

Power Calculations in R

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Documber 00 2021



If you are not cheating, you are not trying







Statistical Concepts

Significance

- Likelihood of results under H0
- α level = Type 1 error = False Positive
- Saying that something exists when it does not
- I tolerate finding a result that does not exist X% of the time
- p-value = How surprising my results are if H0 is true
- Heuristically around .05 (God hates the number .051)

<u>Power</u>

- Probability of correctly H0
- β level = Type 2 error = False Negative
- Saying that something does not exist when it does
- I tolerate not finding a result that exists X% of the time
- Heuristically around .2 (God hates the number even more)





Lakens, 2020

Why justify ?

- Experiments are expensive *Minimum resources*
- Reduce risk of random sampling variability *Increases your confidence in your results.*
- Forces you to think your analysis Improves statistical questions
- Increase generalizability

A justified sample size is easier to reproduce

• Preregistrations, registered reports and grant request it *Helps you get funding and publications*

The lifespan of a-priori power calculations



Practical 1: Understanding parameters of power calculations

Paris wants to determine if there is a significant difference in systolic blood pressure between patients on a new antihypertensive drug and those on a placebo.

- Independent : Treatment group (new drug vs. placebo)
- Dependent: Systolic blood pressure (continuous variable)
- Open R.
- Load 'ex_01_params.R'
- Using the exist parameters
- Explore how different params affect what sample size John needs.
- Check what happens if you use a paired sample test (before / after administration of drug)

Effect of parameters on power calculations

- Alpha level 🕇 Sample
- Beta level
 Sample
- Effect size 🛉 Sample 🛉
- Design ~ Depends



Why parameters affect us

- Alpha
 - The more results we consider false positives, the less studies we end up accepting as significant
- Beta
 - The more studies we consider false negatives, the less studies we end up accepting as significant
- Effect Size
 - The stronger the effect size, the smaller the sample size to detect it
 - The larger the difference in mean, the smaller size we need to reach it
 - The larger the variance of the means, the higher sample sizes we need
- Type of Test
 - Paired / Nested designs allow us to reduce the variance of our estimates
- Type of predictions we make
 - One sided tests require a smaller difference in means to reach significance, making the sample size necessary smaller

Selecting alpha

- 0.05 vs 0.02 vs 0.01
- The higher the statistical power of a test, the less likely it is to observe relatively high *p*-values (e.g., *p* > .02).
- If H0 = True, then p values are uniformly distributed (dotted line). So for highpowered studies, .01evidence for null (????)



Selecting effect sizes or parameters

- Pilot study -> requires high N of participants to be meaningful
- Heuristics (Simmons, 2011) -> use at least 50 (suspicious)
- Previous effect sizes -> approximation of relevant study
- Previous parameters -> approximation of relevant study
- Smallest effect size of interest (SESOI) -> theoretical minimum

Simmons, 2011 Lakens, 2019 Simonsohn, 2015

SESO

- Minimal Statistically Detectable Effect
 - Don't ask what effect another study found, ask what is the minimum they could have found
 - If a study has found an effect, it might have been **inflated**. Being suspicious, I accept that an effect exists, but I will power for the minimal possible effect
 - Driven by sample size
 - If sample is large, your minimal effect is small
 - If sample is small, your minimal effect is large
 - Example: A study found a Cohen's D = .6. With 50 participants in each group, the minimal possible effect size is .4
- Small telescopes
 - Don't ask what effect another study found, assume what it would find if it was underpowered
 - Gamble: I give you 2:1 odds that the study will not have a result (33% power)
 - If that is true, what size can you find?
 - Driven by sample size
 - If sample is large, your minimal effect is small
 - If sample is small, your minimal effect is larger

Simonsohn, 2015 Laken, 2017

Effect size selection



Simonsohn, 2015 Laken, 2017

Practical 2: Selecting SESOI

- Consider a study where 25 smokers evaluated how many cigarettes they smoke per day before and after exposure to scare images on the health detriments of smoking.
- You want to replicate it. Find the smallest effect size of interest and estimate how many people you need.
- Load 'ex_02_sesoi.R'

Software vs Simulations





	Software	Simulations
Easy to use	Maybe	Maybe
Analytical Solution	Yes	No
Any test	No	Yes
Reproducible	Maybe	Yes
Intuitive	No	Yes



Basic Simulation Structure

- For every sample size
 - Create storage for statistic
 - Create storage for p values
 - For every simulation
 - Simulate dataset with required parameters
 - Add noise to the dataset
 - Run statistical test of interest
 - Extract simulated statistic
 - Extract significance
 - Store results
 - Count how many tests were significant / How many simulations you run
 - Congratulations! You estimated power for tested sample size
- Plot power calculation curve (x axis = samples, y axis = achieved power)

Practical 3: Running your first simulation

Paris wants to calculate if smokers have higher rates of anxiety. Previous literature suggests an effect size Cohen' D=.6 (suspicious for psychology). He wants to replicate this study. Help him!

