

## Error & Power in hypothesis testing: Types of Errors:

Type I: Reject  $H_0$  when TRUE - False positive -  $P(\text{Rej } H_0 | H_0 \text{ True}) = \alpha$

Type II: Failed to reject  $H_0$  when  $H_0$  False -  $P(\text{FTR } H_0 | H_0 \text{ False}) = \beta$   
(FTR)

	Reality	
	$H_0 \text{ True}$	$H_0 \text{ False}$
FTR $H_0$	specificity (1- $\alpha$ ) True N	Type II False Neg $\beta$
Decision Rej $H_0$	Type I $\alpha$ (FP)	Power sensitivity (TP) (1- $\beta$ )

Prob (Type I) =  $\alpha$  (we choose  $\alpha$ )

Prob (Type II) = Depends on  $\alpha$ ,  
sample size,  $\mu$

diff. b/w:  $H_0$  vs  $H_A$  hypothesis

### Power of Test:

Hypertensive pop  $\mu = 160, \sigma = 36$

Drug test  $n = 25, \alpha = 0.05$

$H_0: \mu = 160$

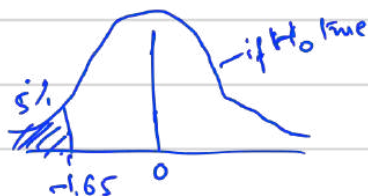
$H_A: \mu \leq 160$

$\alpha = P(\text{Rej } H_0 | H_0 \text{ True})$

$\beta = P(\text{FTR } H_0 | H_0 \text{ False or } H_A \text{ True})$

Power = prob. of rejecting null if  
alternative is true

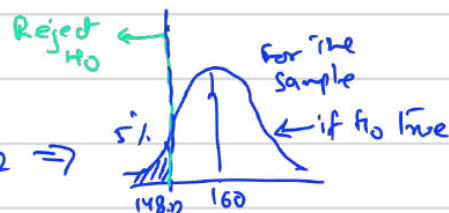
$= P(\text{Rej } H_0 | H_A \text{ True})$



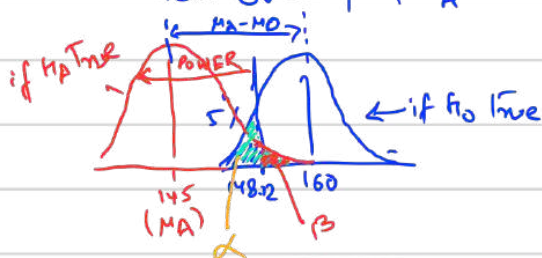
$Z_{\text{stat}} < -1.65 \Rightarrow \text{Rej } H_0$

$$Z_{\text{stat}} = \frac{\bar{X} - \mu_0}{\sigma/\sqrt{n}} = \frac{\bar{X} - 160}{36/\sqrt{25}}$$

$$-1.65 = \frac{\bar{X} - 160}{36/\sqrt{25}} \Rightarrow \bar{X} = 148.12 \Rightarrow$$



lets overlay if  $H_A$  true, assume  $\mu_A = 145$



$$\beta = P(\bar{X} > 148.12 | \mu_A = 145)$$

$$Z_{\beta} = \frac{148.12 - 145}{36/\sqrt{25}} \xrightarrow{\text{standardize}} \frac{31.2}{7.2} = 4.33$$



$\uparrow \alpha - \downarrow \beta$  ( $\uparrow$  Power)

$\uparrow n - \downarrow \text{s.d.} - \downarrow \beta$  ( $\uparrow$  Power)

$\uparrow \mu_A - \mu_0 - \downarrow \beta$  ( $\uparrow$  Power)

So, Power = 1 - 33.3

= 66.7%

is large effect of drug so, if  $H_A$  is true, drug lowers blood press. to 145 on average. There's a 33% chance that we fail to reject  $H_0$

# BIVARIATE ANALYSIS

## Approaches

- Parametric
  - lot of Assumptions, nice mathematical formulation
  - large sample size
  - higher power
  - sensitive to outliers
- Nonparametric
  - Generally work with ranking data

Ex: X - Drug A, Drug B, - **Categorical** Analysis tools - t-test 2 sample  
 Y - Δ SBP (Sis. blood press.) - **Numerical** - one way ANOVA  
 change Wilcoxin ...

Ex: X - Smoker - **Categorical** Analysis - Pearson  $\chi^2$  test  
 Y - Cancer - **Categorical** - Fischer Exact test

Ex: X - Years of education **Numerical** Analysis - Correlation  
 Y - Salary **Numerical** - Lin Reg.

