

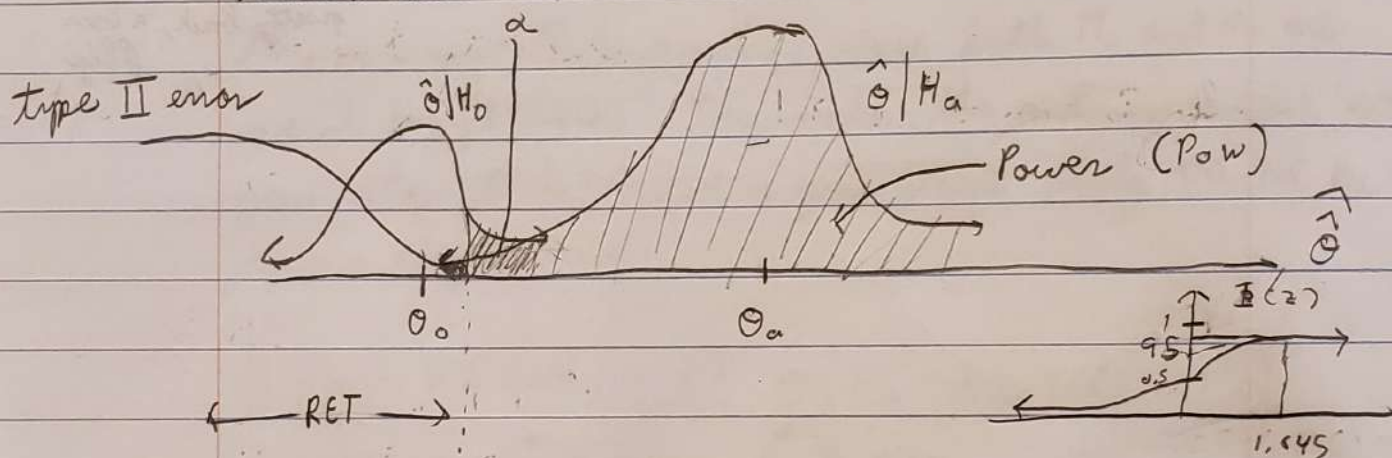
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Let's look at power more generally (beyond two point hypotheses),

at significance level α

$H_0: \theta \leq \theta_0$, $H_a: \theta = \theta_1 > \theta_0$ right-tailed (test)
under i.i.d. Bern (theta) and the normal approximation

trying to get less standard error



$$\theta_0 + z_{1-\alpha} \sqrt{\frac{\theta_0(1-\theta_0)}{n}}$$

let $\Phi(z) = F_2(z)$ CDF of $N(0,1)$

$$\Phi(z_{1-\alpha}) = 1 - \alpha$$

$$\alpha = .05 \Rightarrow z_{1-\alpha} = 1.645$$

$$\begin{aligned} \text{Pow} &= P(\hat{\theta} | H_a > \theta_0 + z_{1-\alpha} \sqrt{\frac{\theta_0(1-\theta_0)}{n}}) \\ &= P\left(\frac{\hat{\theta} | H_a - \theta_a}{\sqrt{\frac{\theta_a(1-\theta_a)}{n}}} > \frac{\theta_0 + z_{1-\alpha} \sqrt{\frac{\theta_0(1-\theta_0)}{n}} - \theta_a}{\sqrt{\frac{\theta_a(1-\theta_a)}{n}}}\right) \end{aligned}$$

mult
top/bot
 \sqrt{n}

z dist.

$$= P\left(z > \frac{-\sqrt{n}(\theta_a - \theta_0) + z_{1-\alpha} \sqrt{\theta_0(1-\theta_0)}}{\sqrt{\theta_a(1-\theta_a)}}\right)$$

↑ realization

$$= 1 - \Phi$$

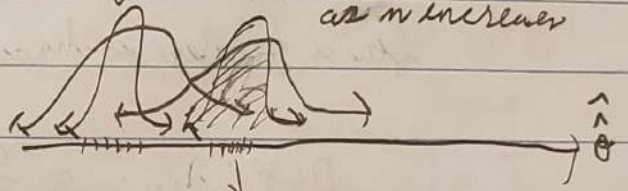
$$= 1 - \Phi \left(\frac{-\sqrt{n}(\theta_a - \theta_0) + Z_{1-\alpha}\sqrt{\theta_0(1-\theta_0)}}{\sqrt{\theta_a(1-\theta_a)}} \right) = \text{Pow}(\theta_a, \theta_0, n, \alpha)$$

