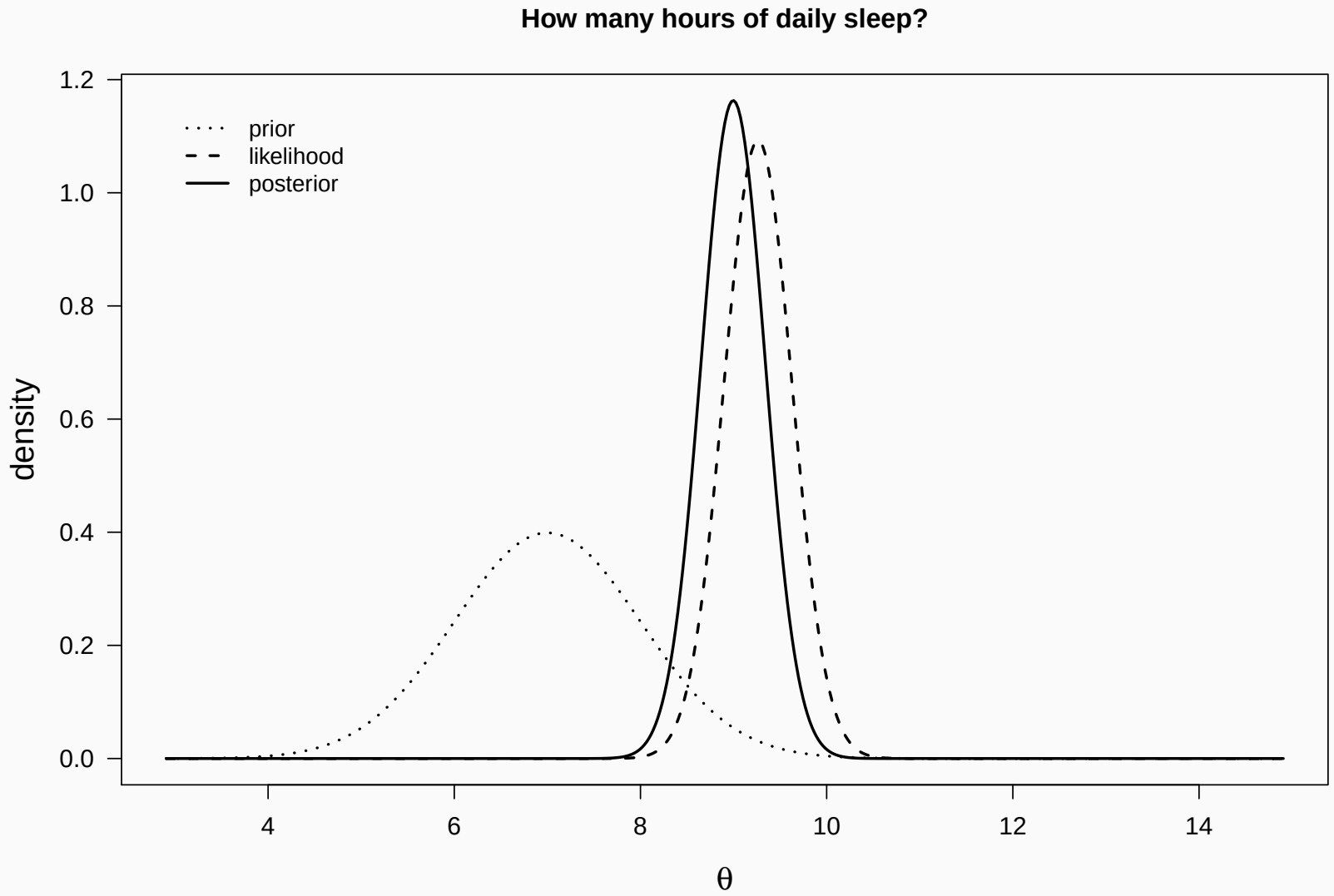


https://seeing-theory.brown.edu/bayesian-inference/index.html

Bayesian inference: prior and likelihood produce posterior



With increasing sample size, likelihood dominates prior



More apps to introduce Bayesian inference

- Bayesian Demo

More apps to introduce Bayesian inference

- Bayesian Demo
- Bayesian inference for a population mean

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Bayesian statistics in practice

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- Large dataset -> prior effect diminishes
- Uncertainty / Propagate errors

Experimental Design

How would you evaluate fertilizer effect?

Discuss with partner (5')

Experimental design principles

Replication

Replication!

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- How many? As much as you can! See Gelman & Carlin 2014.

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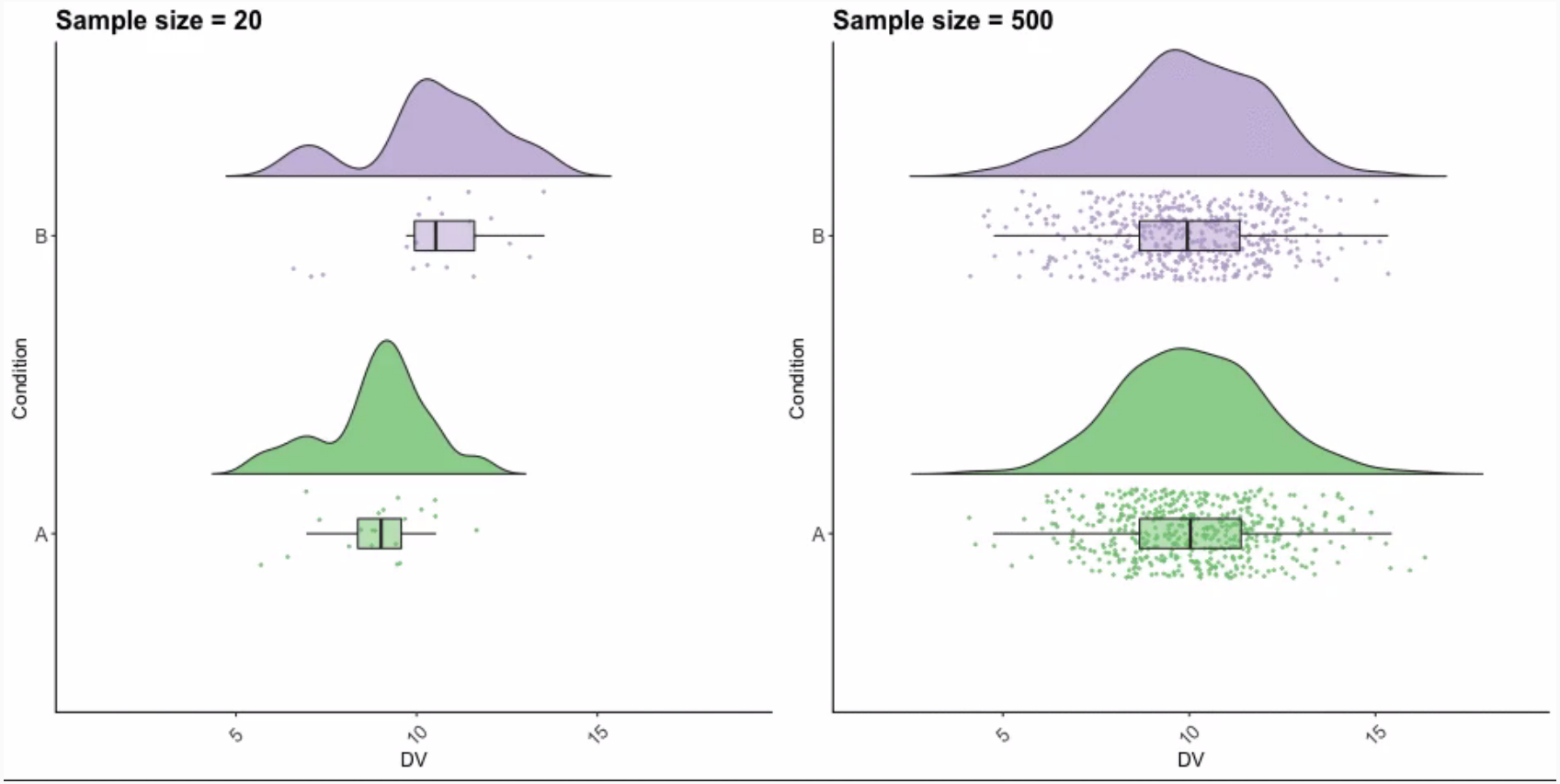
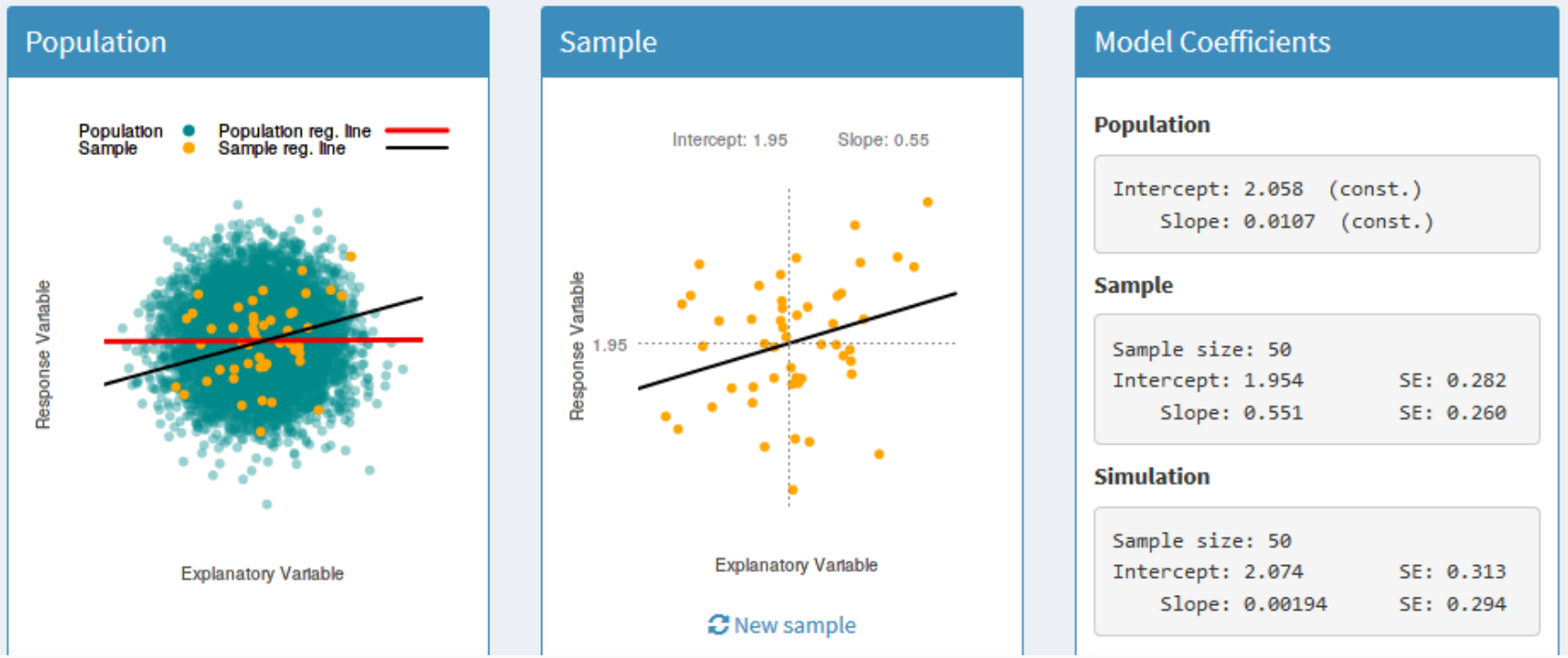
- Replication is key: we need several samples.
- How many? As much as you can! See Gelman & Carlin 2014.
- Traditionally, ecology studies have had **too low sample sizes**.
- Low sample sizes miss subtle effects, but also **prone to bias**.

