STATISTICAL SIGNIFICANCE IN BIOLOGY

Conventions, Abstractions, and the Future



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- 1 The Reproducibility Crisis
 - What crisis?
 - Why are we in this crisis?
- **2** The *p*-Value Conundrum
 - Background
 - Alternatives
- 3 Finding A Solution
 - Summary
 - Discussion

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Reproducibility analyses have shown that only a surprisingly small portion of studies can be replicated.

 \sim Nuzzo (2015). FOOLING OURSELVES. Nature.

This manifests in

- Large sample-to-sample variations of the p-value
 - ~ Halsey et al. (2015). The fickle P value generates irreproducible results. Nature Methods
- Ambiguity in data handling procedures
 - ~ Peng & Leek (2015). P values are just the tip of the iceberg. Nature.
- Difficulty in establishing meta-analyses
 - ~ Cumming (2014). The New Statistics: Why and How. Psychological Science

Thus, our studies become solitary glances behind the curtain.

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Some select phenomena that brought us here:

Dichotomy of p-values

- Arbitrary .05 significance cut-off generates a false dichotomy of 'false' or 'true' conclusions
- Significant effect are not necessarily biologically relevant

 Burnham et al. (2011). AIC model selection and multimodel inference in behavioral ecology: Some background, observations, and comparisons.
 Behavioral Ecology and Sociobiology.

Peer-review shortcommings

- Reluctancy to make corrections
- No clear guidelines on where to direct criticism towards
- No standard process for data and code access

~ Allison (2016). A tragedy of errors. Nature

Research integrity

- Research questions often formulated post-hoc leading to multiple testing issue
- Sloppy reporting of data handling procedures
- Lack of data and code repository guidelines
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What is the *p*-value and why is it isnufficient?

"The p-value is the probability of randomly obtaining an effect at least as extreme as the one in your sample data, given the null hypothesis."

Misconceptions

- The p-value is not designed to tell us whether something is strictly true or false
- It is not the probability of the null hypothesis being true
- The size of p does not yield any information about the strength of an observed effect

Mathematical Quirks

- It varies strongly from sample-to-sample (depending on statistical power of the set-up)
- If the sample size is big enough, the pvalue will always be below the .05 cut-off, no matter the magnitude of the effect

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Effect sizes

"A measure of the magnitude of a statistical effect within the data (i.e. values calculated from test statistics)."

~ Nakagawa & Cuthill (2007). Effect size, confidence interval and statistical significance: A practical guide for biologists. Biological Reviews.

- Intuitive to interpret and often what we are interested in
- Three types for most situations:
 - r statistics (correlations)
 - *d* statistics (comparisons of values)
 - OR (odds ratio) statistics (risk measurements)
- These are point estimates
- Need to be reported alongside some information of credibility
- These are usually standardised thus enabling meta-studies

In R: https://cran.r-project.org/web/packages/compute.es.pdf and https://cran.r-project.org/web/packages/effsize/effsize.pdf

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Confidence Intervals

"Confidence intervals (CIs) answer the questions: 'How strong is the effect' and 'How accurate is that estimate of the population effect'."

~ Halsey (2019). The reign of the p-value is over; what alternative analyses could we employ to fill the power vacuum? Biology Letters.

- Intuitive to interpret
- Answers the questions we are most interested in
- Does not require additional information of statistical certainty
- Combines point estimates and range estimates
- Removes some of the pressure of the "file drawer problem"
- \blacksquare Shares the same mathematical framework as the p-value calculation
- Especially useful in data visualisation

In R, many functions come with in-built ways of establishing CIs.

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Akaike Information Criterion (AIC)

The Akaike Information Criterion (AIC) is a indicator of model fit.

~ Burnham et al. (2011). AIC model selection and multimodel inference in behavioral ecology: Some background, observations, and comparisons.

Behavioral Ecology and Sociobiology.

- Used for model selection and comparison
- Lower AICs indicate better model fit
- One can establish contrasting models adhering to different hypothesis and identify which model suits the data best
- A proper hypothesis selection tool
- Model selection often comes with some degree of uncertainty
- Can be misused in step-wise model building procedures

In $\mathbb R,$ most model outputs can be assessed using the ${\tt AIC}\,(\tt)$ function.

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Bayes Factor

"The minimum Bayes factor is simply the exponential of the difference between the log-likelihoods of two competing models."

~ Goodman (2001). Of P-Values and Bayes: A Modest Proposal. Epidemiology.

- Intuitive to interpret (Bayes Factor of 1/10 means that our study decreased the relative odds of the null hypothesis being true tenfold)
- Uses prior information to establish expected likelihoods thus enabling a progression in science

In R: https://cran.r-project.org/web/packages/BayesFactor/BayesFactor.pdf or direct Bayesian Statistics using JAGS or STAN (for example)

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Research Integrity

- Distinguish between prespecified (answering a question) and exploratory (formulating a question) studies.
- Express research question in terms of expectations of effect sizes
- Identify the effect sizes best suited to answer these questions
- Report full study plan before commencing data collection
- **Calculate measures** of statistical meaning that **enable meta-studies** (e.g. effect sizes and CIs)
- Make sure to **correctly interpret the results** outside of the *p*-value dichotomy of true and false
- Report the findings in a meta-analytic context

Where do we go from here?

"Treat statistics as a science, and not a recipe"

~ Andrew Vickers

"The numbers are where the scientific discussion should start, not end!" \sim Regina Nuzzo