An introduction to statistical inference

Francisco Rodríguez-Sánchez

http://bit.ly/frod_san

Why statistics?

To answer questions like…

- what's the probability that something occurs?

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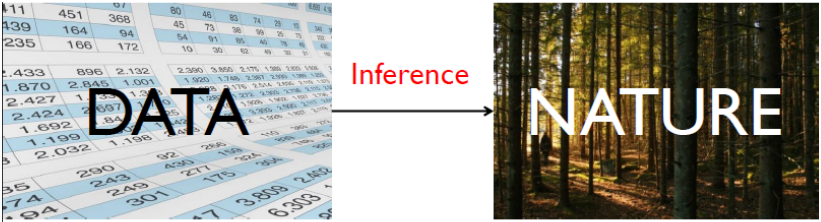
- what's the probability that something occurs?
- does X influence Y? How much?

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’

Figure 1:

To get answers to tough problems

For example. . .

Figure 2:

Inferring tree fecundity

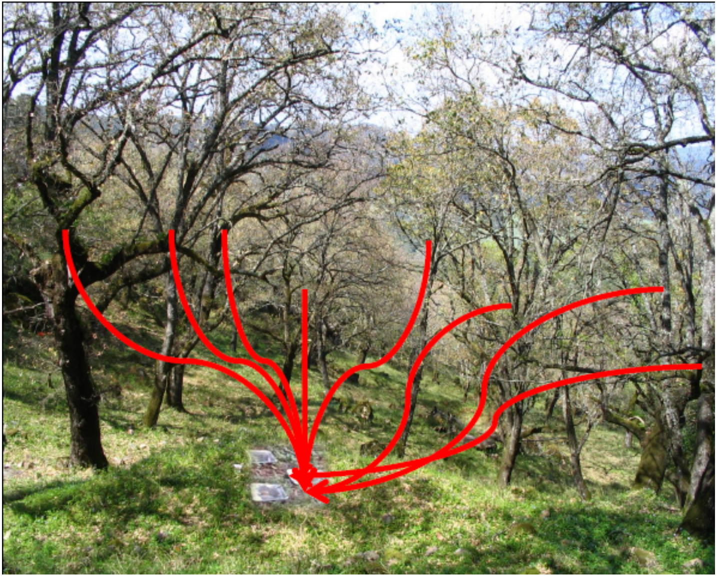


Figure 3:

Course goals

- **Understand** statistical inference

Course goals

- **Understand** statistical inference
- 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

Topics

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- Graphics

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- Descriptive statistics
- Graphics
- Sampling

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- Sampling
- Experimental design

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- Hypothesis testing

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- Bayesian inference

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- Linear models & GLMs

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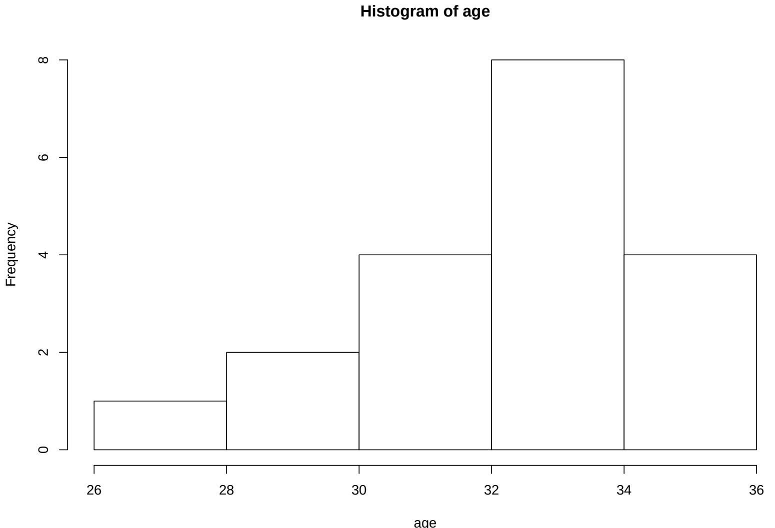
- Experimental design
- Hypothesis testing
- Bayesian inference
- Linear models & GLMs
- Model selection

Descriptive statistics

Guess my age

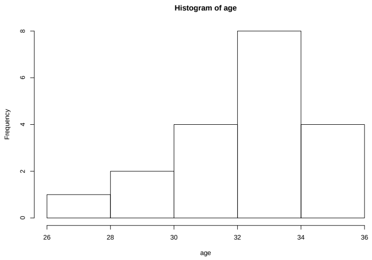
Graph your estimates

```
hist(age)
```



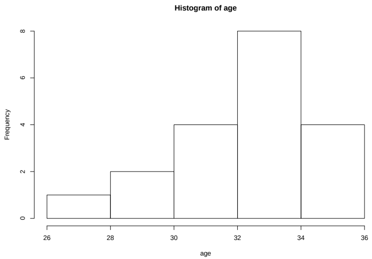
Summarise that distribution

- **Central tendency / location**



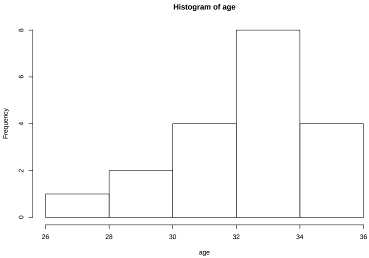
Summarise that distribution

- **Central tendency / location**
  - mean



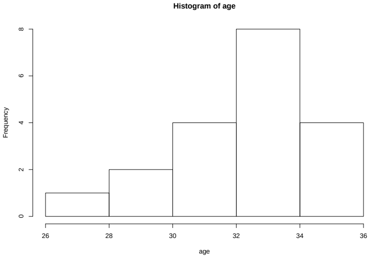
Summarise that distribution

- **Central tendency / location**
  - mean
  - median



Summarise that distribution

- **Central tendency / location**
  - mean
  - median
  - mode



Summarise that distribution

- **Central tendency / location**
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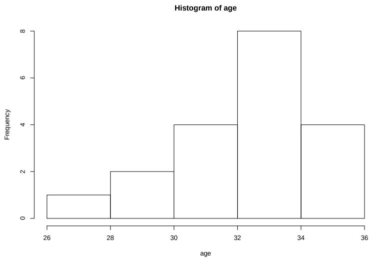
- **Variation / Spread**