Low sample sizes very sensitive to random noise



https://twitter.com/ajstewart_lang/status/1020038488278945797

Low sample sizes may bias inferences about population



http://statisticalgate.com/regression-simulation/

Low sample sizes may bias inferences

See *The evolution of correlations*

Stopping rules

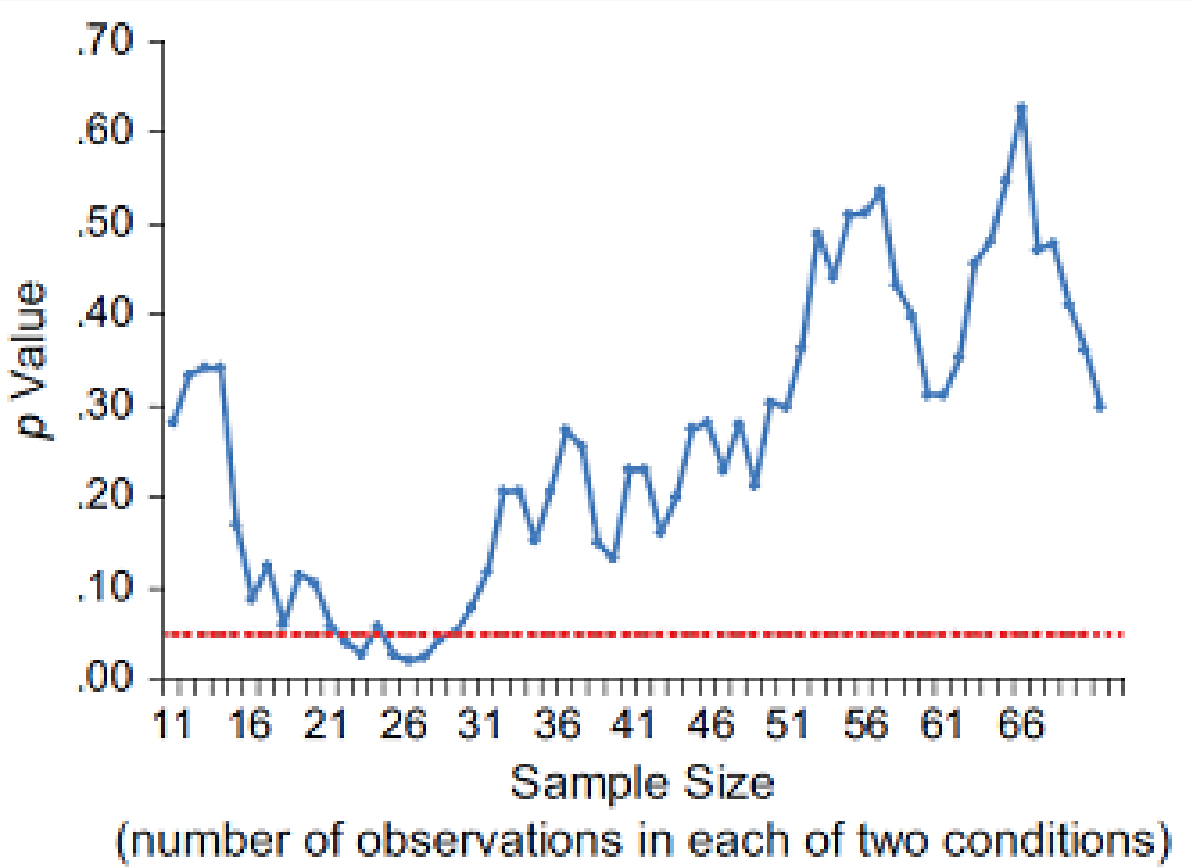


Fig. 2. Illustrative simulation of *p* values obtained by a researcher who continuously adds an observation to each of two conditions, conducting a *t* test after each addition. The dotted line highlights the conventional significance criterion of $p \leq .05$.

Sample size estimation

- Plan model/statistical analysis **before** data collection.

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- Plan to have at least **10-30 observations per predictor**.
- Complex models (w/ many predictors, interactions etc) require **high** sample sizes.

Randomization

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- Haphazard $\neq$ Random

Randomization

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- Stratify: randomize within groups (e.g. species, soil types)

Controls

Have controls

- Untreated individuals, plots... (assigned randomly, of course).

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- **Must differ only in treatment** (i.e. homogeneous environment).
- Measure **before & after** treatment.
- Consider **blind designs** to avoid observer bias.

Experimental design principles

1. Replication

Experimental design principles

1. Replication
2. Randomization

Experimental design principles

1. Replication
2. Randomization
3. Controls

To read more

- Ruxton & Colegrave. Experimental Design for the Life Sciences. OUP

Hypothesis testing

Do sleep hours differ between local and foreign students?

- Daily sleep hours by local students:

```
7 6 7 6 6
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
    6.0     6.0     6.0     6.4     7.0     7.0 
```

```
9 9 9 9 11 8 6 10 8 8
```

```
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```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
    6.0     8.0     9.0     8.7     9.0    11.0
```

- We know what happens in **our samples**, but want to extrapolate to the whole **population**.

If we sample students in this class...

- Can we extrapolate results to

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    - this class?

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  - this class?
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If we sample students in this class...

- Can we extrapolate results to
  - this class?
  - this university?
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  - the world?
- What's the **suitable population** to make inferences given this sample?

NHST concepts

Null and alternative hypotheses

- Tell me...

Null and alternative hypotheses

- Tell me...
- **Null hypothesis**: there is no difference between groups.

Null and alternative hypotheses

- Tell me...
- **Null hypothesis**: there is no difference between groups.
- **Alternative hypothesis**: groups are different.

In ecology, everything is somewhat different

Are there any differences? A non-sensical question in ecology

Alejandro Martínez-Abraín

IMEDEA (CSIC-UIB), C/Miquel Marquès 21, 07190 Esporles, Majorca, Spain

ARTICLE INFO

Article history:
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Keywords:

ABSTRACT

One of the main questions that ecologists pose in their investigations includes the analysis of differences in some trait between two or more populations. I argue here that asking whether there are differences or not between populations is biologically irrelevant, since no two livings things are ever equal. On the contrary the appropriate question to pose is how large differences are between populations. That is, we urge a shift in interest from statistical significance to biological relevance for proper knowledge accumulation. I empha-

What is the p-value?

- The probability that the data were produced by random chance alone

https://pollev.com/franciscorod726

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- The probability of null hypothesis being true

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- Large P-value: data not unusual if H0 was true.

If p-value > 0.05

- the null hypothesis is false, i.e. the alternative hypothesis must be true

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- there is no difference between groups

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https://doi.org/10.1038/d41586-019-00857-9

Are the heights of local and non-local students different?

```r
t.test(h.sevi, h.out)
```

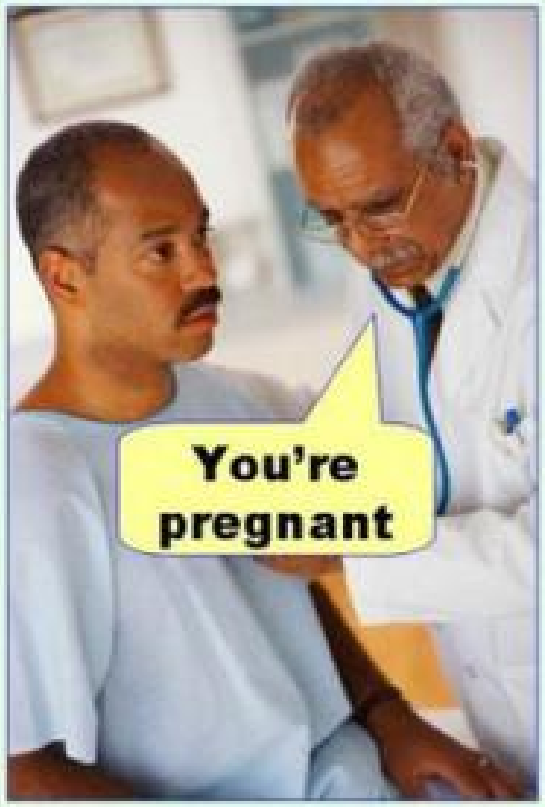
```
    Welch Two Sample t-test

data:  h.sevi and h.out
t = -2.9869, df = 5.8705, p-value = 0.02507
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -21.518508  -2.081492
sample estimates:
mean of x mean of y
    169.2     181.0
```

