Hypothesis testing

NHST concepts

Null and alternative hypotheses

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Null and alternative hypotheses

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- 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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- · What assumptions?
 - · Null hypothesis is true
 - No uncontrolled sources of bias (measurement or programming error, p-hacking, etc)

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 (e.g. sampling not random, measurement error, p-hacking...)
- · See Greenland et al 2016

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- · In reality, measurement error (loose cable)

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- 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

Are these two groups different?

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

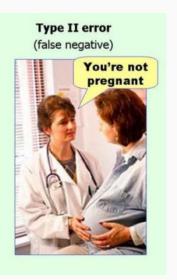
```
Welch Two Sample t-test
data: group.A and group.B
t = -0.60849, df = 5.378, p-value = 0.5677
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -20.54709 12.54709
sample estimates:
mean of x mean of y
```

https://pollev.com/franciscorod726

170.8 174.8

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

1-sample proportions test without continuity correction

```
data: sum(coin) out of ntrials, null probability 0.5
X-squared = 0, df = 1, p-value = 1
alternative hypothesis: true p is not equal to 0.5
95 percent confidence interval:
    0.2365931   0.7634069
sample estimates:
    p
0.5
```

https://pollev.com/franciscorod726

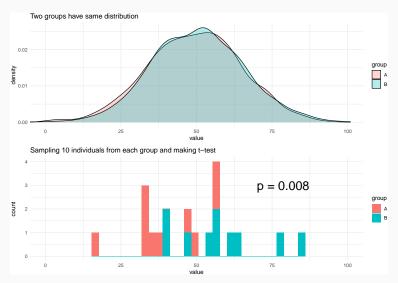
Understanding NHST

```
http://rpsychologist.com/d3/NHST/
http://daniellakens.blogspot.com/2017/12/
understanding-common-misconceptions.html
```

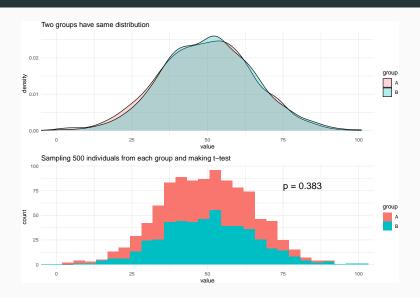
NHST and p-values: common pitfalls

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

Particularly with low sample sizes



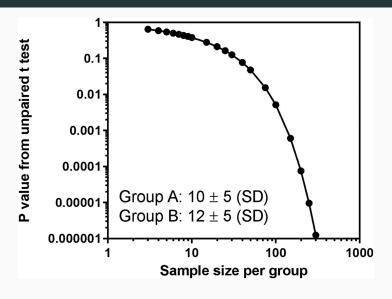
If sample size was larger...



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

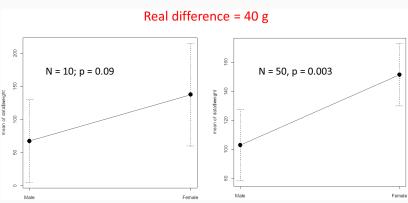
Loken & Gelman 2014, Vasisth et al. 2018

P-value depends on sample size

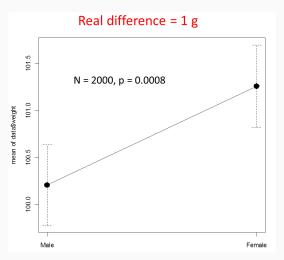


P-value depends on sample size

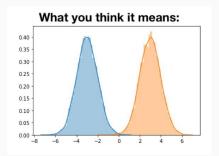
Same real difference is detected as **significant or not depending on sample size**

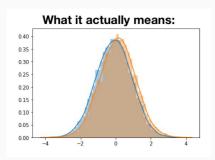


With big sample size, we can find **highly significant but biologically unimportant** differences.

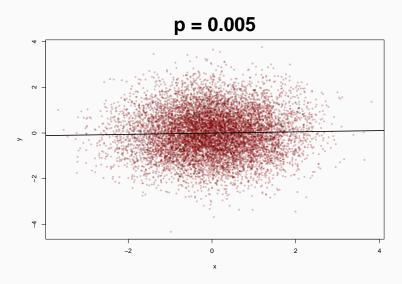








https://twitter.com/weinberz/status/1422405165236178947?s=20



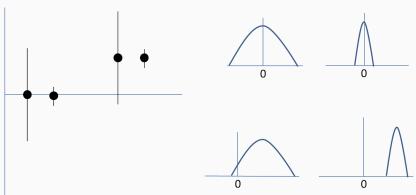
Statistically significant = unlikely to be zero

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- Good read: significantly misleading

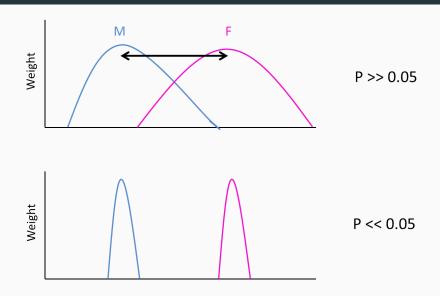
- Statistically significant = unlikely to be zero
- · Good read: significantly misleading
- Beyond significant/not significant, look at effect sizes and their uncertainty.

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

Absence of evidence != Evidence of absence



Failure to reject H0 != H0 is true



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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- Misinterpretation of underpowered study cost lives

0.05 is an arbitrary threshold

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

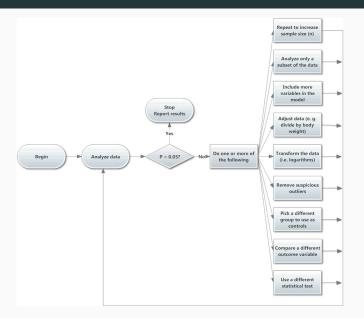
Andrew GELMAN and Hal STERN

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

Multiple hypothesis testing







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· To read more: Simmons et al 2011

p-hacking: try it yourself

https://www.shinyapps.org/apps/p-hacker/

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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.

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 Greenland¹ · Stephen J. Senn² · Kenneth J. Rothman³ · John B. Carlin⁴ · Charles Poole⁵ · Steven N. Goodman⁶ · Douglas G. Altman⁷

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, Patrick G. Cunningham, 3 and John S. Stanovick 4

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...)

ODS
ASSOCIATION FOR
PSYCHOLOGICAL SCIENCE

General Article

The New Statistics: Why and How

Geoff Cumming

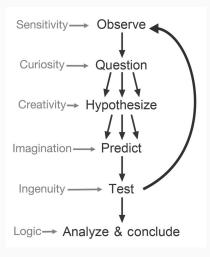
La Trobe University

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

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

Instead of falsifying null model, compare meaningful models



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

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