

# Is $n=3$ enough? How to approach sample size and power calculations

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 [bit.ly/aacr-power](https://bit.ly/aacr-power)

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# Outline

- Why calculate sample size?
- What are the important components?
- Examples
- Software

# Goals of sample size and power calculations

- Design a study that will have enough information about underlying population to reject a hypothesis with high confidence.
- Calculate the number of sampling units (e.g. people, animals) you need to estimate statistics with a certain level of precision.

Design your study

# Step 1: State your research hypothesis

- Define your:
  - Population
  - Outcome variables/measurements
  - Predictor variables (i.e. treatment, age, genetic mutation)
- Be specific!
- Example: Among *women* (population you sample from), the *BRCA1* mutation (predictor) is associated with an increased risk of developing *breast cancer* (outcome).
- Question: How many women do we need to sample/study to determine that *BRCA1* is associated with breast cancer?

**Your hypothesis and design inform your analysis method.**

## Step 2: Choose your analysis and test(s)

- You can't calculate sample size without knowing which test and model you will use.
- How will you measure your outcome? Continuous? Categorical? Binary (yes/no)?
  - choose outcomes with high sensitivity and low measurement error
- How many groups/experimental conditions/predictors?
  - the more you have the more samples you will need
- What test? t-test? Linear regression? Random effects model? Chi-square test?

**Calculate sample size based on analysis method you will use.**

Calculate power and sample  
size

# Need to know (/tell your statistician!):

- Overall design (outcome, endpoint, hypothesis)
- Size/magnitude of effect of interest
  - What do you *hope* to detect
- Variability of measurements
  - Precision of your measurement, biological variability within population
- Level of type I error (significance level,  $\alpha$ )
- Level of power
- Other design details (number of groups, clustering, repeated measures)



# Components of Sample Size

Need to know 3 of the 4 to determine the 4th:

Measure	Definition
Effect Size	Magnitude of difference or association; i.e. (difference in means)/(population standard deviation) = $\frac{\mu_1 - \mu_0}{\sigma}$ = $\Delta$
Sample Size	N
Type I Error / Significance level	$\alpha$ = probability of rejecting null hypothesis when it is true
Power	$1 - \beta$ = 1 - Type II error = probability of rejecting null hypothesis when it is false

# Components of Sample Size

Need to know 3 of the 4 to determine the 4th:

Do We Know?	Measure	Definition
??	Effect Size	Magnitude of difference or association; i.e. (difference in means)/(population standard deviation) = $\frac{\mu_1 - \mu_0}{\sigma}$ = $\Delta$
??	Sample Size	N
0.05, 0.01	Type I Error / Significance level	$\alpha$ = probability of rejecting null hypothesis when it is true
0.9, 0.8	Power	$1 - \beta$ = 1 - Type II error = probability of rejecting null hypothesis when it is false

# What is effect size?

- Summarizes the outcome of interest
- Magnitude of difference or association
- Specification depends on study design and statistical model/test

## Examples:

- Difference in treatment and control mean outcomes, relative to variance (standard deviation)
- Correlation coefficient of two biomarkers
- Risk ratio of breast cancer comparing BRCA carriers to non-carriers
- Magnitude of regression coefficient

# Effect size must be

- pre-specified
- based on what is meaningful biologically or clinically (not statistical significance)
- based on pilot data or literature review if available

# Simple example

Outcome = Continuous measurement

Predictor = Treatment yes/no (treatment vs control group)