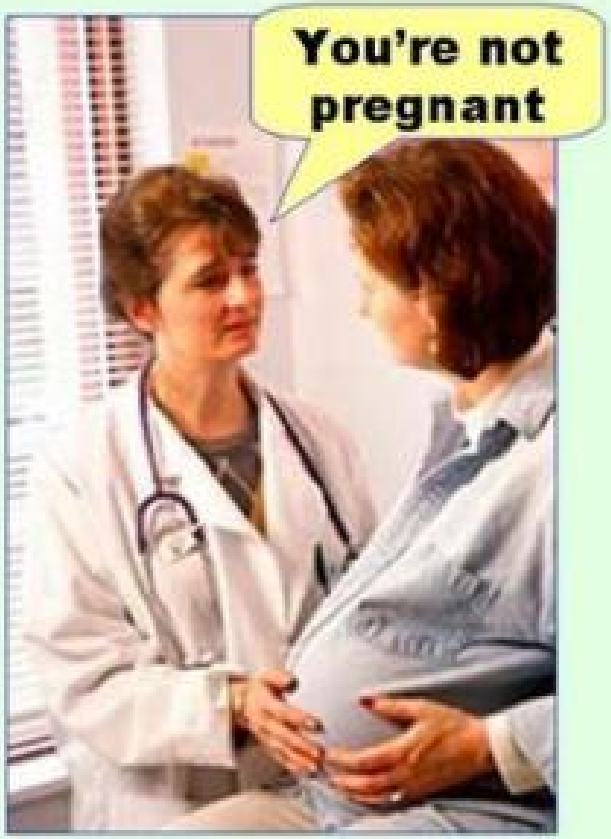
https://pollev.com/franciscorod726

Rejecting hypotheses: two types of error

Type I error
(false positive)



Type II error
(false negative)



Rejecting hypotheses: two types of error

Statistics: Hypothesis Test	Null Hypothesis is True	Null Hypothesis is False
Reject Null Hypothesis	Type I Error	Correct
Fail to Reject Null Hypothesis	Correct	Type II Error

Power: Probability of detecting true difference (rejecting H0 when it's false).

Understanding NHST

http://rpsychologist.com/d3/NHST/

Example: biased coin

```
 [1] 0 1 0 1 1 1 1 1 0 0
```

```
    1-sample proportions test with continuity correction

data:  sum(coin) out of ntrials, null probability 0.5
X-squared = 0.1, df = 1, p-value = 0.7518
alternative hypothesis: true p is not equal to 0.5
95 percent confidence interval:
 0.2736697 0.8630694
sample estimates:
  p
0.6
```

https://pollev.com/franciscorod726

Correlation between variables

http://rpsychologist.com/d3/correlation/

Common pitfalls and good practice

A must read

Eur J Epidemiol (2016) 31:337–350
DOI 10.1007/s10654-016-0149-3

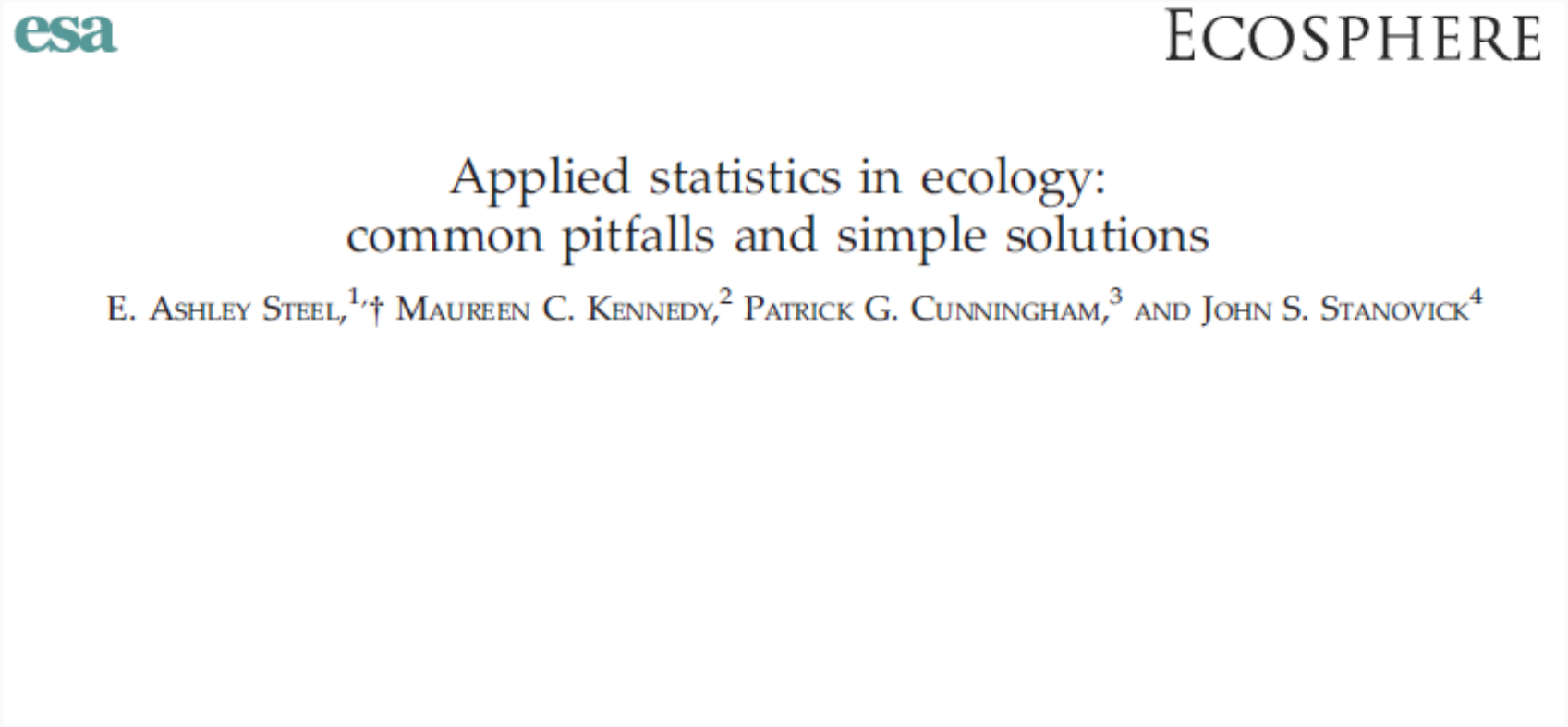
ESSAY

Statistical tests, *P* values, confidence intervals, and power: a guide to misinterpretations

Sander Greenland[1] · Stephen J. Senn[2] · Kenneth J. Rothman[3] · John B. Carlin[4] · Charles Poole[5] · Steven N. Goodman[6] · Douglas G. Altman[7]