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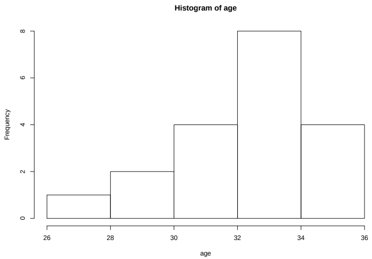
- **Variation / Spread**
  - min, max, range



Summarise that distribution

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  - min, max, range
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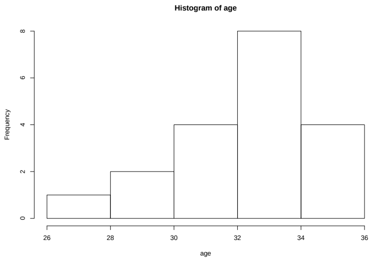

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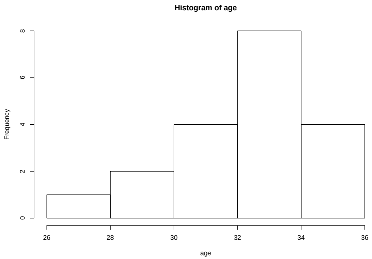
  - standard deviation



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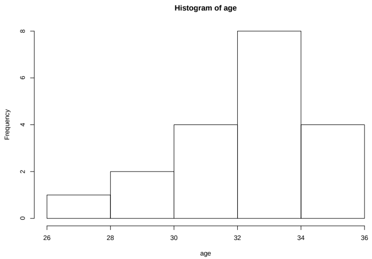
  - standard error



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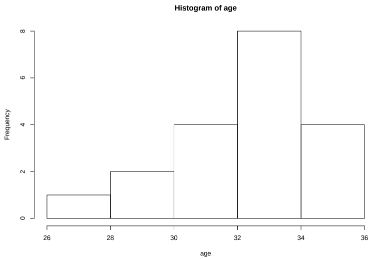

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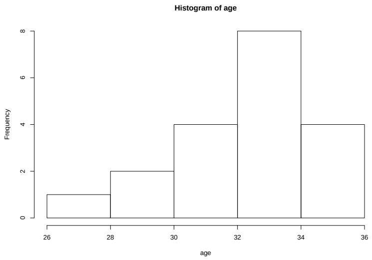
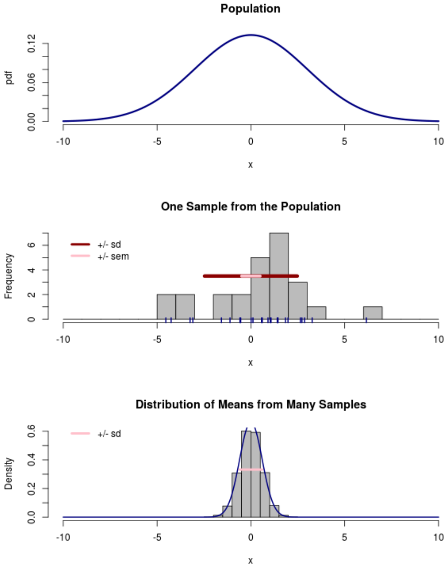


Relationship between SD and SEM



- SD quantifies scatter in population

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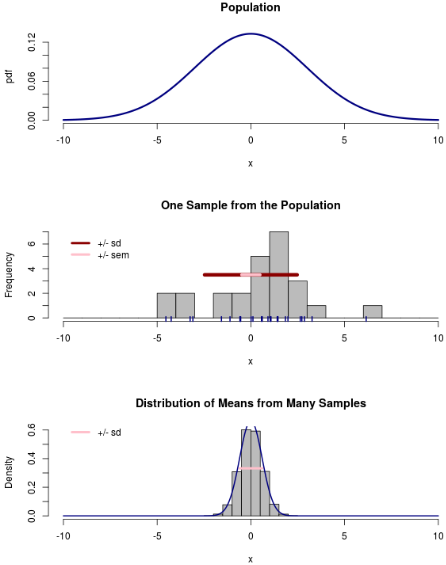

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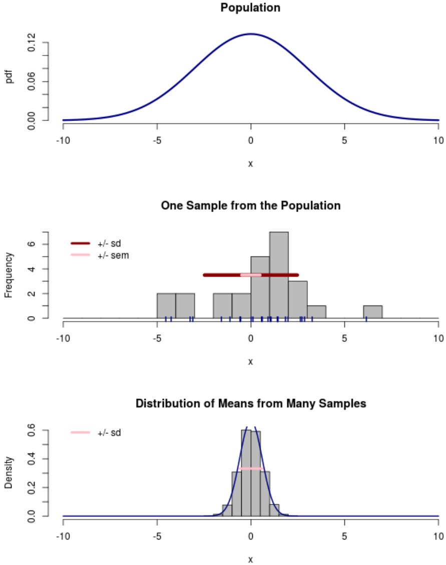

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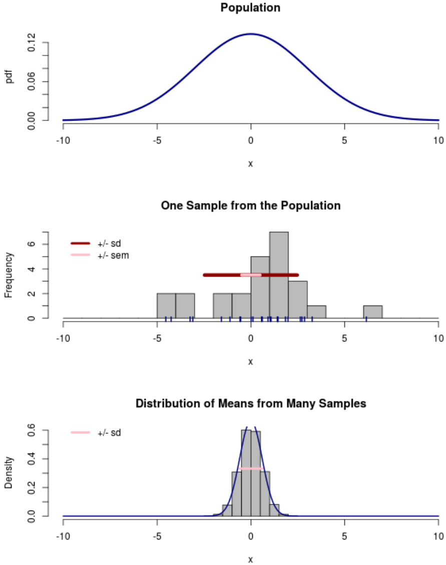