Test: two sample T-test, equal variance

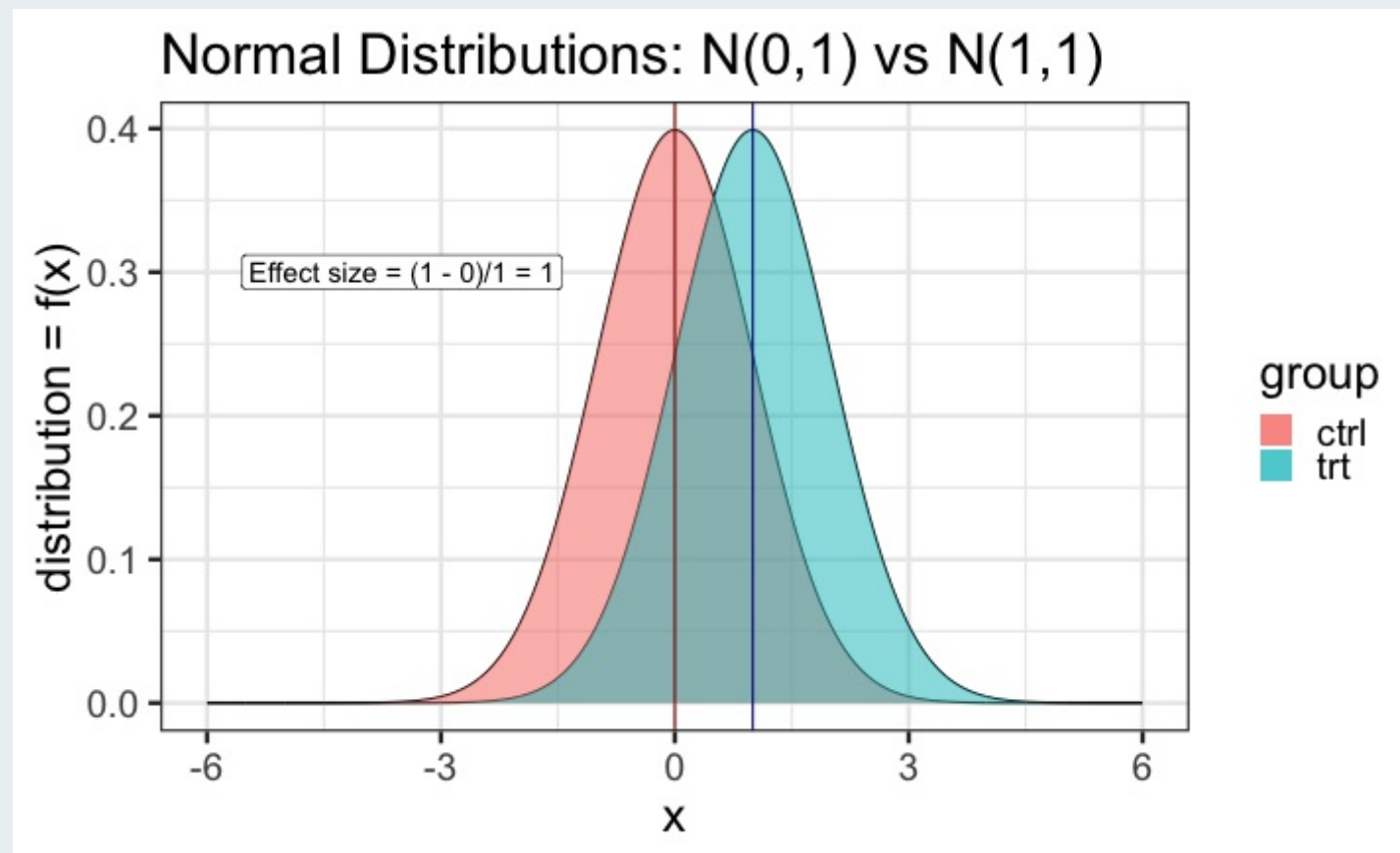
Effect Size: difference in means divided by standard deviation of population  $\frac{\mu_{\text{trt}} - \mu_{\text{ctrl}}}{\sigma}$

Null Hypothesis: Difference in means = 0

Alternative Hypothesis: Difference in means  $\neq 0$

"Given a desired effect size (difference in means relative to the variance), what sample size gives us enough information to reject the null hypothesis with power 90%?"