https://doi.org/10.1007/s10654-016-0149-3

Good read



https://doi.org/10.1890/ES13-00160.1

Also http://www.statisticsdonewrong.com/

Good read

Twenty tips for interpreting scientific claims

https://doi.org/10.1038/503335a

Visualisation of data and models is key

First things first

- Always

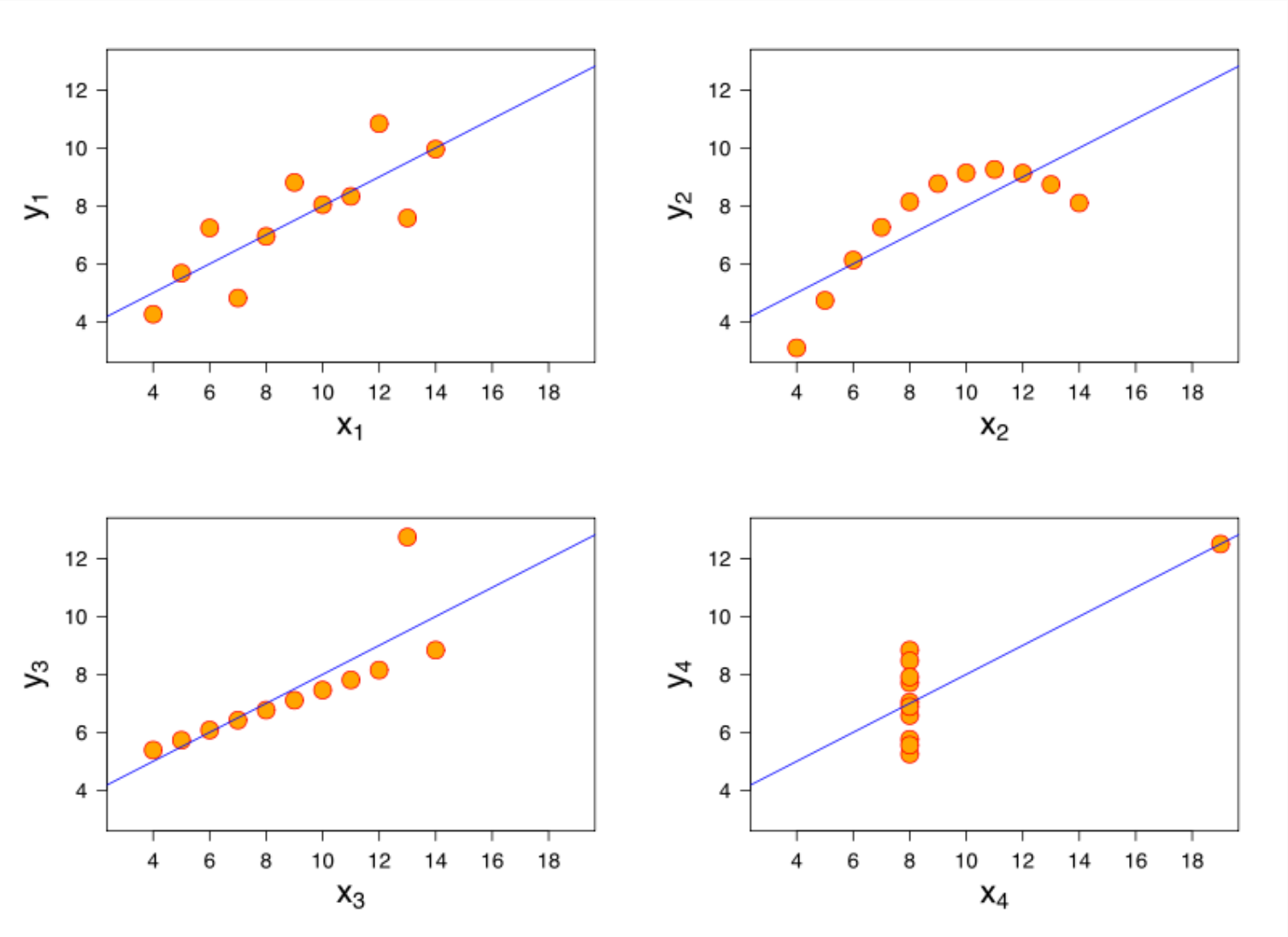
First things first

- Always
- Always

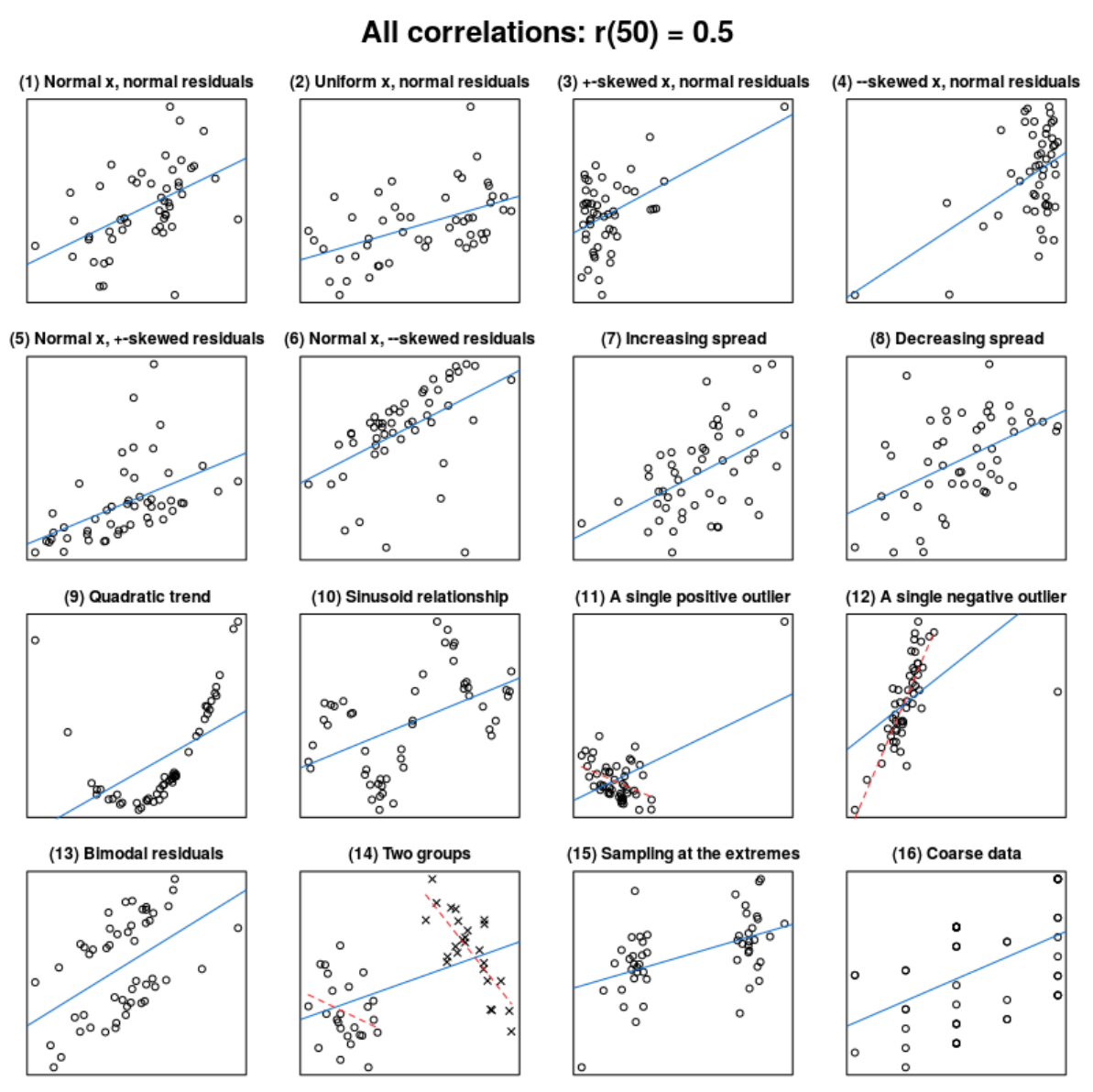
First things first

- Always
- Always
- Always

Plot data and models



Don’t use statistics blindly: *Visualise*



https://janhove.github.io/teaching/2016/11/21/what-

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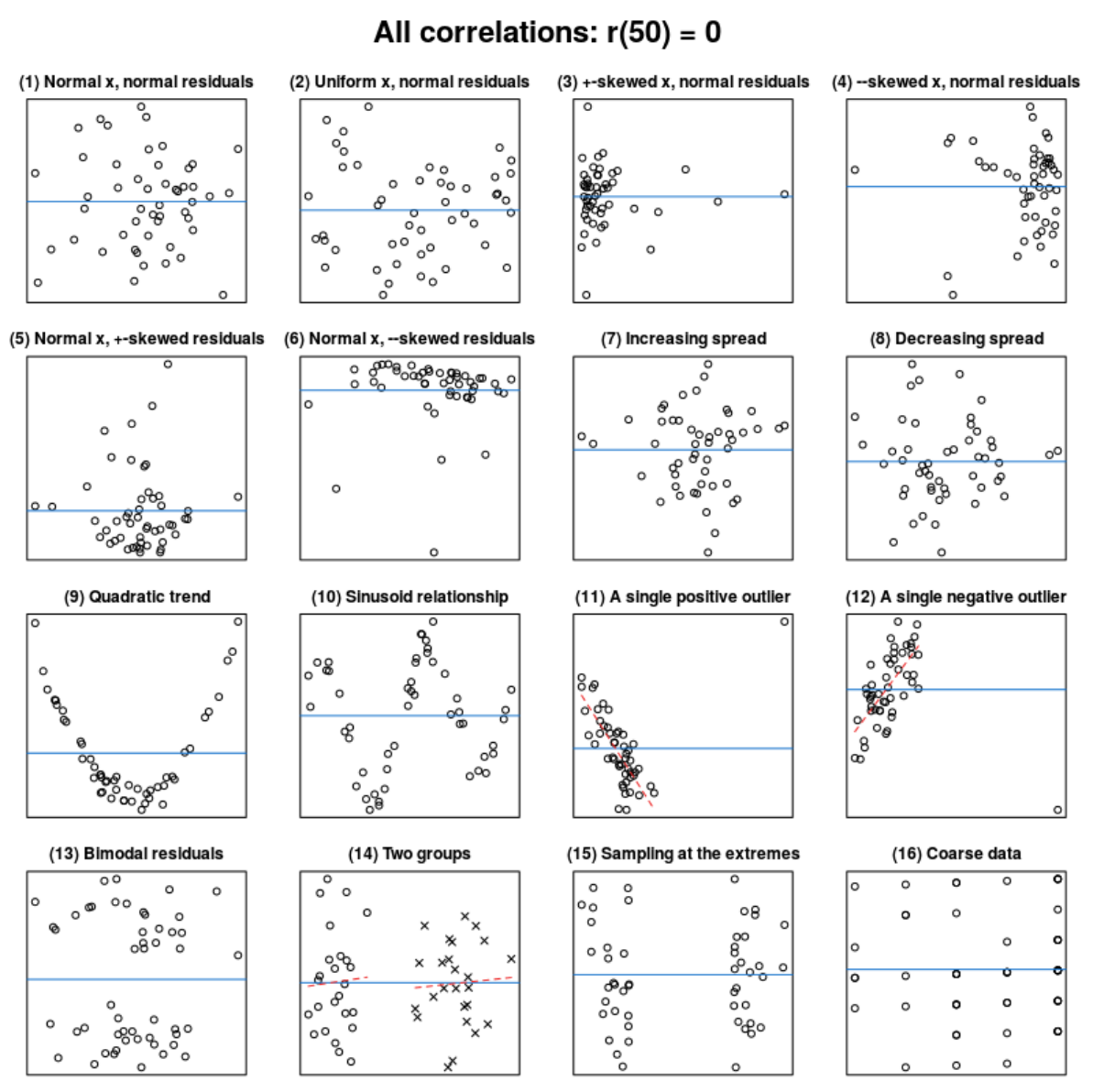