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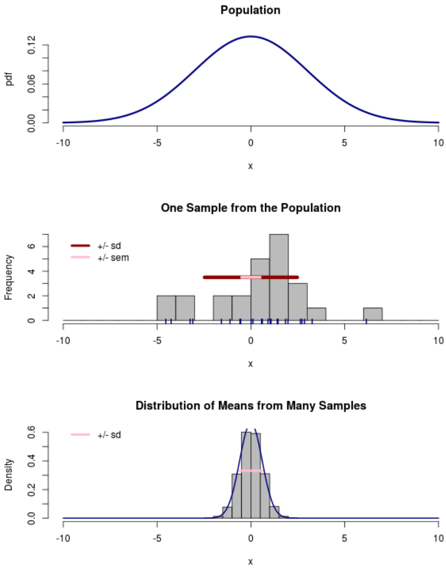

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- https://gallery.shinyapps.io/sampling_and_stderr/

In a Normal distribution

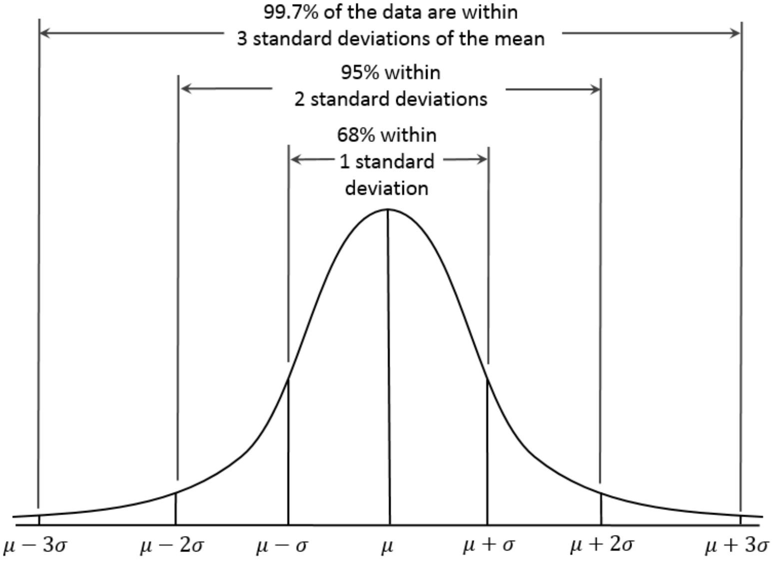
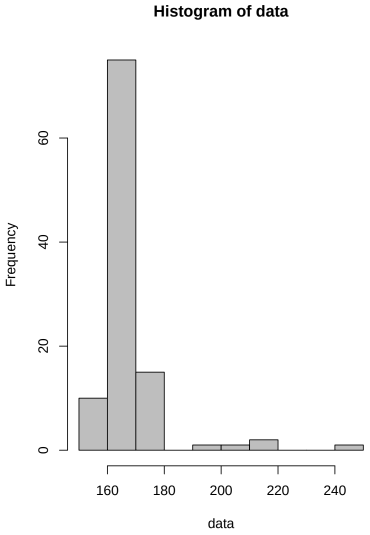
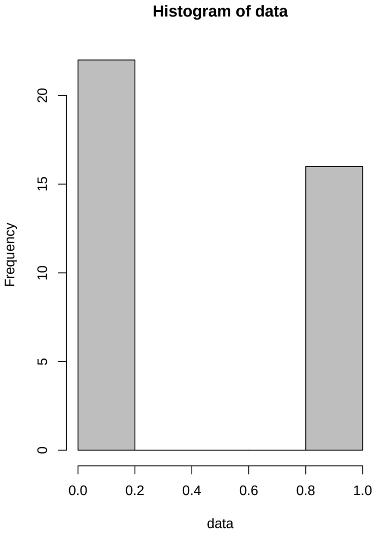


Figure 4:

What statistical descriptors are best? (and why)

https://pollev.com/franciscorod726





Sampling, confidence intervals, and Bayesian inference

Inference: from samples to population

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

Figure 5:

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1. Write down your height and place of origin (Sevilla or other) in a piece of paper and put it in the bag.

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5. Do all CIs contain true mean height?

If the 95% CI of X is (120, 150)...

- There is a 95% probability that X lies between 120 and 150

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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?

https://rpsychologist.com/d3/CI/

- CI width *decreases*...

What happens if we increase sample size?

https://rpsychologist.com/d3/CI/

- CI width *decreases*...
- 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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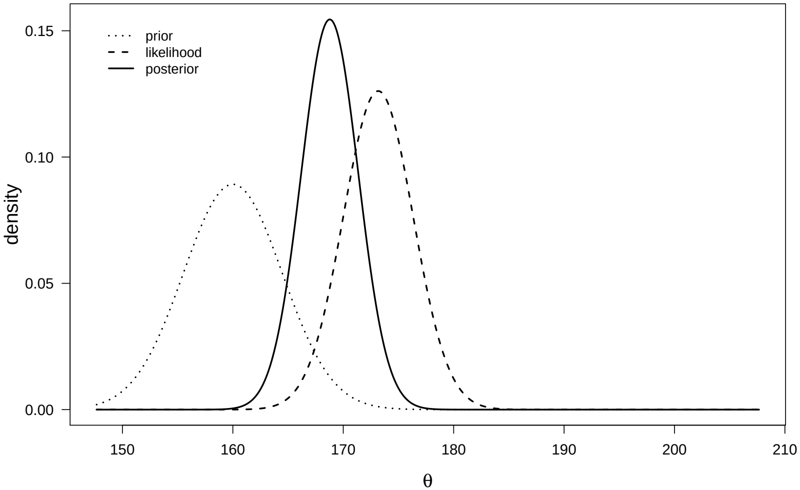
- Frequentist CIs and Bayesian credible intervals can be similar, but not always.

