

## Power of hypothesis tests

# Packages

```
library(tidyverse)
```

# Errors in testing

What can happen:

Decision		
Truth	Do not reject	Reject null
Null true	Correct	Type I error
Null false	Type II error	Correct

Tension between truth and decision about truth (imperfect).

- ▶ Prob. of type I error denoted  $\alpha$ . Usually fix  $\alpha$ , eg.  $\alpha = 0.05$ .
- ▶ Prob. of type II error denoted  $\beta$ . Determined by the planned experiment. Low  $\beta$  good.
- ▶ Prob. of not making type II error called **power** ( $= 1 - \beta$ ).  
*High power good.*

## Power 1/2

- ▶ Suppose  $H_0 : \theta = 10$ ,  $H_a : \theta \neq 10$  for some parameter  $\theta$ .
- ▶ Suppose  $H_0$  wrong. What does that say about  $\theta$ ?
- ▶ Not much. Could have  $\theta = 11$  or  $\theta = 8$  or  $\theta = 496$ . In each case,  $H_0$  wrong.

## Power 2/2

- ▶ How likely a type II error is depends on what  $\theta$  is:
  - ▶ If  $\theta = 496$ , should reject  $H_0 : \theta = 10$  even for small sample, so  $\beta$  small (power large).
  - ▶ If  $\theta = 11$ , hard to reject  $H_0$  even with large sample, so  $\beta$  would be larger (power smaller).
- ▶ Power depends on true parameter value, and on sample size.
- ▶ So we play “what if”: “if  $\theta$  were 11 (or 8 or 496), what would power be?”.

## Figuring out power

- ▶ Time to figure out power is before you collect any data, as part of planning process.
- ▶ Need to have idea of what kind of departure from null hypothesis of interest to you, eg. average improvement of 5 points on reading test scores. (Subject-matter decision, not statistical one.)
- ▶ Then, either:
  - ▶ “I have this big a sample and this big a departure I want to detect. What is my power for detecting it?”
  - ▶ “I want to detect this big a departure with this much power. How big a sample size do I need?”

## How to understand/estimate power?

- ▶ Suppose we test  $H_0 : \mu = 10$  against  $H_a : \mu \neq 10$ , where  $\mu$  is population mean.
- ▶ Suppose in actual fact,  $\mu = 8$ , so  $H_0$  is wrong. We want to reject it. How likely is that to happen?
- ▶ Need population SD (take  $\sigma = 4$ ) and sample size (take  $n = 15$ ). In practice, get  $\sigma$  from pilot/previous study, and take the  $n$  we plan to use.
- ▶ Idea: draw a random sample from the true distribution, test whether its mean is 10 or not.
- ▶ Repeat previous step “many” times: simulation.

# Making it go

- ▶ Random sample of 15 normal observations with mean 8 and SD 4:

```
x <- rnorm(15, 8, 4)
x
```

```
[1] 14.487469  5.014611  6.924277  5.201860  8.852952 10.8
[8] 11.165242  8.016188 12.383518  1.378099  3.172503 13.0
[15]  5.015575
```

- ▶ Test whether  $x$  from population with mean 10 or not (over):



...continued

```
t.test(x, mu = 10)
```

### One Sample t-test

```
data: x
```

```
t = -1.8767, df = 14, p-value = 0.08157
```

```
alternative hypothesis: true mean is not equal to 10
```

```
95 percent confidence interval:
```

```
5.794735 10.280387
```

```
sample estimates:
```

```
mean of x
```

```
8.037561
```

- ▶ P-value 0.081, so fail to reject the mean being 10 (a Type II error).

or get just P-value

```
ans <- t.test(x, mu = 10)  
ans$p.value
```

```
[1] 0.0815652
```

## Run this lots of times via simulation

- ▶ draw random samples from the truth
- ▶ test that  $\mu = 10$
- ▶ get P-value
- ▶ Count up how many of the P-values are 0.05 or less.