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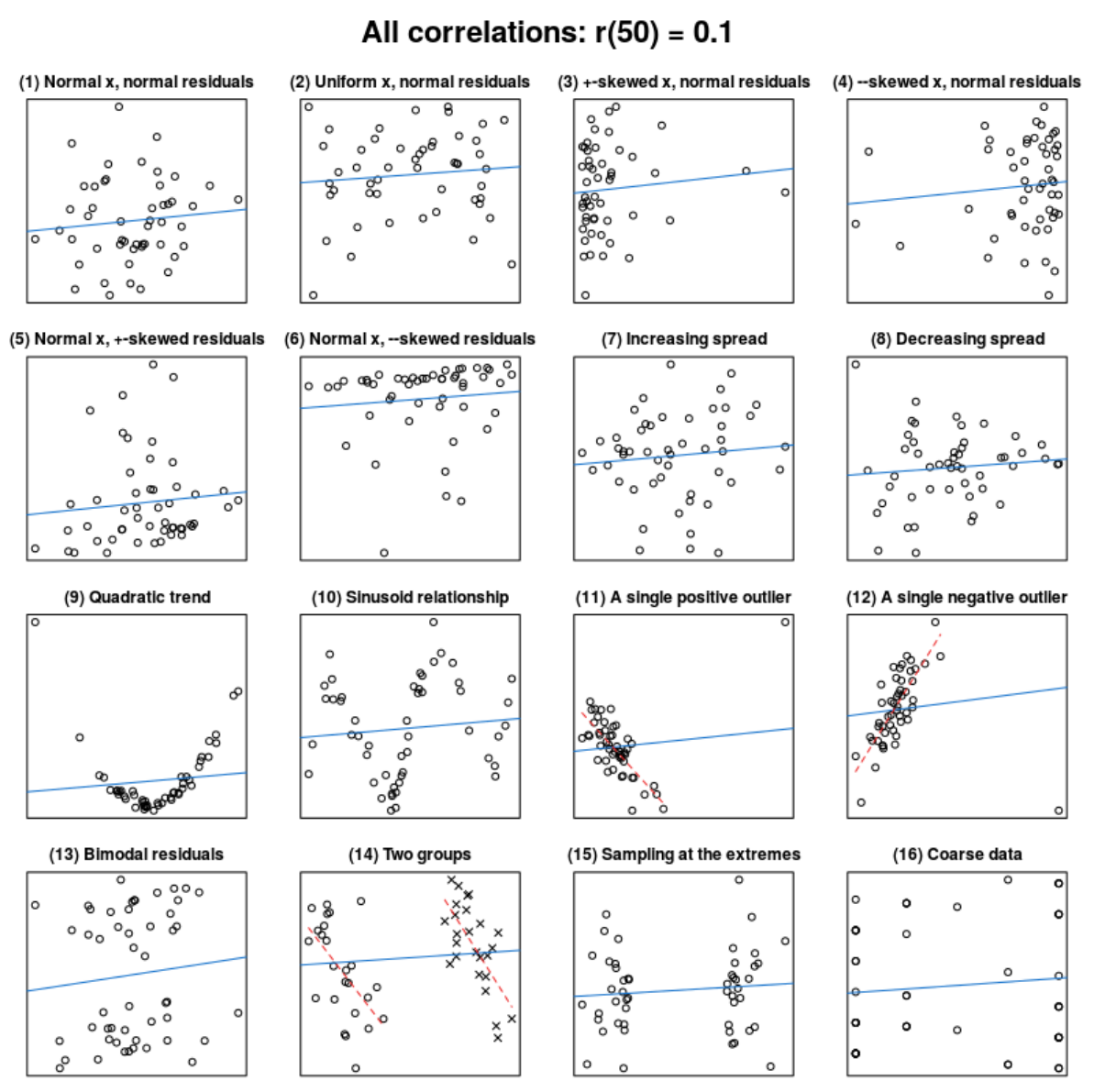

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Plot. Check models. Plot. Check assumptions. Plot.

Lavine 2014 *Ecology*

Inference from observational studies

News: Hamburgers increase risk of heart attack

- In a sample of 10,000 people, it was found that people eating >2 hamburgers a week had 20% higher probability of heart attack.

News: Hamburgers increase risk of heart attack

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- **Do hamburgers increase heart attacks?**

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Bigger flowers increase reproductive success

- We found that plants with big flowers produced 30% more seeds...

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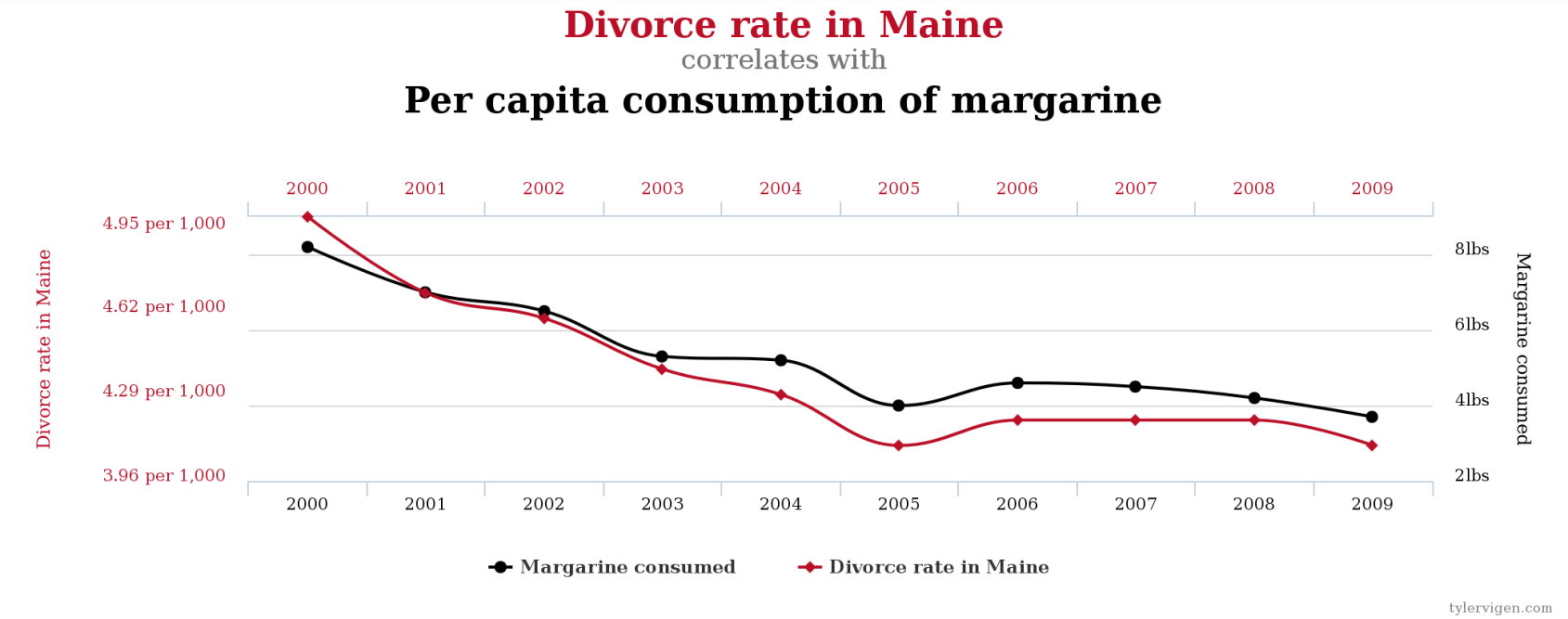
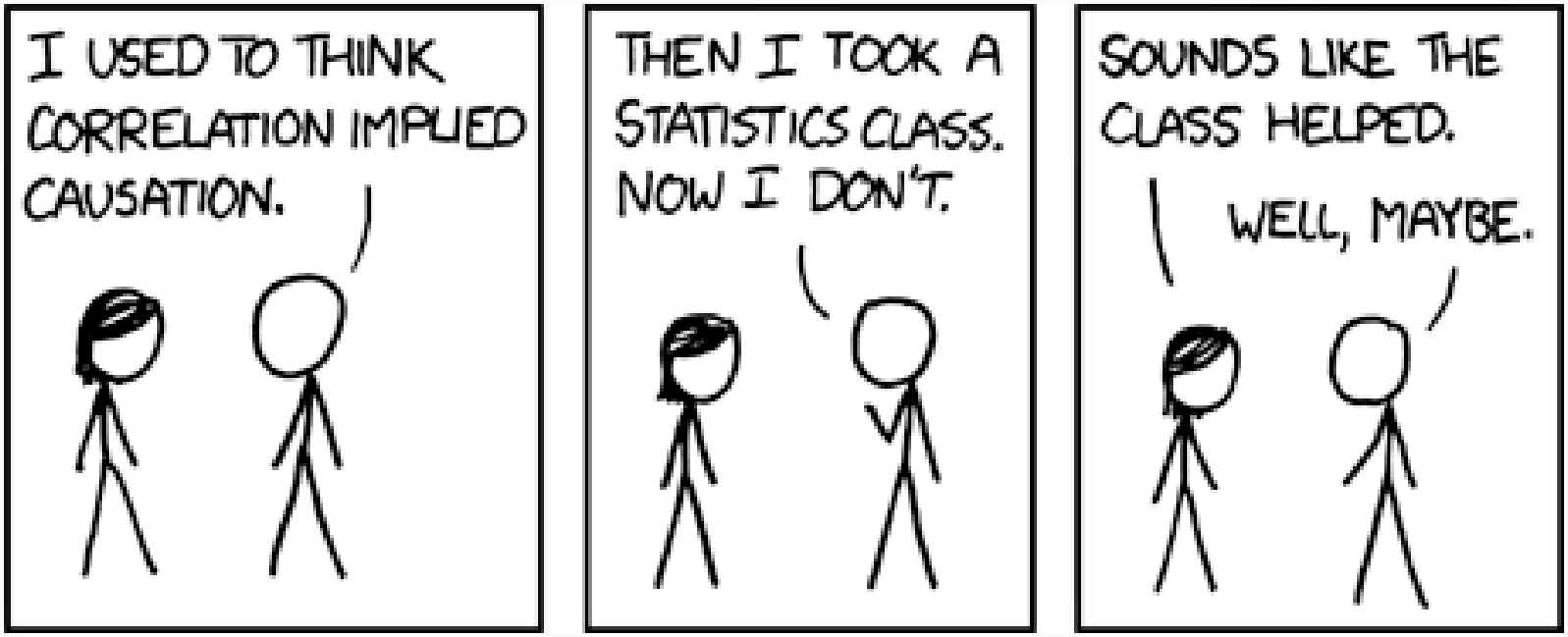
Correlation vs Causation