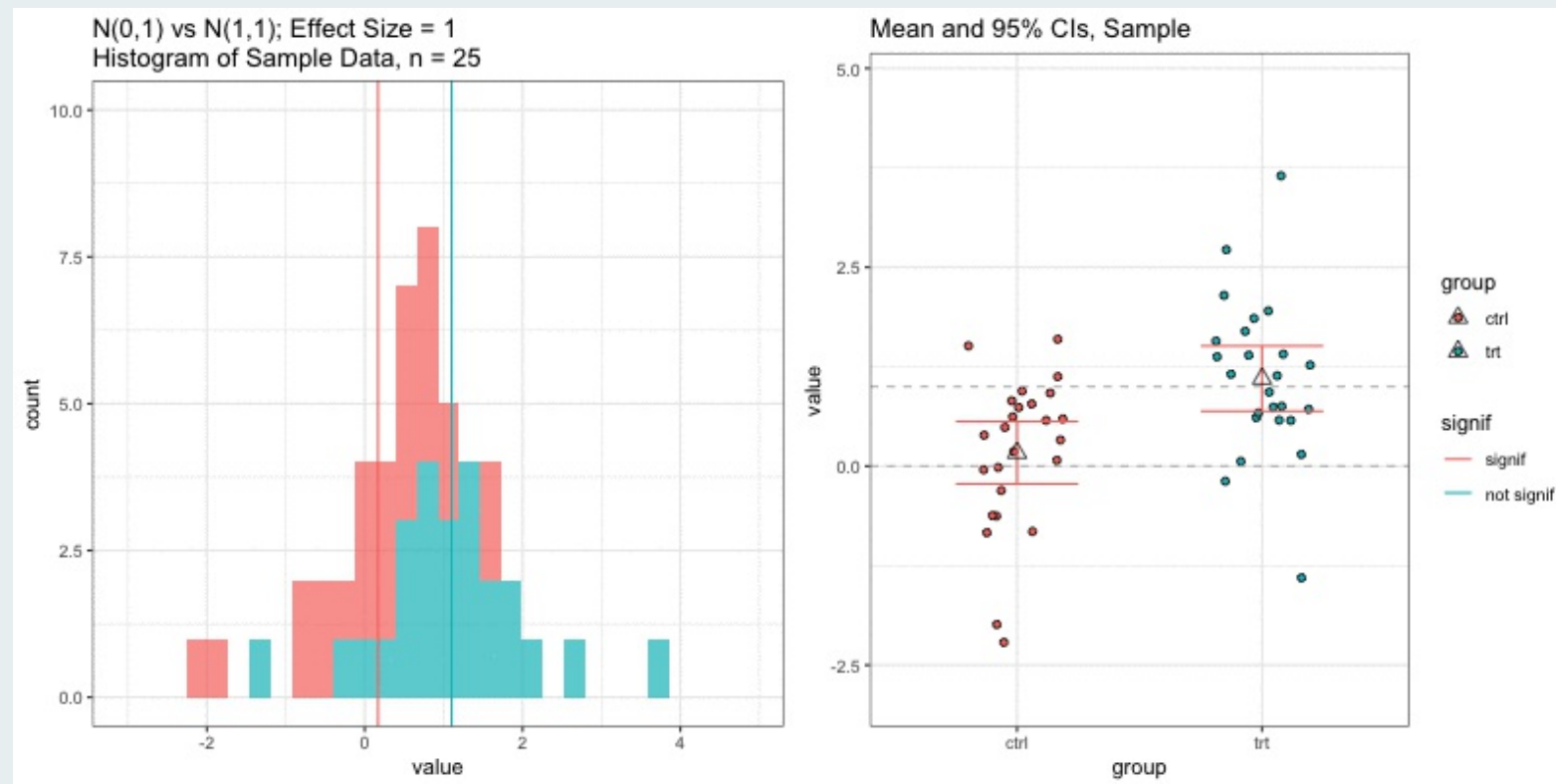
# Underlying data distributions



# $n=25$ , effect size = 1

Power = 0.93

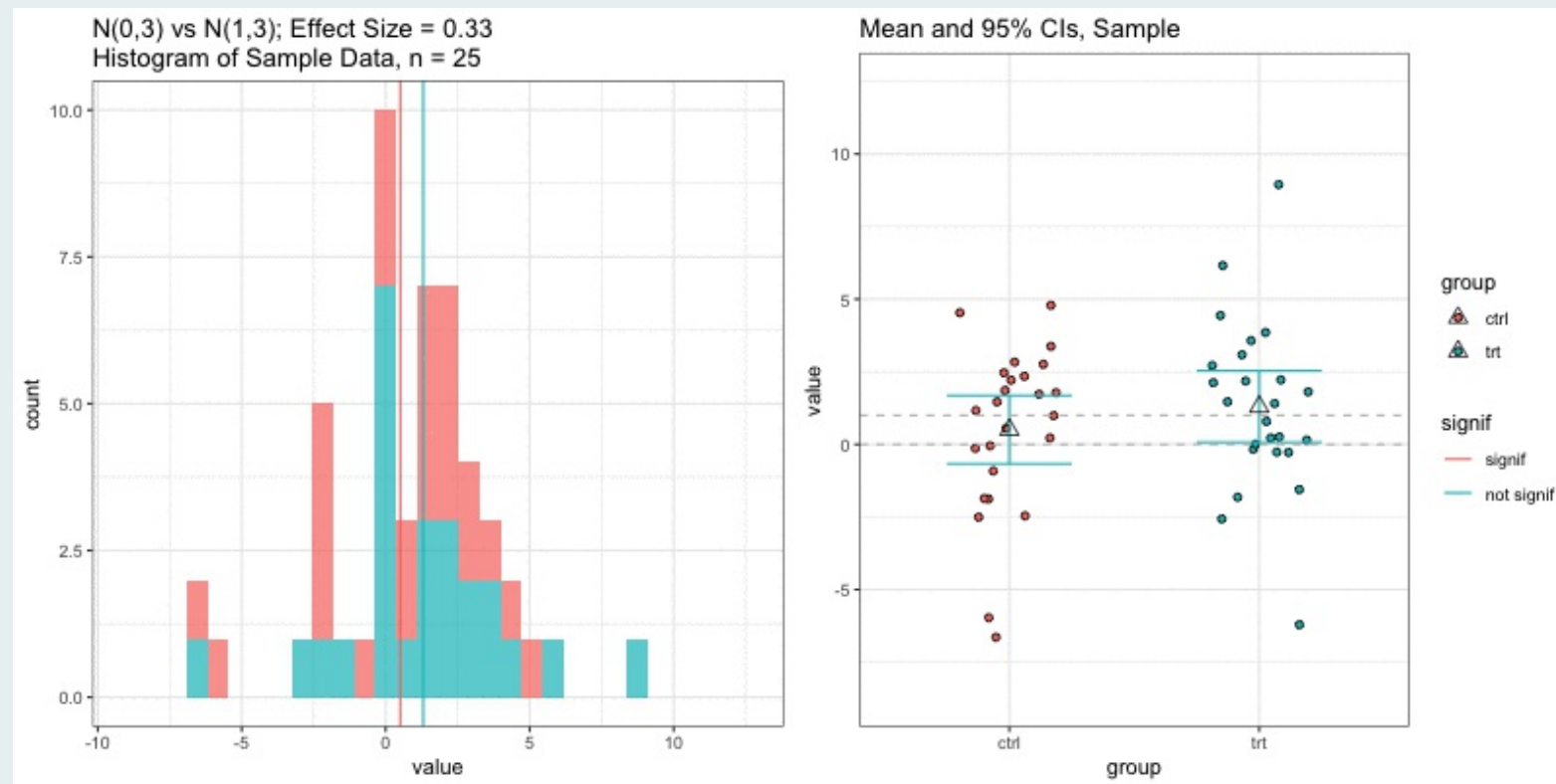
(Significance based on two sample t-test for difference in means)



# $n=25$ , effect size = 0.33

Increase standard deviation from 1 to 3, divides effect size by 3

Power = 0.21





To detect an effect size of 0.33 with power = 0.9 and type I error = 0.05, what sample size would we need? n=194 in each group!

```
power.t.test(delta = 0.33, sd = 1, sig.level = 0.05, pow
```