X-cat Y-cat :

## Paired / Dependent

- Before / After Treatment
- Left / Right - left side  
 - Right side
- Cross over design Treatment A then after gap Treatment B
- Matching - 2 groups (A, B) then match on other variable  
 (Sex, Age)  
 - Twins

## Independent

- Different people on Treatment  
 Smoker / Non smoker
- Exposed / Non-exposed
- Male / Female

## CONSIDERATIONS:

- ↓ Biological variability
- matching is subjective and not always possible
- Must ensure groups are similar
- Randomize
- Adjustment bet<sup>n</sup> groups
- simple MATH

- So what are we analysing

## 2 Paired

- Parametric → Paired t-test
- Non-parametric → Wilcoxin signed Rank

## 3 or more Paired

- Repeated Measures ANOVA
- Friedman's test

## 2 Independent

- 2 sample t-test
- Rank Sum (Mann-Whitney)

## 3+ Independent

- One-way ANOVA
- KRUSKAL WALLIS

## Paired t-test:

- Compares mean of 2 paired groups / dependent groups
- Same individual
- Or Diff. individuals matched on Age, gender etc.

Assumption

- independent observation
- Paired
- Large sample
- $\Delta BP$  is normally distributed

$$H_0: \mu_A = \mu_B \text{ or, } H_0: \mu_A - \mu_B = 0$$

$$H_1: \mu_A < \mu_B \text{ or, } H_1: (\mu_A - \mu_B) < 0$$

Now  $\mu_A - \mu_B$  using  $\Delta BP$  is a single variable

$$\text{Mean } \bar{d} = \frac{\sum \Delta BP}{n} = -6.18$$

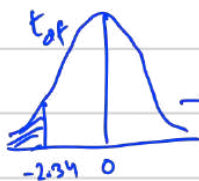
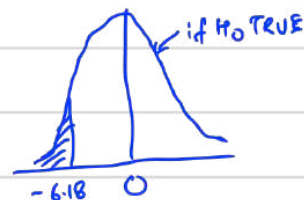
$$\text{std. dev. } s_d = 8.96$$

Now; we can write  $H_0: \mu_A = 0$

$$H_1: \mu_A < 0$$

$$t_{STAT} = \frac{\bar{d} - \mu_A}{SE_{\bar{d}}} = \frac{-6.18 - 0}{8.96/\sqrt{11}} = -2.34$$

Pair	Before	After	$\Delta BP$
1	135	127	-8
2	142	145	+3
3	137	131	-6
...			



$\rightarrow p\text{-value} = 0.0207 = 2.07\%$ . If  $H_0$  is true There is 2% chance of getting a value that is less by 6.18

Reject  $H_0$ .

Now C.I (this is a 2 sided C.I; but for now it's ok)

$$95\% = \text{Est} \pm t^* SE_{\text{Est}}$$

$$= -6.18 \pm (2.22) \frac{8.96}{\sqrt{11}} = (-12.1, -0.30) \text{ this is CI for } \Delta BP \text{ change}$$

↑  
t for 95%

0 is not there

WILCOXIN SIGNED TEST :

- small sample size
- if we want to look at median change
- do not assume normality

$$H_0: \text{median } \Delta BP = 0$$

$$H_1: \text{m.d.} < 0$$

If  $H_0$  is true

50% should decrease

50% should show inc.

5.5 individuals of 11

Pair	Before	After	$\Delta BP$	
1	135	127	-8	Decrease
2	142	145	+3	Increase
3	137	131	-6	Decrease
...				
11				

9 total  
8 dec.  
3 inc.

P-value = Prob. of 8 or more dec. while should be 5.5

$$\sim \text{Binomial dist}^{\circ} \quad P(X \geq 8 | X \sim \text{BIN}, n=11, P=0.5) \quad \swarrow 50\%$$

$$= 0.11$$

Another Example: say 4 dec., 3 inc. of 7 people. Expect 3.5

-20, +1, -18, +2, -10, +1.5, -14  $\leftarrow$  note there are people that show a large dec. in BP after treatment but the extent is ignored.

just the worst matters - DRAWBACK

## WILCOXIN SIGNED RANK TEST:

OBS: -20, +1, -18, +2, -10, +1.5, -14

RANK: 7 1 6 3 4 2 5

OBS: 4↓, 3↓

EXPED: 3.5↓, 2.5↑

Tie then  
average RANK

-20, +1, +1, +2

4 1.5 1.5 3 RANK

for RANK SUM THE RANK:  $(1+2+\dots+7)/2 = 14$

↖ for 0.5 or 50%

SD, expect: 14↓, 14↑

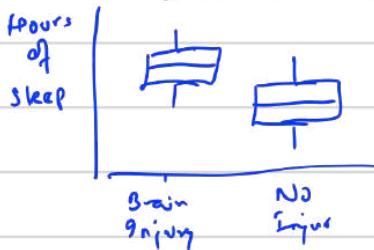
OBS: 22↓, 6↑

P-val: Prob sum↓ ≥ 22 if  $H_0$  True (i.e. 14)