http://tylervigen.com/spurious-correlations

Learning statistics through xkcd



NHST and p-values

In ecology, everything is somewhat different

Are there any differences? A non-sensical question in ecology

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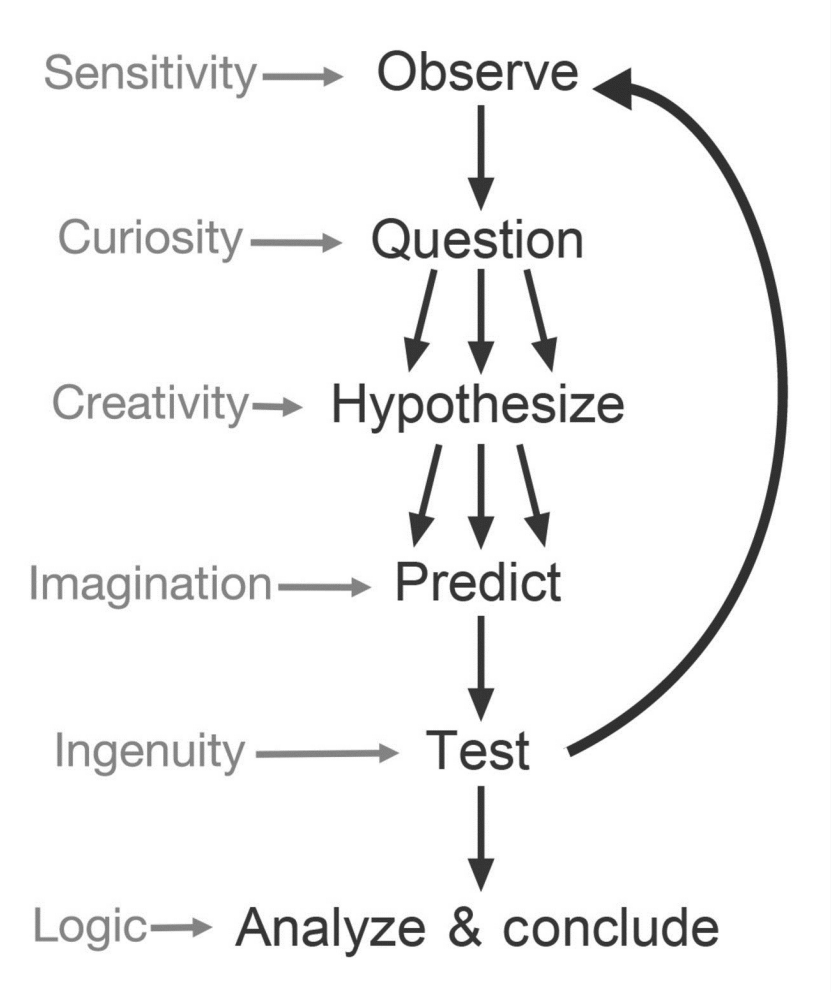
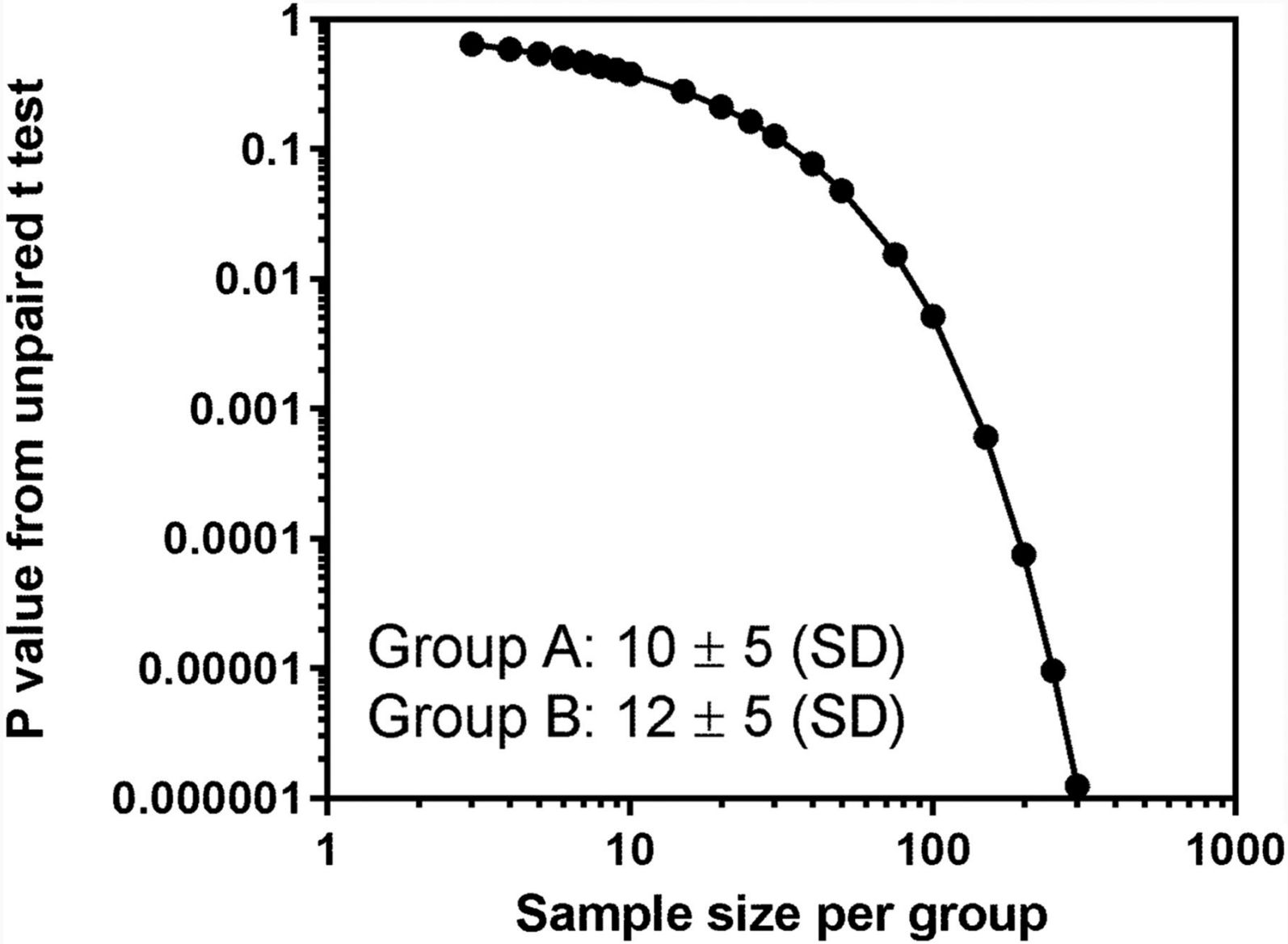
Instead of falsifying null model, compare meaningful models