Bayesian inference: prior, posterior, and likelihood

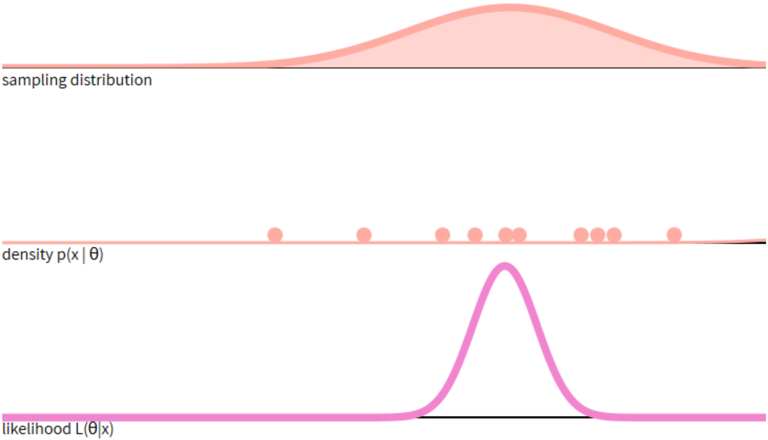
$P(H|D) \propto P(D|H)xP(H)$

$Posterior \propto Likelihood \cdot Prior$



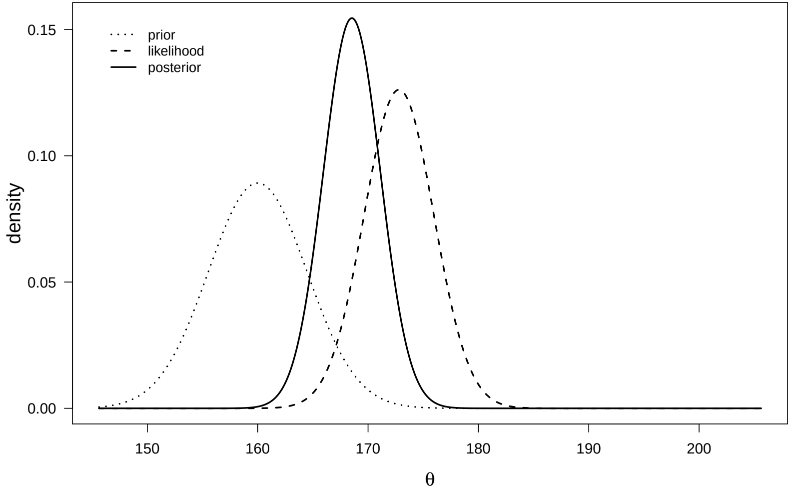
What is the likelihood?

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



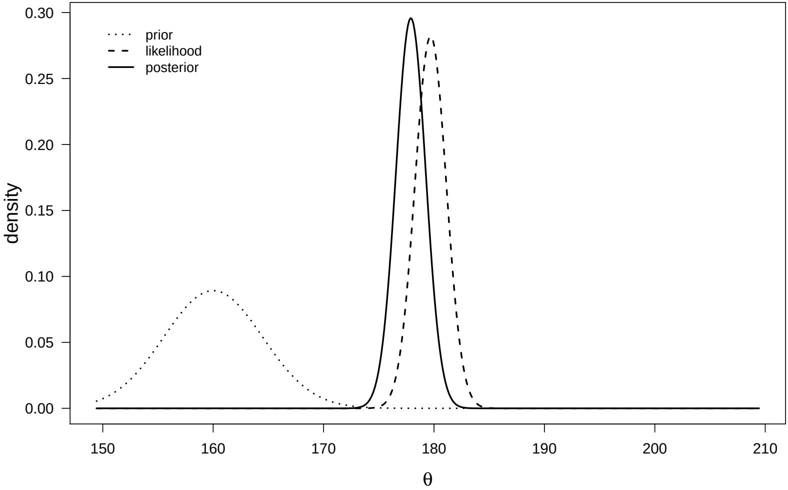
https://seeing-theory.brown.edu/bayesian-inference/index.html

Bayesian inference: prior and likelihood produce posterior




```
$posterior.mean
```

With increasing sample size, likelihood dominates prior

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More apps to introduce Bayesian inference

- Normal

More apps to introduce Bayesian inference

- Normal
- Binomial

More apps to introduce Bayesian inference

- Normal
- Binomial
- Own data

More apps to introduce Bayesian inference

- Normal
- Binomial
- Own data
- Bayesian t-test

Experimental Design

How would you evaluate fertilizer effect?

Discuss with partner (5')

Figure 6:

Experimental design principles

Replication

Replication!

Figure 7:

Replication

- Replication is key: we need several samples.

Replication

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

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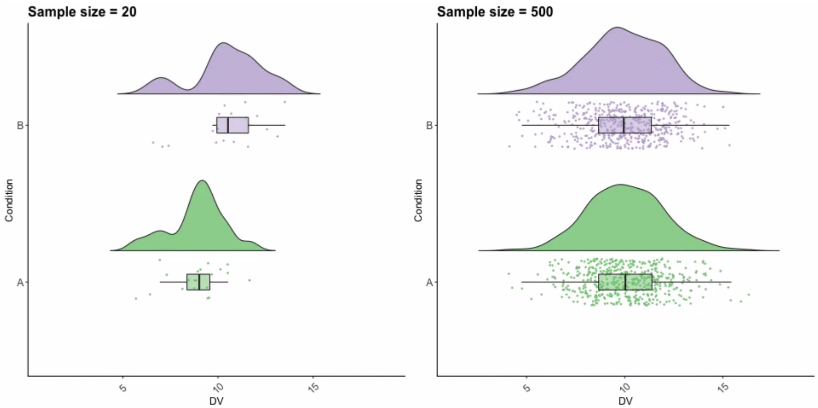
Replication

- 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

Sample size is very important

See *The evolution of correlations*

Stopping rules:

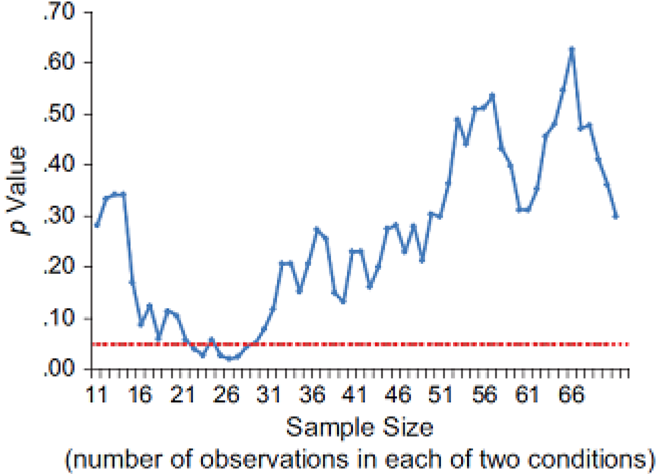


Fig. 2. Illustrative simulation of *p* values obtained by a researcher who continuously adds an observation to each of two conditions, conducting a *t* test after each addition. The dotted line highlights the conventional

Sample size estimation

- Plan model **before** data collection.

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- Do simulations. Power/Sample size analyses (e.g.).

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- Do simulations. Power/Sample size analyses (e.g.).
- Plan to have at least **10-30 observations per predictor**.
- Complex models (w/ many predictors, interactions etc) require **high** sample sizes.

Randomization

Randomization

Figure 9:

Randomization

- Haphazard $\neq$ Random

Randomization

- Haphazard $\neq$ Random
- Stratify: randomize within groups (e.g. species, soil types)

Controls

Have controls

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

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- Measure before & after treatment.

Have controls

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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

Does height differ between local and foreign students?

- Local people heigths:

```
171 168 182 164 160

   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
    160     164     168     169     171     182
```

```
177 172 195 174 173 182 163 169 170 180

   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
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- We know what happens in **our samples**, but want to extrapolate to the whole **population**.

If we sample students' heights in this class...

- Can we extrapolate results to

If we sample students' heights in this class. . .

- Can we extrapolate results to
  - this class?

If we sample students' heights in this class...

- Can we extrapolate results to
  - this class?
  - this university?

If we sample students' heights in this class...

- Can we extrapolate results to
  - this class?
  - this university?
  - this city?

If we sample students' heights in this class. . .

- Can we extrapolate results to
  - this class?
  - this university?
  - this city?
  - the world?

If we sample students' heights in this class. . .

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

NHST concepts

Null and alternative hypotheses

- Tell me...

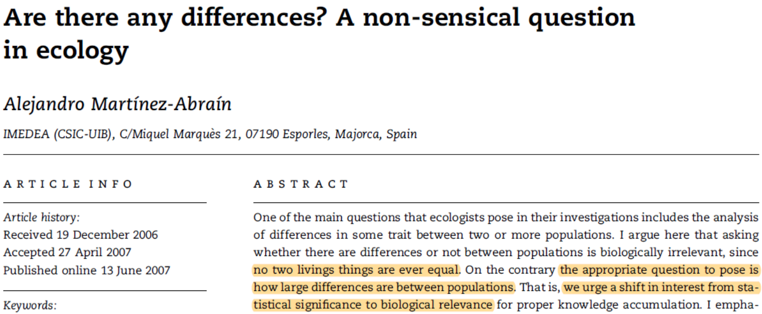
Null and alternative hypotheses

- 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

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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-

P value

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- Very complicated concept: even statisticians fail to describe it well.

P value

- Tell me...
- Very complicated concept: even statisticians fail to describe it well.
- Probability of observing data as or more extreme than these *if H0 was true*.

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- Tell me...
- Very complicated concept: even statisticians fail to describe it well.
- Probability of observing data as or more extreme than these *if H0 was true*.
- Low P-value: data unlikely if H0 was true.

P value

- Tell me. . .
- Very complicated concept: even statisticians fail to describe it well.
- Probability of observing data as or more extreme than these *if H0 was true*.
- Low P-value: data unlikely if H0 was true.
- Large P-value: data not unusual if H0 was true.

Are differences *significant*?

- If $p < 0.05$, we **reject** H0.

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- If $p < 0.05$, we **reject** H0.
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- This is **very widespread, but incorrect** practice.

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- P-value is continuous. We must **avoid binary decisions** based on **arbitrary thresholds**.

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- P-value is continuous. We must **avoid binary decisions** based on **arbitrary thresholds**.
- More on this later.

Let's do the test

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