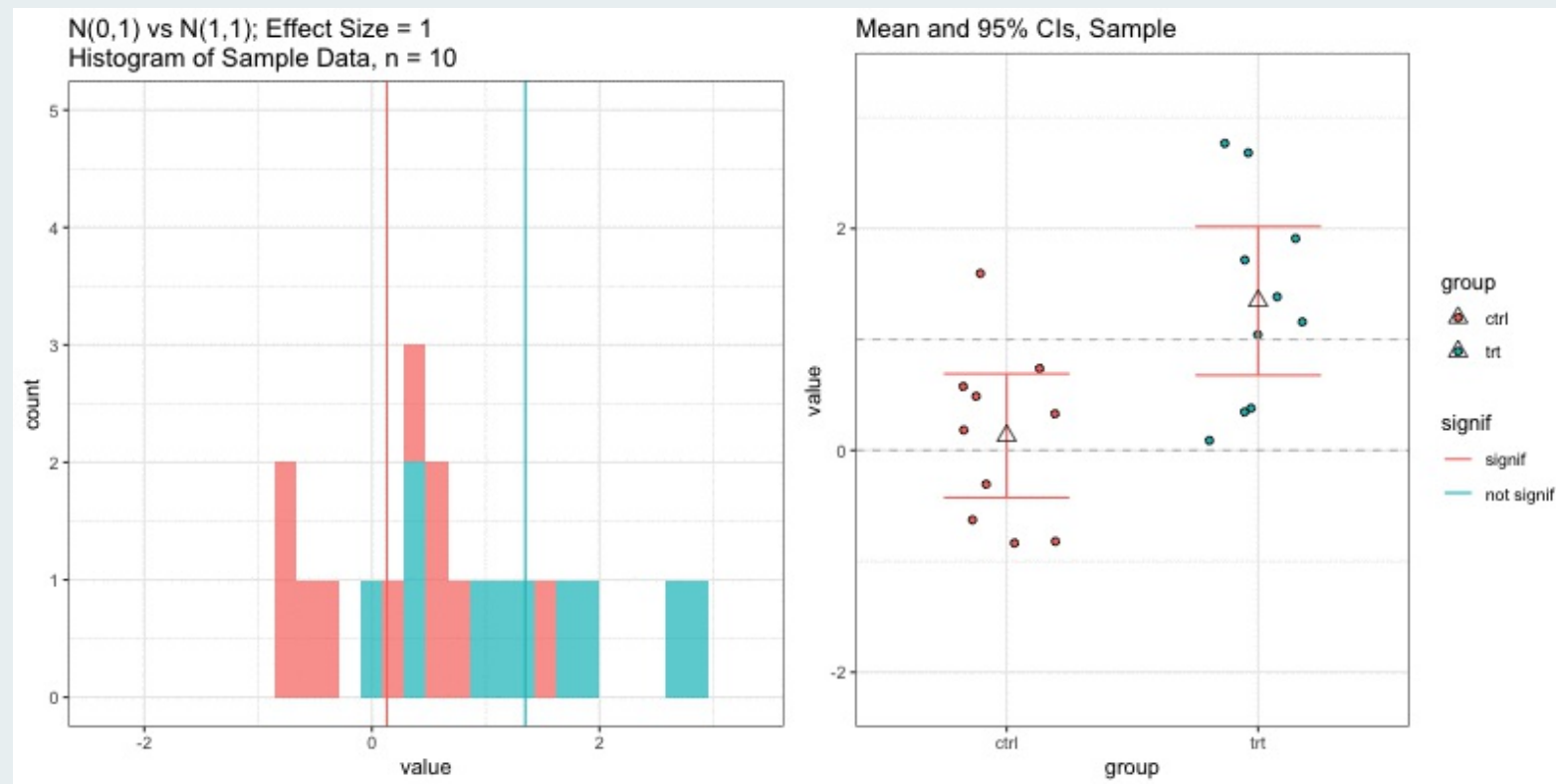
Two-sample t test power calculation

```
      n = 193.9392
delta = 0.33
sd = 1
sig.level = 0.05
power = 0.9
alternative = two.sided
```

