Hypothesis testing

NHST concepts

Null and alternative hypotheses

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Null and alternative hypotheses

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

In biology, everything is somewhat different

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

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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-

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- Probability of observing data as or more extreme than these if every model assumption were correct
- · What assumptions?
 - · Null hypothesis is true
 - No uncontrolled sources of bias (measurement or programming error, p-hacking, etc)

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- · A famous experiment found neutrinos faster than light
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- · In reality, measurement error (loose cable)

Testing a new fertiliser: Does it work?

10 treatment, 10 control plots Crop biomass (treatment): $10kg \pm 2kg$ Crop biomass (control): $6kg \pm 2kg$

Welch Two Sample t-test

```
data: tr and ct
t = 4.1858, df = 17.872, p-value = 0.0005631
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
    1.857902 5.606112
sample estimates:
mean of x mean of y
10.149251 6.417244
```

Testing a new fertiliser: Does it work?

10 treatment, 10 control plots

Crop biomass (treatment): $10kg \pm 2kg$

Crop biomass (control): $9kg \pm 2kg$

```
Welch Two Sample t-test
```

10.149251 9.417244

```
data: tr and ct
t = 0.82102, df = 17.872, p-value = 0.4225
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
   -1.142098    2.606112
sample estimates:
mean of x mean of y
```

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 (e.g. sampling not random, measurement error, p-hacking...)

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- · See Greenland et al 2016

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- the alternative hypothesis is false, i.e. the null hypothesis must be true
- it's unclear if there are differences between groups
- there is no difference between groups

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

S (Surprise) values as alternative to p-values

• A p-value of 0.05 is as surprising as getting 4.3 heads in a row when flipping a coin.

Rafi & Greenland 2020

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- A p-value of 0.01 is as surprising as getting 6.6 heads in a row when flipping a coin.

Rafi & Greenland 2020

S (Surprise) values as alternative to p-values

- A p-value of 0.05 is as surprising as getting 4.3 heads in a row when flipping a coin.
- A p-value of 0.01 is as surprising as getting 6.6 heads in a row when flipping a coin.
- A p-value of 0.001 is as surprising as getting 10 heads in a row when flipping a coin.

Rafi & Greenland 2020

Are these two groups different?

```
t.test(group.A, group.B)
```

Welch Two Sample t-test

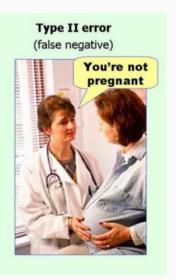
```
data: group.A and group.B
t = -5.0271, df = 12.464, p-value = 0.0002632
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
    -24.91029    -9.88971
sample estimates:
mean of x mean of y
```

https://pollev.com/franciscorod726

162.8 180.2

Rejecting hypotheses: two types of error

Type I error (false positive) You're pregnant



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).

Is this coin biased?

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

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

Understanding NHST

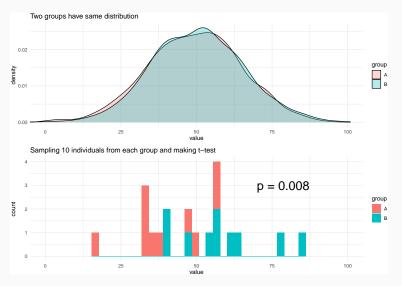
```
http://rpsychologist.com/d3/NHST/
https://lakens.github.io/statistical_inferences/
01-pvalue.html
```

NHST and p-values: common pitfalls

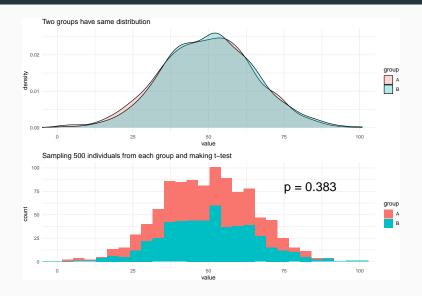
A significant p-value does NOT mean we found a true difference

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Particularly with low sample sizes



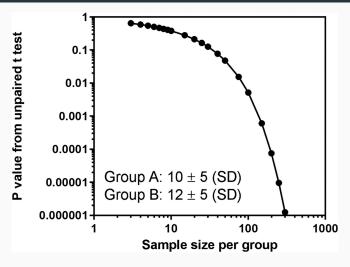
If sample size was larger...



With low sample size (power), significant p-values are most likely overestimates

Loken & Gelman 2014, Vasisth et al. 2018

P-value depends on sample size

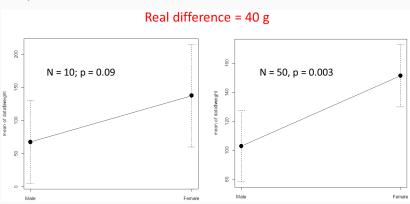


https://doi.org/10.1002/prp2.93

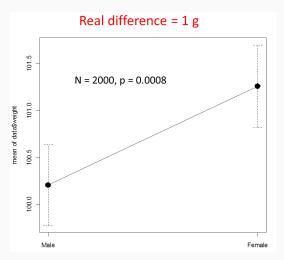
Try yourself here!