## In code

```
tibble(sim = 1:1000) %>%  
  rowwise() %>%  
  mutate(my_sample = list(rnorm(15, 8, 4))) %>%  
  mutate(t_test = list(t.test(my_sample, mu = 10))) %>%  
  mutate(p_val = t_test$p.value) %>%  
  count(p_val <= 0.05)
```

# A tibble: 2 x 2

# Rowwise:

	`p_val <= 0.05`	n
	<lgl>	<int>
1	FALSE	578
2	TRUE	422

We correctly rejected 422 times out of 1000, so the estimated power is 0.422.

## Try again with bigger sample

```
tibble(sim = 1:1000) %>%  
  rowwise() %>%  
  mutate(my_sample = list(rnorm(40, 8, 4))) %>%  
  mutate(t_test = list(t.test(my_sample, mu = 10))) %>%  
  mutate(p_val = t_test$p.value) %>%  
  count(p_val <= 0.05)
```

# A tibble: 2 x 2

# Rowwise:

	`p_val <= 0.05`	n
	<lgl>	<int>
1	FALSE	119
2	TRUE	881

Power is (much) larger with a bigger sample.

## How accurate is my simulation?

- ▶ At our chosen  $\alpha$ , each simulated test independently either rejects or not with some probability  $p$  that I am trying to estimate (the power)
- ▶ Estimating a population probability using the sample proportion (the number of simulated rejections out of the number of simulated tests)
- ▶ hence, `prop.test`.
- ▶ inputs: number of rejections, number of simulations.

Sample size 15, rejected 422 times

```
prop.test(422, 1000)
```

1-sample proportions test with continuity correction

data: 422 out of 1000, null probability 0.5

X-squared = 24.025, df = 1, p-value = 9.509e-07

alternative hypothesis: true p is not equal to 0.5

95 percent confidence interval:

0.3912521 0.4533546

sample estimates:

p

0.422

95% CI for power: 0.391 to 0.453

## To estimate power more accurately

► Run more *simulations*:

Change 1000 to eg 10,000:

```
tibble(sim = 1:10000) %>%  
  rowwise() %>%  
  mutate(my_sample = list(rnorm(15, 8, 4))) %>%  
  mutate(t_test = list(t.test(my_sample, mu = 10))) %>%  
  mutate(p_val = t_test$p.value) %>%  
  count(p_val <= 0.05)
```

# A tibble: 2 x 2

# Rowwise:

	`p_val <= 0.05`	n
	<lgl>	<int>
1	FALSE	5647
2	TRUE	4353



## Accuracy of power now

```
prop.test(4353, 10000)
```

1-sample proportions test with continuity correction

data: 4353 out of 10000, null probability 0.5

X-squared = 167.18, df = 1, p-value < 2.2e-16

alternative hypothesis: true p is not equal to 0.5

95 percent confidence interval:

0.4255594 0.4450905

sample estimates:

p

0.4353

0.426 to 0.445, about factor  $\sqrt{10}$  shorter because number of simulations 10 times bigger.

## Calculating power

- ▶ Simulation approach very flexible: will work for any test. But answer different each time because of randomness.
- ▶ In some cases, for example 1-sample and 2-sample t-tests, power can be calculated.
- ▶ `power.t.test`. Input delta is difference between null and true mean:

```
power.t.test(n = 15, delta = 10-8, sd = 4, type = "one.samp
```

One-sample t test power calculation

```
      n = 15
  delta = 2
     sd = 4
sig.level = 0.05
  power = 0.4378466
alternative = two.sided
```

## Comparison of results

Method	Power
Simulation (10000)	0.4353
<code>power.t.test</code>	0.4378

- ▶ Simulation power is similar to calculated power; to get more accurate value, repeat more times (eg. 100,000 instead of 10,000), which takes longer.
- ▶ With this small a sample size, the power is not great. With a bigger sample, the sample mean should be closer to 8 most of the time, so would reject  $H_0 : \mu = 10$  more often.