```

    Welch Two Sample t-test

data:  h.sevi and h.out
t = -0.20558, df = 6.346, p-value = 0.8436
alternative hypothesis: true difference in means is not equal to
95 percent confidence interval:
 -14.0216  11.8216
sample estimates:
mean of x mean of y
    172.2     173.3
```

Are heights different then?

Rejecting hypotheses: two types of error

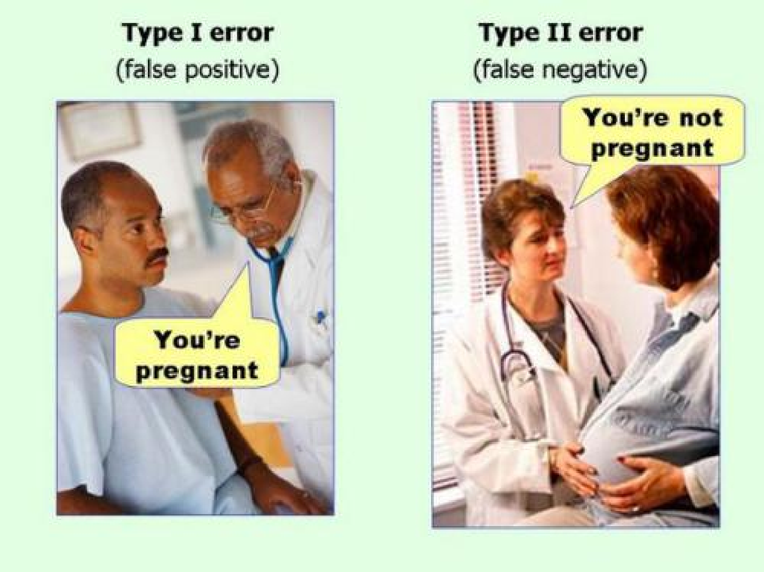


Figure 10:

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

Figure 11:

Understanding NHST

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

Example: biased coin

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

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

CrossMark

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

esa

ECOSPHERE

Applied statistics in ecology: common pitfalls and simple solutions

E. Ashley Steel,[1,†] Maureen C. Kennedy,[2] Patrick G. Cunningham,[3] and John S. Stanovick[4]

Figure 12:

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

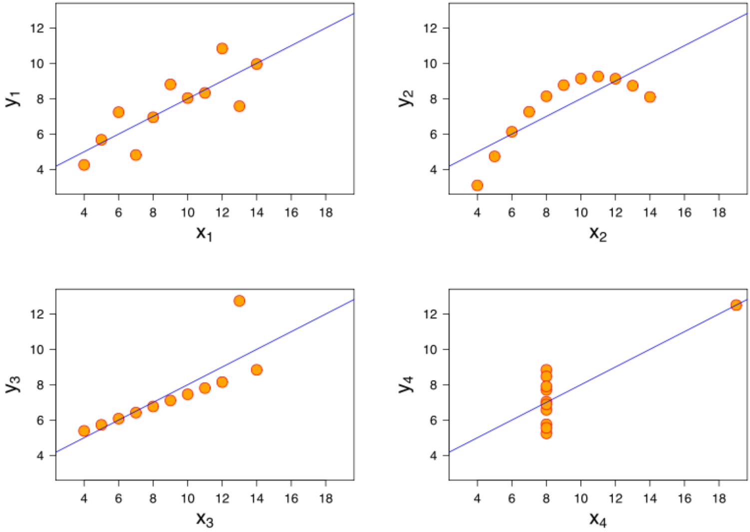
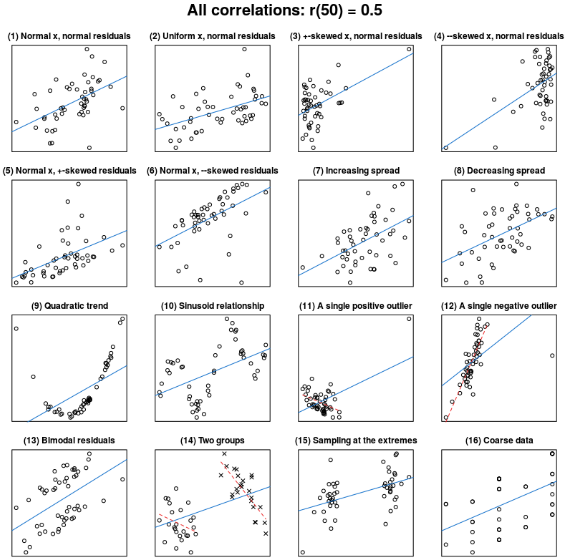


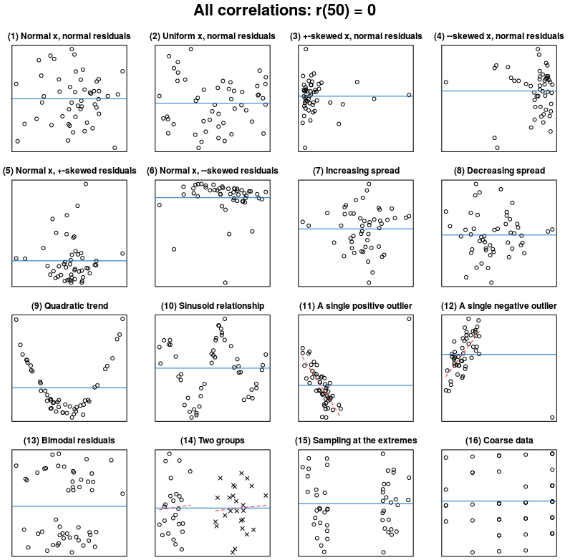
Figure 13:

Don't use statistics blindly: *Visualise*



https://ianhove.github.io/teaching/2016/11/21/what-correlations-look-like

Don't use statistics blindly: *Visualise*



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

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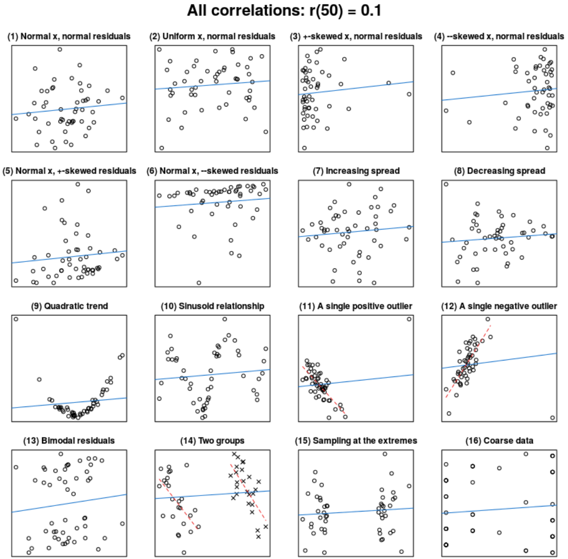


https://janhove.github.io/teaching/2016/11/21/what-correlations-look-like

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

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

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.
- **Do hamburgers increase heart attacks?**
- https://pollev.com/franciscorod726

Bigger flowers increase reproductive success

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

Bigger flowers increase reproductive success

- We found that plants with big flowers produced 30% more seeds...
- **Do big flowers increase reproductive success?**