Power Function

Observations about the power function

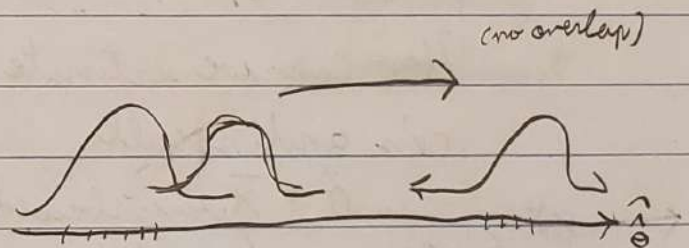
If $n \rightarrow \infty \Rightarrow \text{Pow} \rightarrow 1$

as n increases



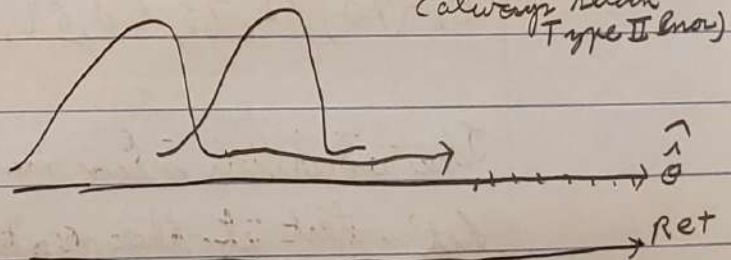
If $\theta_a \rightarrow \infty \Rightarrow \text{Pow} \rightarrow 1$

(If H_0 is true)



As $\alpha \rightarrow 0 \Rightarrow \text{Pow} \rightarrow 1$

(always retain Type II error)



new type of survey. We ask "How tall are you (in inches)?" for men only. I'll ask 10 male students and get x_1, \dots, x_{103} (i.e. my data). The data is now continuous (no longer zeroes and ones). Heights for a gender is known to be normally distributed

DGP: $x_1, \dots, x_n \stackrel{iid}{\sim} N(\theta, \sigma^2)$. Assume σ^2 is known and 4^2

How can we estimate theta? Theta is the mean of the r.v.s and recall

test $\leftarrow \hat{\theta} = \bar{x}$ is unbiased, let's use this estimator
one sample z-test

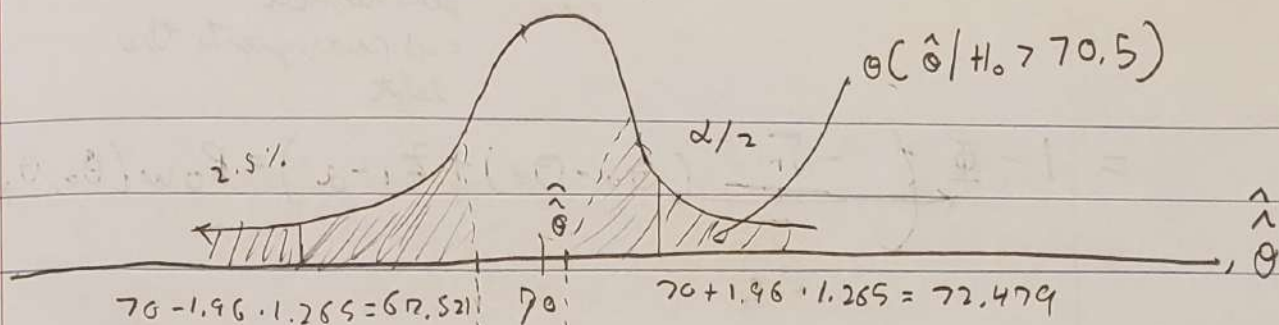
$$\bar{x}_1 = (70, 72, 73, 68, 69, 70, 67, 72, 71, 73) \quad \hat{\theta} = \bar{x} = 70.5$$

The american mean male adult height is "70".

Let's test if the mean of the population where this class is drawn from is different than "70"

$$H_a: \theta \neq 70, H_0: \theta = 70 \quad \alpha = 5\%$$

$$\hat{\theta} | H_0 \sim N(70, \frac{4^2}{10}) = N(70, 1.265^2)$$



← RET →

← RET →

$\hat{\theta} \in \text{RET} \Rightarrow \text{Fail to Reject}$

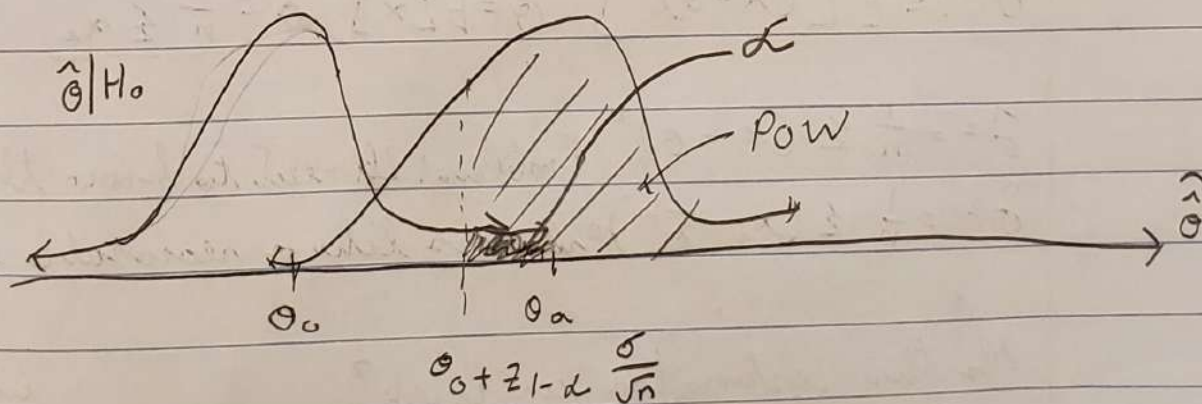
$P_{val} = P(\text{estimate is more extreme than observed} | H_0)$