https://doi.org/10.1242/jeb.104976

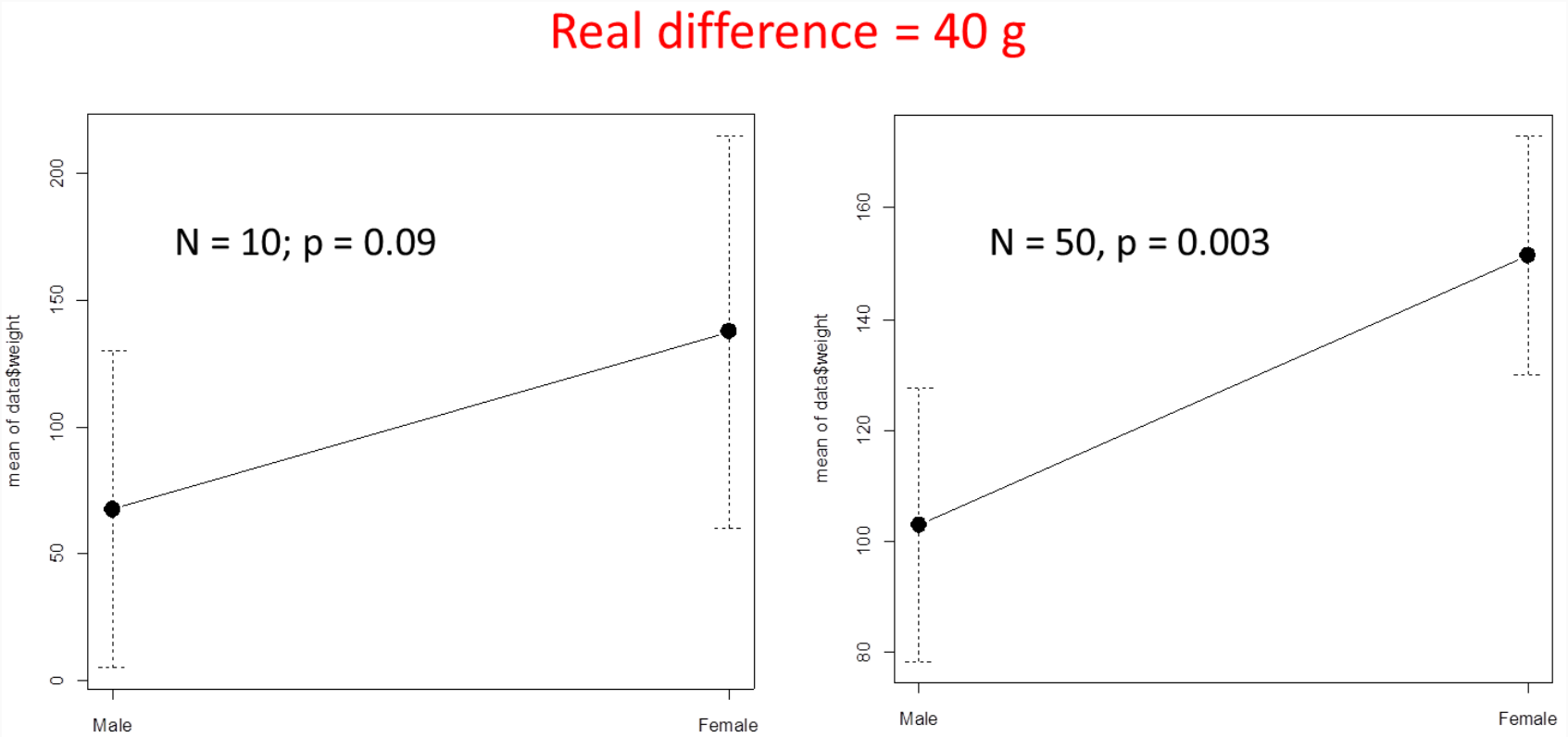
P-value depends on sample size



https://doi.org/10.1002/prp2.93

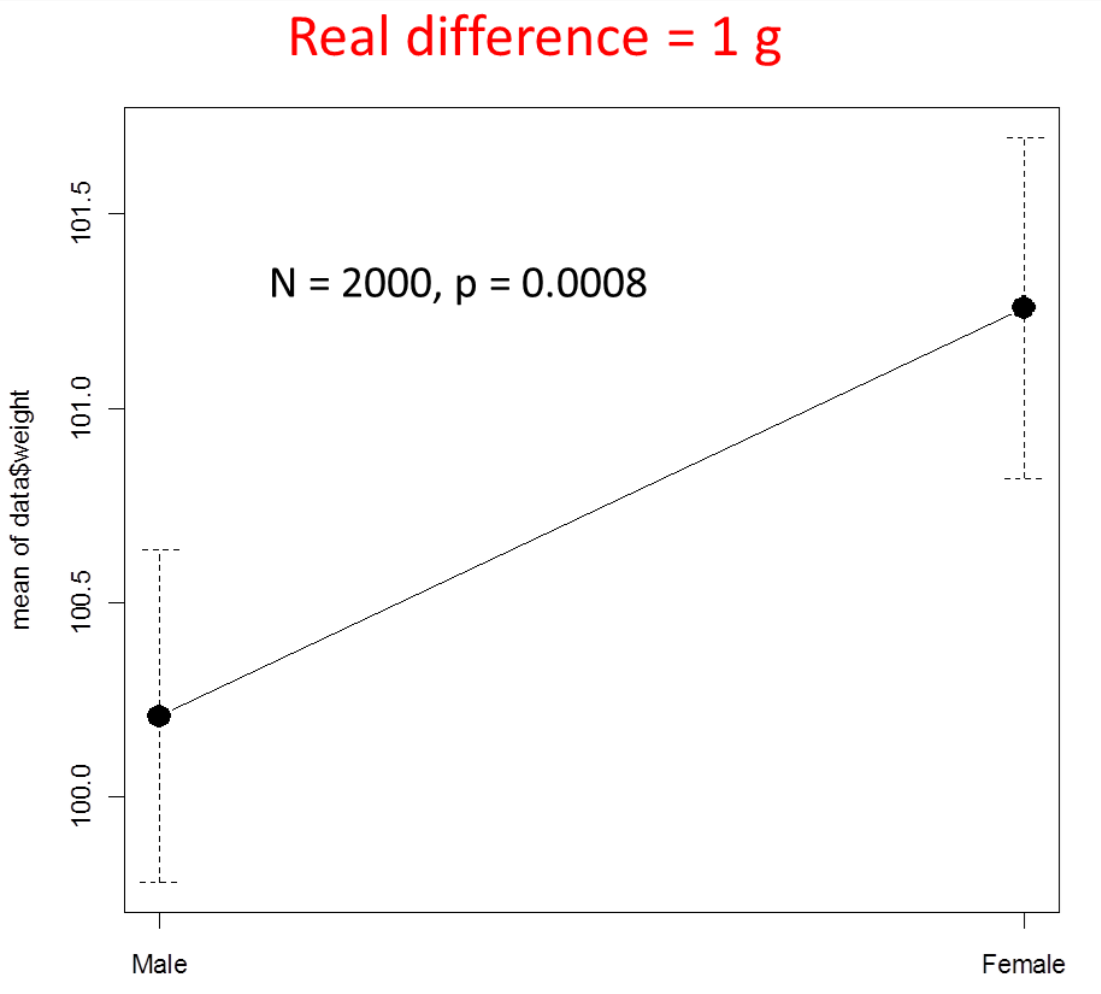
P-value depends on sample size

Same real difference is detected as significant or not depending on sample size:



Statistically significant != biologically important

With big sample size, we can find **highly significant but biologically unimportant** differences.



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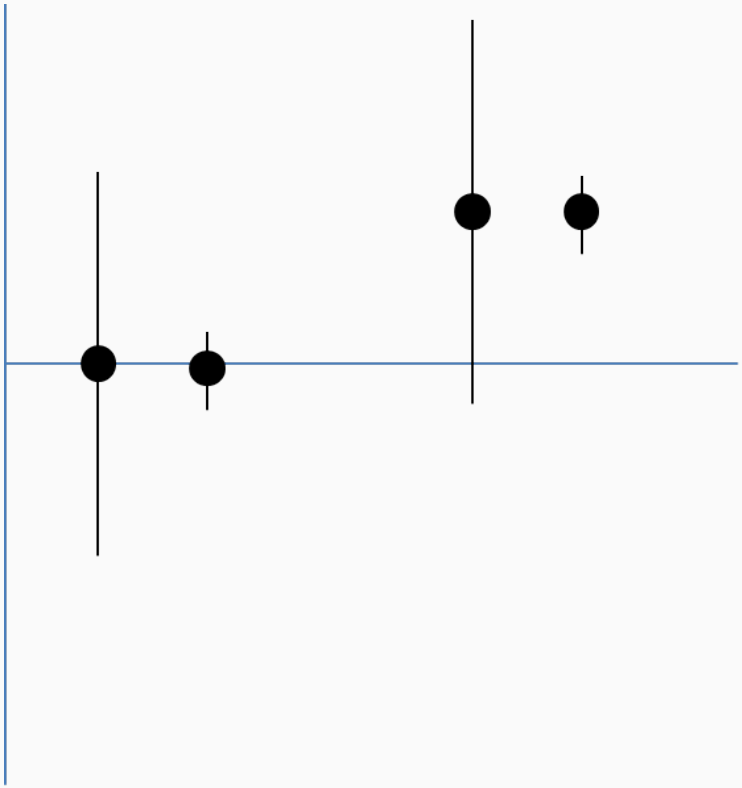
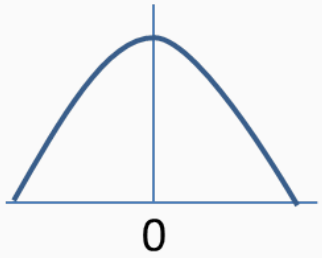
- My suggestion: avoid significant/not significant (and maybe p-values too)

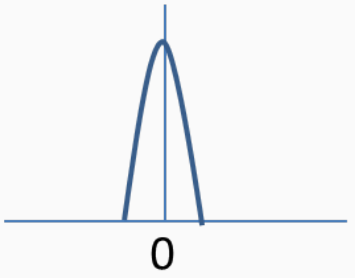
Statistically significant != biologically important

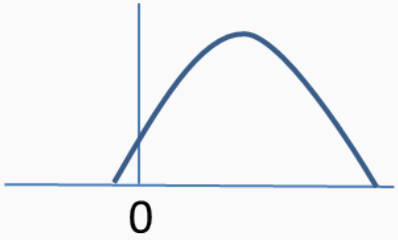
- Statistically significant = unlikely to be zero
- Good read: *significantly misleading*
- My suggestion: avoid significant/not significant (and maybe p-values too)
- Beyond significance, look at *effect sizes*.

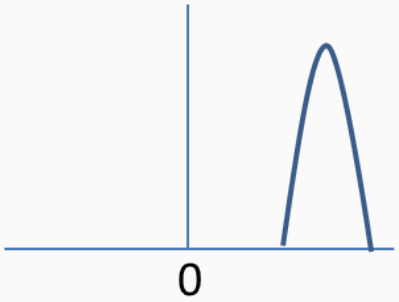
‘Not significant’ does NOT mean ‘there is no effect’





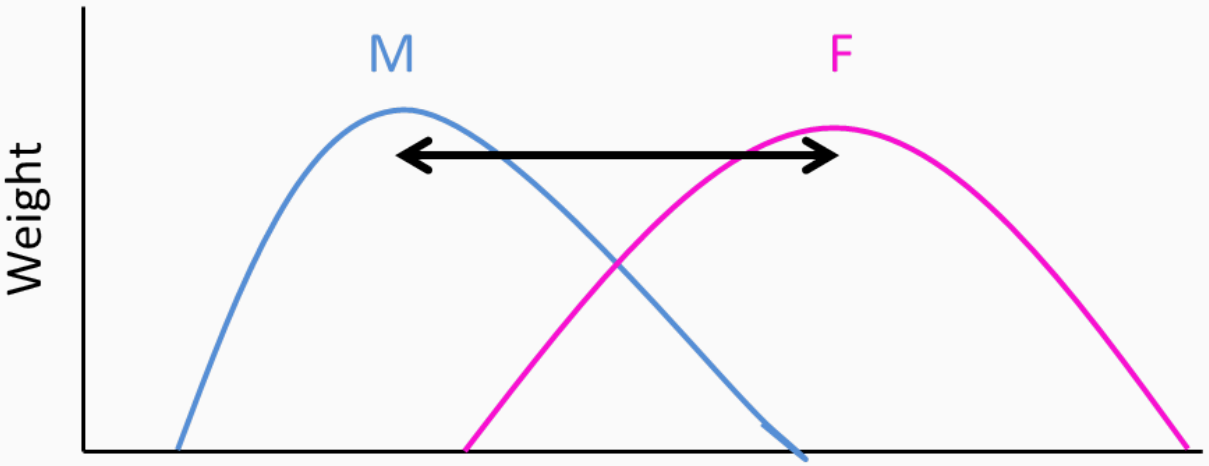




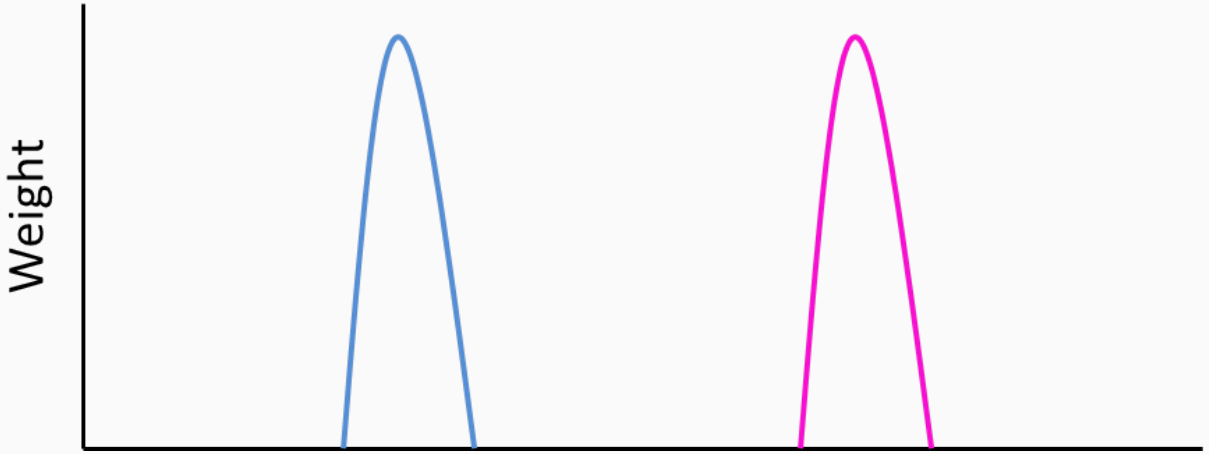


- Absence of evidence != Evidence of absence

Failure to reject H0 != H0 is true



P >> 0.05



P << 0.05

p-value > 0.05?