- Set control group mean = 0
- Assume a noise level of SD=1
- Specify a=.01, b=.05
- Test sample size from 10 to 200, in increments of 5
- Run 500 simulations per sample size

Hierarchical Designs

- Factorial Designs
- Random effects (multiple measurements per run / subject)
- Random slopes (multiple measurements per run / subject)
- No analytical solution
- Yet easy to conceptualize using simulations

Basic Hierarchical Simulation Structure (and many more ...)

- For every sample size
 - Create storage for statistic
 - Create storage for p values
 - For every simulation
 - Simulate dataset with required parameters
 - Add noise to the dataset
 - Run statistical test of interest
 - Extract simulated statistic
 - Extract significance
 - Store results
 - Count significant / tests run
 - You estimated power for tested sample size
- Plot power curve

- For every sample size
 - Create storage for statistic
 - Create storage for p values
 - For every simulation
 - Simulate dataset
 - For every subject
 - Simulate noisy, multi-trial
 - Add constant noise per subject.
 - Run statistical test of interest
 - Extract simulated statistic
 - Extract significance
 - Store results
 - Run an equivalence test to test whether HO stands
 - Count significant / total tests you run
 - Congratulations! You estimated power for tested sample size
- Plot power curve

Optional Stopping vs Sequential Sampling

Sample sizes. For optogenetic activation experiments, cell-type-specific ablation experiments, and in vivo recordings (optrode recordings and calcium imaging), we continuously increased the number of animals until statistical significance was reached to support our conclusions. For rabies-mediated and anterograde tracing

Heart is the right place ... Is it possible to do ?

Optional Stopping vs Sequential Sampling

Optional Stopping: Cohen's D=0 Sequential Sampling: Cohen's D=.3 1.0 5 0.8 0.8 0.6 0.6 p-value p-value 0.4 0.4 0.2 0.2 0.0 0.0 50 100 150 200 50 100 150 200 sample size sample size

Lakens, MOOC

Sequential Sample Size Estimation

- You power analysis said you need 150 people 🛞
- You can do interim analysis at intervals (50,100 participant.) *IF* you control for your Type 1 error.
- You have a set amount of error budget (.05) and you need to spend it across all your interim analysis.
- GOAL = Find how to split the bill

Pocock algorithm

List of *p*-values used at each interim analysis, assuming the overall *p*-value for the trial is 0.05

Number of planned analyses	Interim analysis	<i>p</i> -value threshold
2	1	0.0294
	2 (final)	0.0294
3	1	0.0221
	2	0.0221
	3 (final)	0.0221
4	1	0.0182
	2	0.0182
	3	0.0182
	4 (final)	0.0182
5	1	0.0158
	2	0.0158
	3	0.0158
	4	0.0158
	5 (final)	0.0158

Jennison & Turnbull, 2000 Wassmer & Brannath, 2016

WP3: Help Paris create the best study ever

Paris is a psychologist who studies how reaction times track arousal level. Going over the literature, he found that a previous study with 50 well-rested participants in one group and 50 sleep-deprived participants in the other. There was an effect size of Cohen's D = .4, where well-rested participants were faster in detecting a familiar faces compared to sleep deprived participants.

- 1. Find the smallest effect size of interest
- 2. Simulate how many people Paris needs to achieve a power of .95 at an error rate of .01 (or just use an analytic solution ...).
- 3. Find a way to adjust the error rate so that Paris can acquire data with 4 interim analysis.

Tutorial Inspirations

- Improving your Statistical Inferences by Daniel Lakens
- Improving your Statistical Questions by Daniel Lakens
- Statistical Rethinking by Richard McElreath
- Being bullied at Stack Overflow and Cross Validated

Time for you to design the best study ever