NOTE: n is number in *\*each\** group

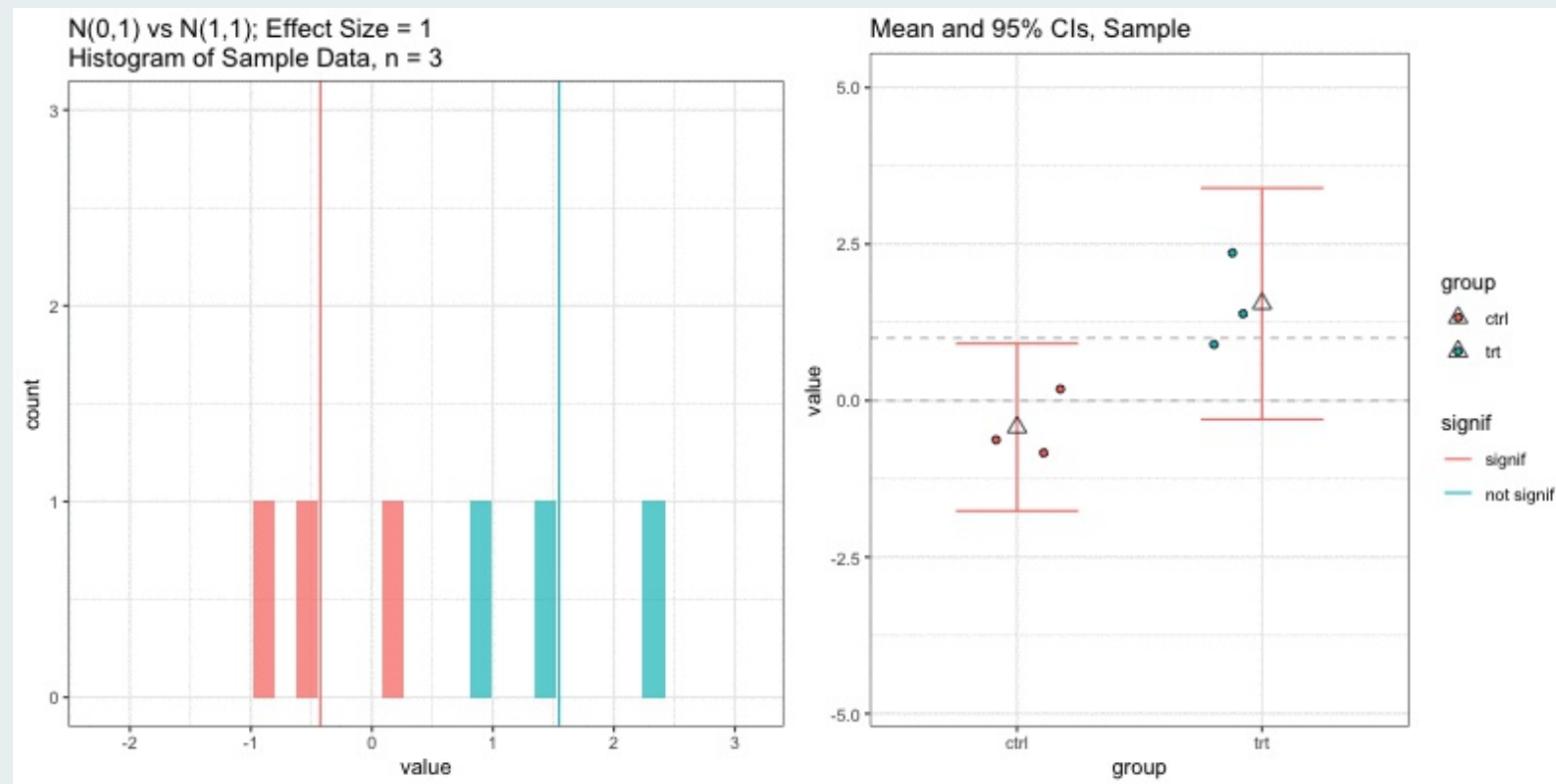
# $n=10$ , effect size = 1

Decrease sample size  
Power = 0.56



# $n=3$ , effect size = 1

Decrease sample size even more  
Power = 0.16



$n = 3$ , power = 0.9, effect size  
= ?

In the R output below, the effect size is  $\text{delta}/\text{sd} = 3.59/1 = 3.59$ .

```
power.t.test(n=3, sd=1, sig.level=0.05, power=0.9)
```

Two-sample t test power calculation

```
      n = 3
    delta = 3.589209
      sd = 1
sig.level = 0.05
  power = 0.9
alternative = two.sided
```

NOTE: n is number in \*each\* group

# Other reasons to calculate sample size

## Precision of statistics

- Sample sizes can also be calculated for a specific maximum width in confidence interval around an estimate
- i.e. we will estimate the proportion with a 95% confidence interval of width 0.1 such as  $[0.2, 0.3]$

## Prediction models

- Large sample sizes are needed for complex prediction models.
- Stability of prediction model accuracy measures depends on sample size.

# Important to remember:

## Sample size estimates are ESTIMATES.

- based on assumptions that could be incorrect
- based on pilot data that could be a poor sample or too small
- the more you don't know, the more conservative you should be (inflate your  $n$ )
- good to provide multiple estimates for a variety of scenarios/effects