$$= P(\hat{\theta} | H_0: \theta = 70.5) = 2 P(\hat{\theta} | H_0: \theta = 70.5)$$

$$= 2 P\left(Z > \frac{70.5 - 70}{1.265}\right) = 69.3\% \quad \& \text{ statistically insignificant}$$

0.39525

$H_0: \theta \leq \theta_0, H_a: \theta = \theta_a > \theta_0$ size α



$$POW = P(\hat{\theta} | H_a > \theta_0 + z_{1-\alpha} \frac{\sigma}{\sqrt{n}})$$

$$= P\left(\frac{\hat{\theta} | H_a - \theta_a}{\frac{\sigma}{\sqrt{n}}} > \frac{\theta_0 + z_{1-\alpha} \frac{\sigma}{\sqrt{n}} - \theta_a}{\frac{\sigma}{\sqrt{n}}}\right)$$

$\sigma \rightarrow$ gets smaller,
gets tighter
and power goes to the
left

$$= 1 - \Phi \left(\frac{-\sqrt{n}}{\sigma} (\theta_a - \theta_o) + z_{1-\alpha} \right) = \text{Pow}(\theta_o, \theta_o, n, \alpha, \sigma)$$

More realistic: we don't know sig^2 . but... sig^2 is a "nuisance parameter". It means we need to estimate it in order to estimate theta but we don't intrinsically care about it

DGP: $X_1, \dots, X_n \stackrel{\text{iid}}{\sim} N(\theta, \sigma^2)$ and both θ, σ^2 are unknown

How do we estimate sig^2 ? Recall... for a rv X ,

$$\sigma^2 := E[(X - \theta)^2] \quad \theta = E[X], \quad \hat{\theta} = \frac{1}{n} \sum x_i$$

$$\hat{\sigma}^2 = \frac{1}{n} \sum (x_i - \theta)^2 \quad \text{Problem! It needs to know theta!}$$

$$\hat{\sigma}^2 = \frac{1}{n} \sum (x_i - \bar{x})^2 \quad \text{Seems like a reasonable estimator!}$$

Is this estimator unbiased?

$$E[\hat{\sigma}^2] = E\left[\frac{1}{n} \sum (x_i - \bar{x})^2\right] \stackrel{\text{iid}}{=} \frac{1}{n} \sum E(x_i - \bar{x})^2 \stackrel{\text{iid}}{=} \frac{1}{n} \times n E[(x_i - \bar{x})^2]$$

$$= E[x_1^2 - 2x_1 \bar{x} + \bar{x}^2] = E[x_1^2] - 2E[x_1 \frac{x_1 + \dots + x_n}{n}] + E[\bar{x}^2]$$

Recall $\text{Var}[x] = E[x^2] - E[x]^2$

$$= \sigma^2 + \theta^2 - \frac{2}{n} E[x_1^2 + x_1 x_2 + \dots + x_1 x_n] + \left(\frac{\sigma^2}{n} + \theta^2 \right)$$

$$= \frac{n+1}{n} \sigma^2 + 2\theta^2 - \frac{2}{n} (\sigma^2 + \theta^2 + \theta^2 + \dots + \theta^2)$$

cancels out

$$= \frac{n-1}{n} \sigma^2 \neq \sigma^2 \Rightarrow \text{It's a little bit biased} \dots \dots$$

(towards 0)

However, it is "asymptotically unbiased" meaning...

$$\lim_{n \rightarrow \infty} E[\hat{\sigma}^2] = \sigma^2 \quad \text{eg} \quad \lim_{n \rightarrow \infty} E[\hat{\sigma}^2] = \lim_{n \rightarrow \infty} \frac{n-1}{n} \sigma^2 = \sigma^2 \nearrow$$

Consider the following estimator:

$$S^2 = \frac{n}{n-1} \hat{\sigma}^2 = \frac{n}{n-1} \frac{1}{n} \sum (x_i - \bar{x})^2 = \frac{1}{n-1} \sum (x_i - \bar{x})^2$$

The beauty of this estimator is that

$$E[S^2] = E\left[\frac{n}{n-1} \hat{\sigma}^2\right] = \frac{n}{n-1} E[\hat{\sigma}^2] = \frac{n}{n-1} \frac{n-1}{n} \sigma^2 = \sigma^2 \text{ is unbiased}$$

and it's the default estimator for sigsq (variances in DGP) and it's really important in normal theory...