Bigger flowers increase reproductive success

- We found that plants with big flowers produced 30% more seeds…
- **Do big flowers increase reproductive success?**
- https://pollev.com/franciscorod726

Correlation vs Causation

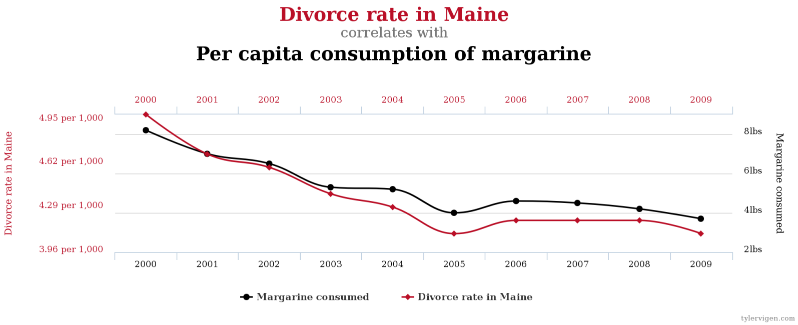
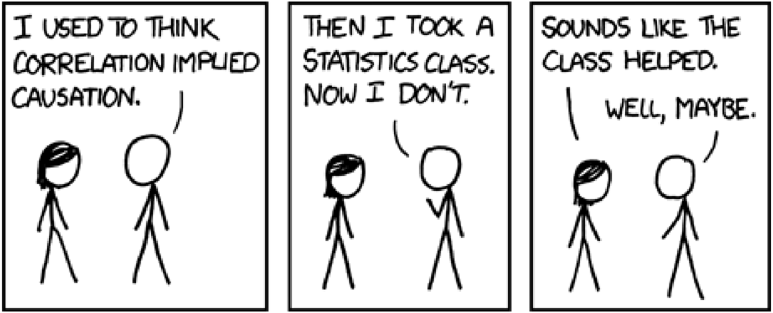


Figure 14:

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

Alejandro Martínez-Abraín

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

ARTICLE INFO

Article history:
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Accepted 27 April 2007
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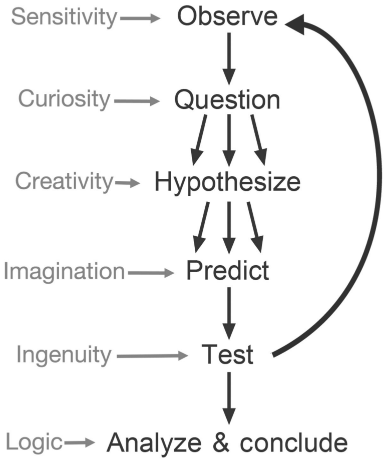
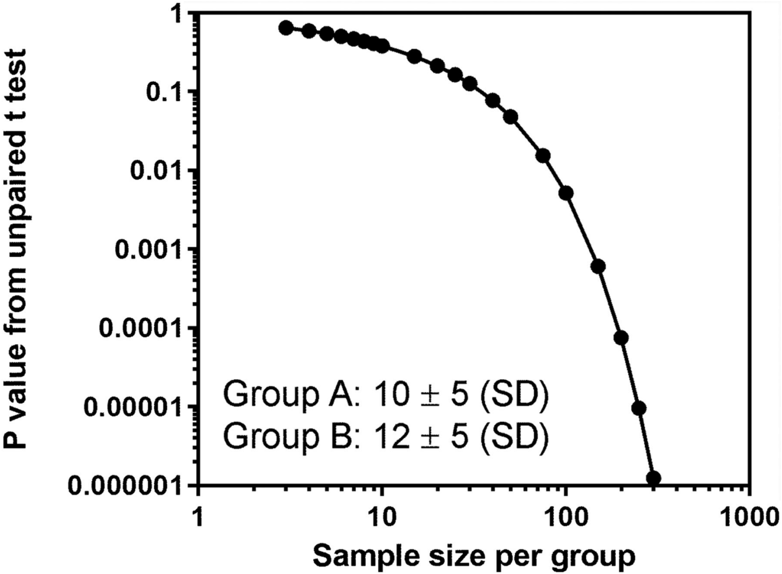
ABSTRACT

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-

Instead of falsifying a null model, estimate effects and compare meaningful models



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:

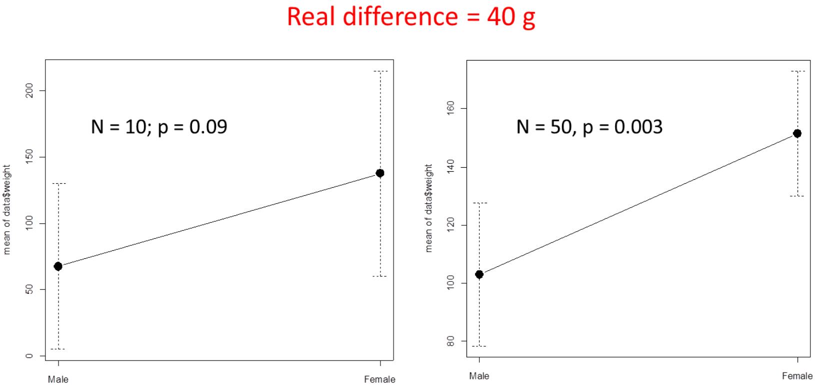
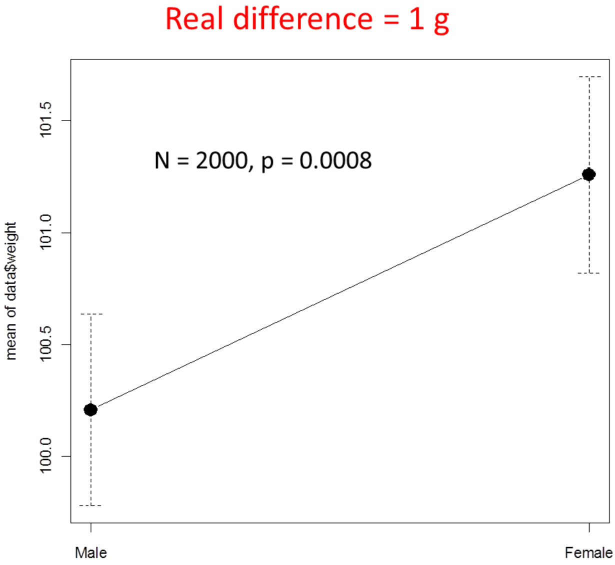


Figure 15:

Statistically significant != biologically important

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



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- Statistically significant = unlikely to be zero

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- Good read: *significantly misleading*

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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’

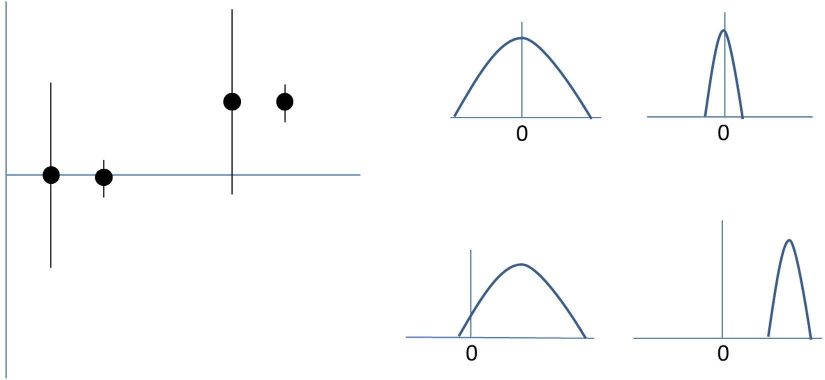

Figure 17:

- **Absence of evidence != Evidence of absence**

Failure to reject H0 != H0 is true

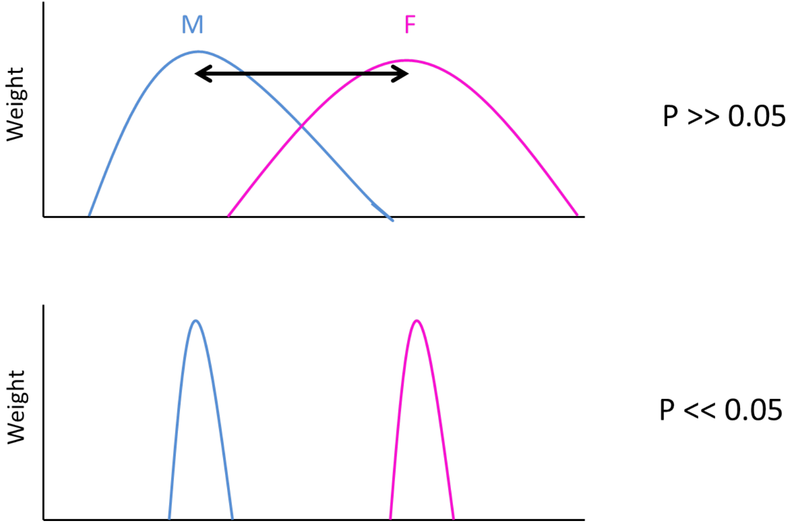

Figure 18:

p-value > 0.05?

"We were unable to find evidence against the hypothesis that $A = B$ with the current sample size"

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

Is it safe to allow right turn with red lights?

- Right turn not allowed: 308 accidents
- Right turn allowed: 337 accidents

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Is it safe to allow right turn with red lights?

- Right turn not allowed: 308 accidents