Free online software

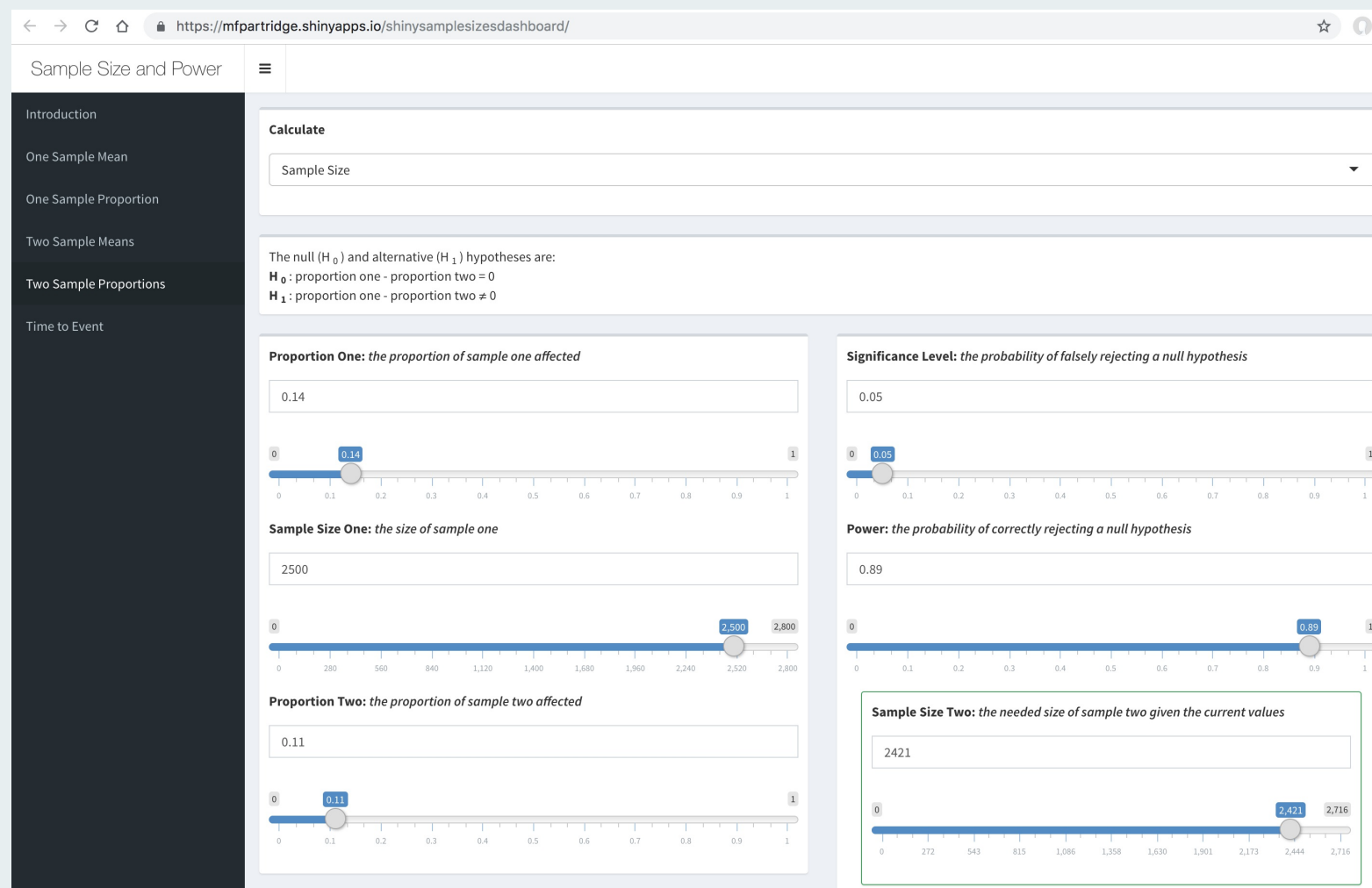
# G\*power

(examples of how to use it:

<http://www.ats.ucla.edu/stat/gpower/>)



# Shiny Dashboard for Sample Size and Power Calculations



# Others

- [TrialDesign.org](https://www.trialdesign.org/)
- [GLIMMPSE](#)
- [CRAB Stat tools](#)
- [The Shiny CRT Calculator: Power and Sample size for Cluster Randomised Trials](#)
- [Cal Poly Stats Dept Apps](#)
- Statistical software such as R, SAS, STATA

Take home message:

Do your research before you do your  
research!

# Thank you!

Contact me: ✉ minnier-[at]-ohsu.edu,  [datapointier](#),  [jminnier](#)

Slides available: [bit.ly/aacr-power](https://bit.ly/aacr-power)

Slide code available at: [github.com/jminnier/talks-etc](https://github.com/jminnier/talks-etc)

## References

- Some of this talk adapted from: [David Yanez's Sample Size](#) talk at [OCTRI Research Forum \(OHSU\)](#)
- [Statistical Rules of Thumb, Chapter 2](#)