## Calculating required sample size

- ▶ Often, when planning a study, we do not have a particular sample size in mind. Rather, we want to know how big a sample to take. This can be done by asking how big a sample is needed to achieve a certain power.
- ▶ The simulation approach does not work naturally with this, since you have to supply a sample size.
  - ▶ For that, you try different sample sizes until you get power close to what you want.
- ▶ For the power-calculation method, you supply a value for the power, but leave the sample size missing.
- ▶ Re-use the same problem:  $H_0 : \mu = 10$  against 2-sided alternative, true  $\mu = 8$ ,  $\sigma = 4$ , but now aim for power 0.80.

## Using power.t.test

- ▶ No n=, replaced by a power=:

```
power.t.test(power=0.80, delta=10-8, sd=4, type="one.sample")
```

One-sample t test power calculation

```
      n = 33.3672
delta = 2
    sd = 4
sig.level = 0.05
  power = 0.8
alternative = two.sided
```

- ▶ Sample size must be a whole number, so round up to 34 (to get at least as much power as you want).

## Power curves

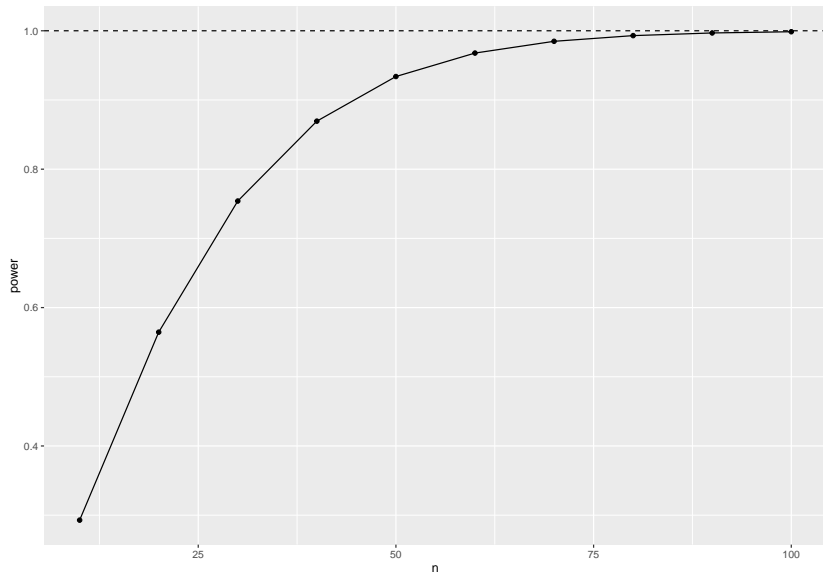
- ▶ Rather than calculating power for one sample size, or sample size for one power, might want a picture of relationship between sample size and power.
- ▶ Or, likewise, picture of relationship between difference between true and null-hypothesis means and power.
- ▶ Called power curve.
- ▶ Build and plot it yourself.

## Building it:

```
tibble(n=seq(10, 100, 10)) %>% rowwise() %>%  
  mutate(power_output =  
    list(power.t.test(n = n, delta = 10-8, sd = 4,  
                      type = "one.sample")))) %>%  
  mutate(power = power_output$power) %>%  
  ggplot(aes(x=n, y=power)) + geom_point() + geom_line() +  
    geom_hline(yintercept=1, linetype="dashed") -> g2
```

# The power curve

g2





## Power curves for means

- ▶ Can also investigate power as it depends on what the true mean is (the farther from null mean 10, the higher the power will be).
- ▶ Investigate for two different sample sizes, 15 and 30.
- ▶ First make all combos of mean and sample size:

```
means <- seq(6,10,0.5)
ns <- c(15,30)
combos <- crossing(mean=means, n=ns)
```

# The combos

```
combos
```

```
# A tibble: 18 x 2
```

	mean	n
	<dbl>	<dbl>
1	6	15
2	6	30
3	6.5	15
4	6.5	30
5	7	15
6	7	30
7	7.5	15
8	7.5	30
9	8	15
10	8	30
11	8.5	15
12	8.5	30
13	9	15
14	9	30
15	9.5	15
16	9.5	30
17	10	15
18	10	30