- 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

Figure 19:

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

Multiple hypothesis testing

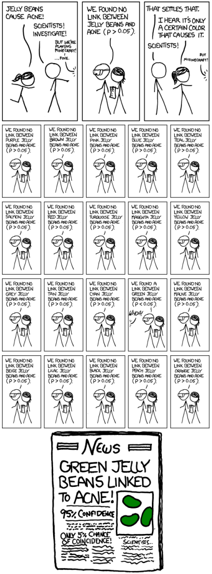
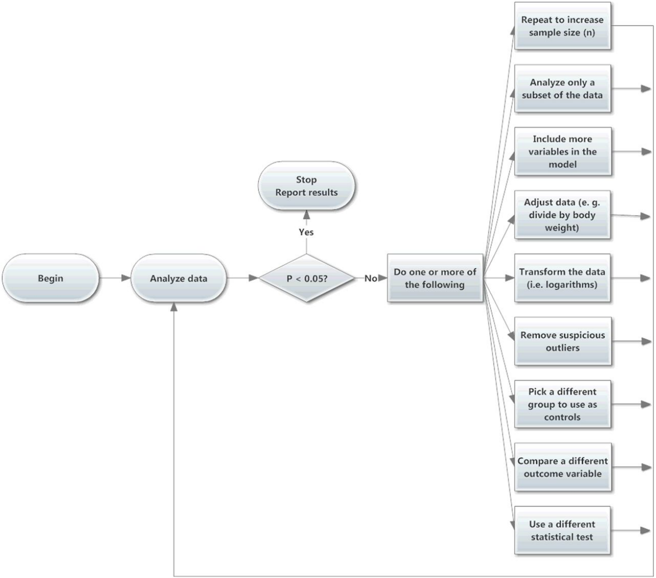


Figure 20:

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



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

1. Test multiple variables, then report the ones that are significant.

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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

- P-values do not measure the **probability of hypothesis** being true, or the probability that the data were produced by **random chance** alone.

https://doi.org/10.1080/00031305.2016.1154108

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- P-value, or statistical significance, does not measure the **size of an effect** or the **importance** of a result.

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- Scientific conclusions or policy decisions should NOT be based only on **whether a p-value passes a specific threshold**.
- P-value, or statistical significance, does not measure the **size of an effect** or the **importance** of a result.
- By itself, a p-value does NOT provide a good **measure of evidence** regarding a model or hypothesis.

https://doi.org/10.1080/00031305.2016.1154108

The New Statistics

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

General Article

The New Statistics: Why and How

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

DOI: 10.1177/0956797613504966
pss.sagepub.com
SAGE

Geoff Cumming
La Trobe University

Figure 21:

http://dx.doi.org/10.1177/0956797613504966

How many types of errors?

- **Type I**: False positive (incorrect rejection of null hypothesis).

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- **Type M (Magnitude)**: Misestimating magnitude of the effect (under or overestimating).
- Beyond Power Calculations: Assessing Type S (Sign) and Type M (Magnitude) Errors

END

Figure 22:

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