- “We were **unable to find evidence** against the hypothesis that A = B **with the current sample size**” (Harrell)

p-value > 0.05?

- "We were **unable to find evidence** against the hypothesis that A = B **with the current sample size**" (Harrell)
- "Differences between groups were **not statistically clear**" (Dushoff et al)

Is it safe to allow right turn with red lights?

- Right turn not allowed: 308 accidents

https://www.statisticsdonewrong.com/power.html#the-wrong-turn-on-red

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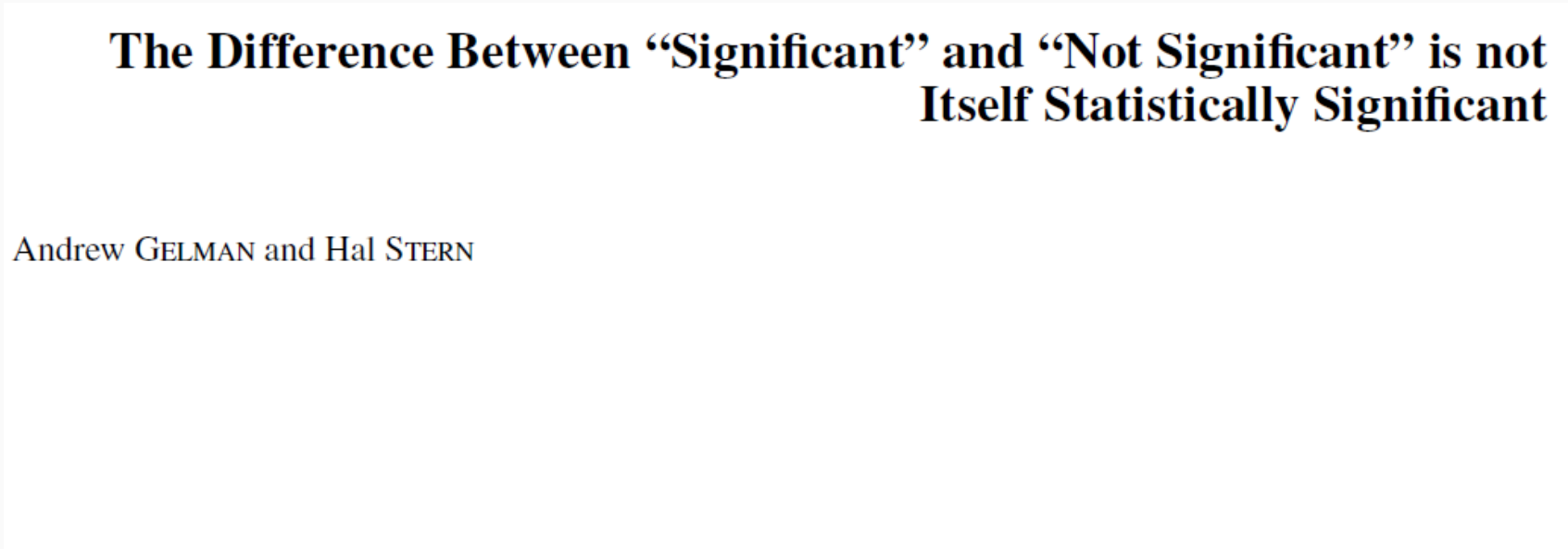
- Right turn allowed: 337 accidents
- No *significant* difference, hence safe
- Misinterpretation of underpowered study cost lives

https://www.statisticsdonewrong.com/power.html#the-wrong-turn-on-red

0.05 is an arbitrary threshold

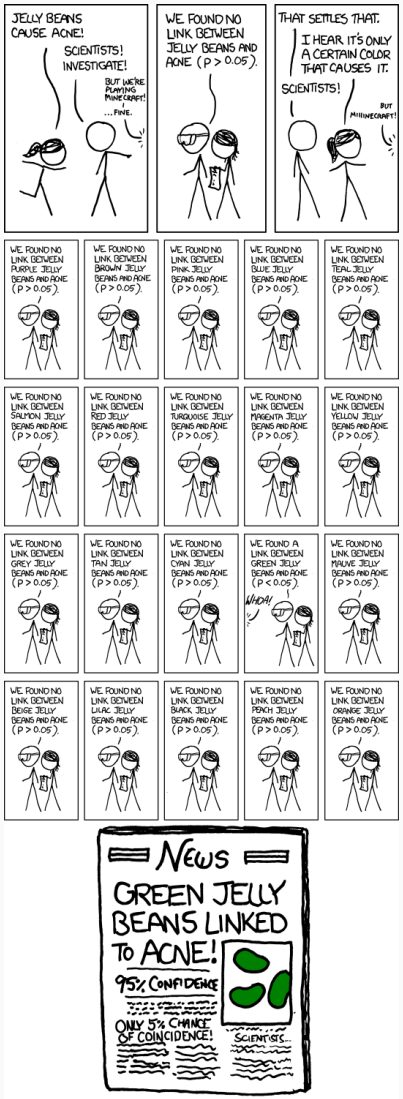


The Difference Between "Significant" and "Not Significant" is not Itself Statistically Significant

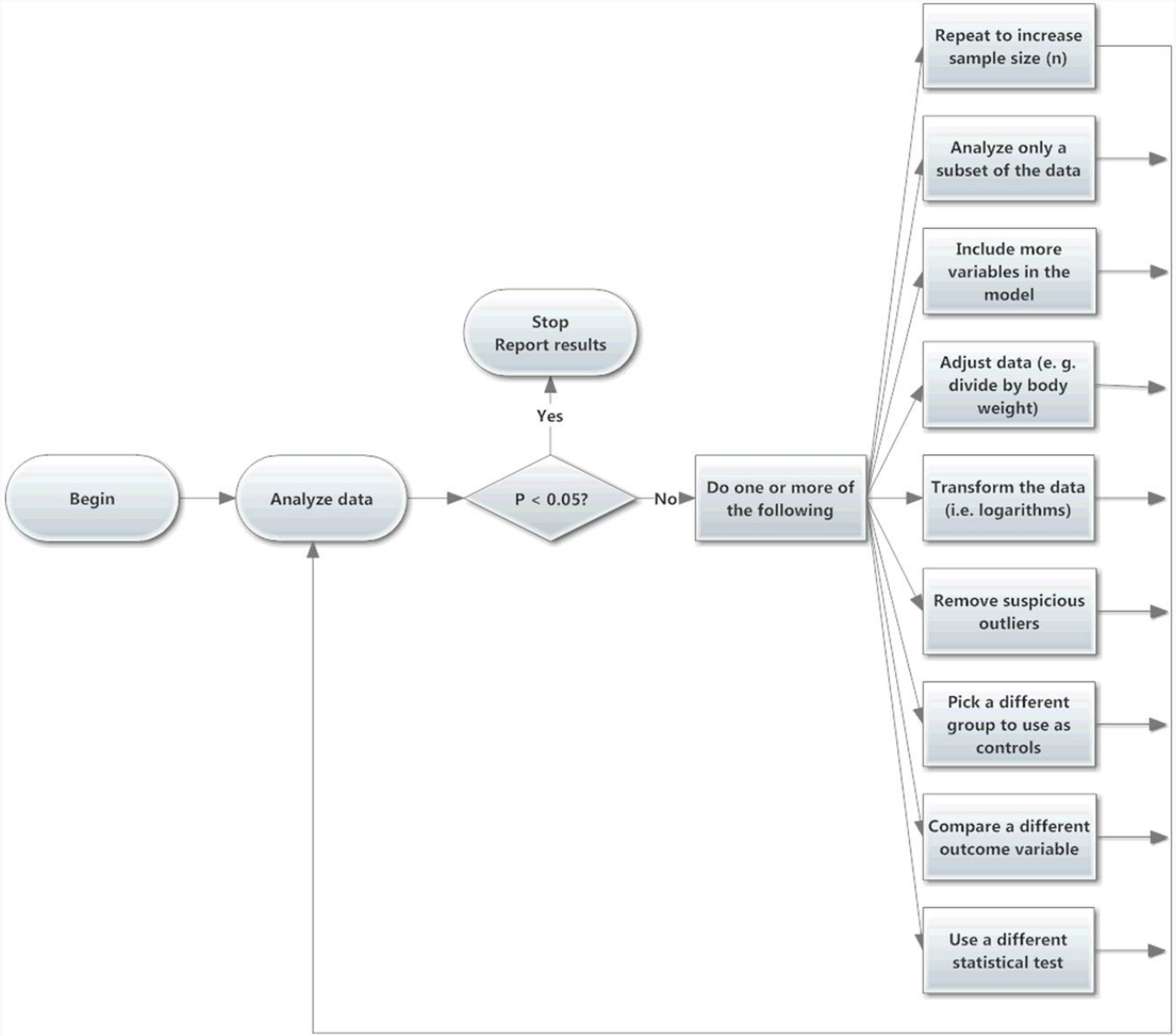
Andrew GELMAN and Hal STERN

http://dx.doi.org/10.1198/000313006X152649

Multiple hypothesis testing



How to make your results significant: *p-hacking*



http://dx.doi.org/10.1002/prp2.93

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- To read more: Simmons et al 2011

How to make your results significant: *p-hacking*

https://www.youtube.com/watch?v=ZaNtz76dNSI

ASA statement on p-values

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https://doi.org/10.1080/00031305.2016.1154108

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The New Statistics

Aim for estimation of effects and their uncertainty (SE, CI...)

General Article

The New Statistics: Why and How

Geoff Cumming
La Trobe University

Psychological Science
2014, Vol. 25(1) 7–29

DOI: 10.1177/0956797613504966
pss.sagepub.com

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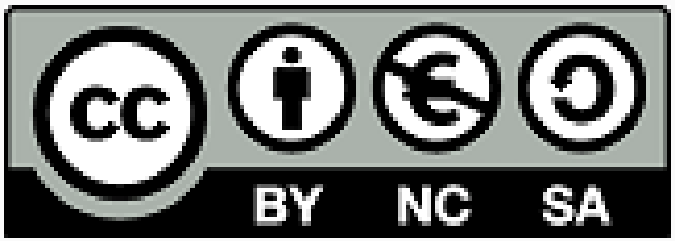
END



Source code and materials: https://github.com/Pakillo/stats-intro