## Calculate powers:

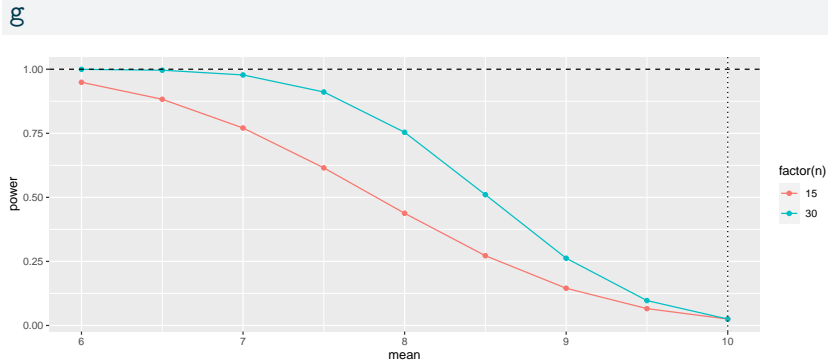
```
combos %>%  
  rowwise() %>%  
  mutate(power_stuff = list(power.t.test(n=n, delta=10-mean,   
                                         type="one.sample")))) %>%  
  mutate(power = power_stuff$power) -> powers
```

then make the plot:

```
g <- ggplot(powers, aes(x = mean, y = power, colour = fac  
  geom_point() + geom_line() +  
  geom_hline(yintercept = 1, linetype = "dashed") +  
  geom_vline(xintercept = 10, linetype = "dotted")
```

► Need `n` as categorical so that `colour` works properly.

# The power curves



## Comments

- ▶ When mean=10, that is, the true mean equals the null mean,  $H_0$  is actually true, and the probability of rejecting it then is  $\alpha = 0.05$ .
- ▶ As the null gets more wrong (mean decreases), it becomes easier to correctly reject it.
- ▶ The blue power curve is above the red one for any mean  $< 10$ , meaning that no matter how wrong  $H_0$  is, you always have a greater chance of correctly rejecting it with a larger sample size.
- ▶ Previously, we had  $H_0 : \mu = 10$  and a true  $\mu = 8$ , so a mean of 8 produces power 0.42 and 0.80 as shown on the graph.
- ▶ With  $n = 30$ , a true mean that is less than about 7 is almost certain to be correctly rejected. (With  $n = 15$ , the true mean needs to be less than 6.)

## Two-sample power

- ▶ For kids learning to read, had sample sizes of 22 (approx) in each group
- ▶ and these group SDs:

```
kids %>% group_by(group) %>%  
  summarize(n=n(), s=sd(score))
```

```
# A tibble: 2 x 3  
  group      n      s  
  <chr> <int> <dbl>  
1 c      23  17.1  
2 t      21  11.0
```

## Setting up

- ▶ suppose a 5-point improvement in reading score was considered important (on this scale)
- ▶ in a 2-sample test, null (difference of) mean is zero, so  $\delta$  is true difference in means
- ▶ what is power for these sample sizes, and what sample size would be needed to get power up to 0.80?
- ▶ SD in both groups has to be same in power.t.test, so take as 14.



## Calculating power for sample size 22 (per group)

```
power.t.test(n=22, delta=5, sd=14, type="two.sample",  
             alternative="one.sided")
```

Two-sample t test power calculation

```
      n = 22  
    delta = 5  
      sd = 14  
sig.level = 0.05  
  power = 0.3158199  
alternative = one.sided
```

NOTE: n is number in *each* group

## sample size for power 0.8

```
power.t.test(power=0.80, delta=5, sd=14, type="two.sample",  
             alternative="one.sided")
```

Two-sample t test power calculation

```
      n = 97.62598  
delta = 5  
  sd = 14  
sig.level = 0.05  
  power = 0.8  
alternative = one.sided
```

NOTE: n is number in *each* group

## Comments

- ▶ The power for the sample sizes we have is very small (to detect a 5-point increase).
- ▶ To get power 0.80, we need 98 kids in *each* group!