P-value depends on sample size

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

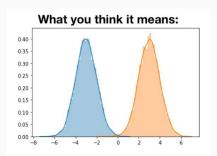


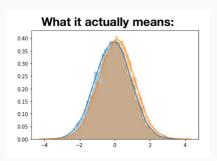
With big sample size, we can find **highly significant but biologically unimportant** differences.



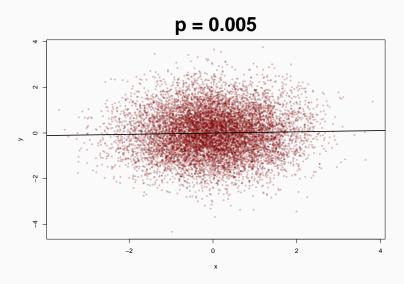


friendly reminder about p < 0.0001:





https://twitter.com/weinberz/status/1422405165236178947?s=20



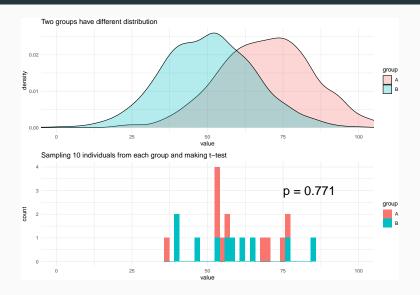
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- Good read: significantly misleading

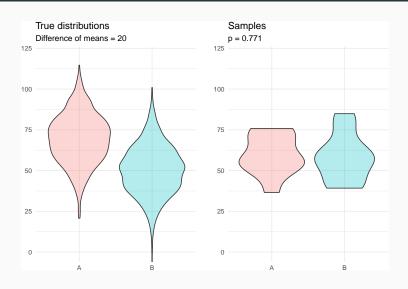
- Statistically significant = unlikely to be zero
- · Good read: significantly misleading
- Beyond significant/not significant, look at effect sizes and their uncertainty.

'Not significant' does NOT mean 'there is no effect'

'Not significant' does NOT mean 'they are equal'



'Not significant' does NOT mean 'there is no effect'



Failure to reject H0 != H0 is true

Absence of evidence != Evidence of absence

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)

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- · Right turn allowed: 337 accidents
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- Failure to reject H0 does NOT mean H0 is true!
- Misinterpretation of underpowered study cost lives



0.05 is an arbitrary threshold

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

Andrew GELMAN and Hal STERN

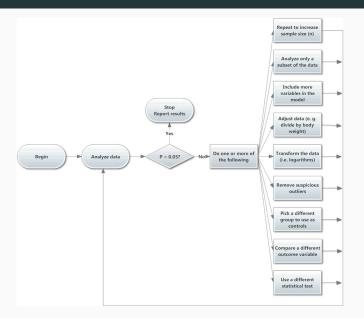
https://dx.doi.org/10.1198/000313006X152649

Multiple hypothesis testing





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



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- · To read more: Simmons et al 2011

p-hacking: try it yourself

```
https://www.shinyapps.org/apps/p-hacker/
https://shiny.psy.lmu.de/felix/ShinyPHack/
```

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

• 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

See also $https://lakens.github.io/statistical_inferences/01-pvalue.html\\$

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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

See also https://lakens.github.io/statistical_inferences/01-pvalue.html

Good practice

A must read

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



ESSAY

Statistical tests, ${\it P}$ 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



ECOSPHERE

Applied statistics in ecology: common pitfalls and simple solutions

E. ASHLEY STEEL, The Maureen C. Kennedy, Patrick G. Cunningham, and John S. Stanovick

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

Also http://www.statisticsdonewrong.com/

Good read



Twenty tips for interpreting scientific claims

The New Statistics

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

General Article



Psychological Science

The New Statistics: Why and How

2014, Vol. 25(1) 7–29 © The Author(s) 2013 Reprints and permissions: sagepub.com/journalsPermissions.nav DOI: 10.1177/0956797613504966 pss.sagepub.com

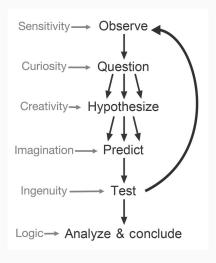
Geoff Cumming

La Trobe University



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

Instead of falsifying null model, compare meaningful models



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- Beyond Power Calculations: Assessing Type S (Sign) and Type M (Magnitude) Errors