## INDEPENDENT 2 sample t-TEST: mean of 2 independent

X is categorical

Y - numerical



$\bar{Y}_{inj} = 8.1, s_{inj} = 0.7, n_{inj} = 20$

$\bar{Y}_{no} = 7.4, s_{no} = 0.9, n_{no} = 25$

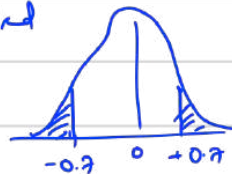
We estimate EST =  $(\bar{Y}_{inj} - \bar{Y}_{no}) = 8.1 - 7.4 = 0.7$  pop. mean

SE<sub>EST</sub> = for now assume 0.24 assuming  $\mu_1$  for inj &  $\mu_2$  for no injury.

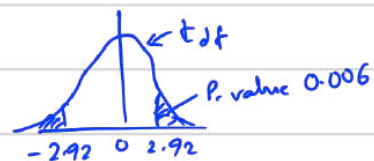
$H_0: (\mu_1 - \mu_2) = 0$

$H_1: (\mu_1 - \mu_2) \neq 0$

let's do 2-sided



$$t_{STAT} = \frac{(\bar{Y}_1 - \bar{Y}_2) - 0}{SE_{\bar{Y}_1 - \bar{Y}_2}} = \frac{0.7 - 0}{0.24} = 2.92$$

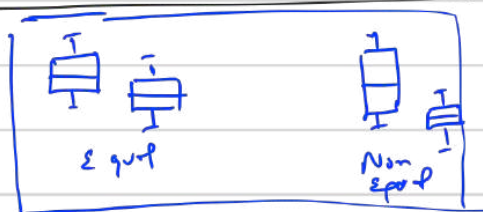


95% CI:  $(\bar{Y}_1 - \bar{Y}_2) \pm t_{\alpha/2, df} SE_{\bar{Y}_1 - \bar{Y}_2}$

=  $0.7 \pm 2(0.24) = (0.22, 1.18)$  sleep 0.22 to 1.18 hrs. more  
↖ 0 is not here



## Equal Vs. Non Equal Variance Assumption



①  $SD_{large}/SD_{small} > 2 \Rightarrow \text{Non Equal}$

②  $H_0: \sigma_1 = \sigma_2 \quad H_1: \sigma_1 \neq \sigma_2$   
(at pop. level)

③ Tests: Levene's test  
Bartlett's test

Eq.  
also call.  $SE(\bar{Y}_1) \rightarrow SD(\bar{Y}_1) = \frac{s_1}{\sqrt{n_1}} \Rightarrow Var(\bar{Y}_1) = \frac{s_1^2}{n_1}$   
 $SD(\bar{Y}_2) = \frac{s_2}{\sqrt{n_2}} \Rightarrow Var(\bar{Y}_2) = \frac{s_2^2}{n_2}$

Property:  $Var(X+Y) = Var(X) + Var(Y)$ , if  $X, Y$  independent of variance

So,  
Non Equal Variance  
 $Var(\bar{Y}_1 - \bar{Y}_2) = \frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}$   
 $\Rightarrow SD_{\bar{Y}_1 - \bar{Y}_2} = \sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}$  or  $SE_{\bar{Y}_1 - \bar{Y}_2}$  d.f:  $\min(n_1-1, n_2-1), n_1+n_2-2$

Equal Variance: take pooled estimate  $\Rightarrow$  weighted average  
i.e. 2 different estimates of same thing, pool them

$$s^2_{pooled} = \frac{(n_1-1)s_1^2 + (n_2-1)s_2^2}{(n_1-1) + (n_2-1)}$$

$$SE_{(\bar{Y}_1 - \bar{Y}_2)} = \sqrt{\frac{s^2_{pooled}}{n_1} + \frac{s^2_{pooled}}{n_2}} \quad \text{with d.f} = n_1 + n_2 - 2$$

## Bootstrap Hypothesis Testing:

Eq.

X-Feed type	Y weight
M	325
M	257
M	303
C	390
C	260

tests one could do:

- two sample t-test: mean of 2 groups M & C
- Wilcoxon R test: median of 2 groups (Mann Whitney U test)
- Bootstrapping - small sample size  
- Difficult to measure S.E for test-statistic

$H_0$ : weight same

$H_1$ : not same

Bootstrapping: Pick any number and randomly assign to label

g. Sample #1

X-Feed type      Y-Weight      #1      #2,...

M	$\bar{y}_{obs}$	$\begin{bmatrix} 325 \\ 257 \\ 303 \end{bmatrix}$	$\begin{bmatrix} 260 \\ 303 \\ 257 \end{bmatrix}$	M	$\bar{y}_{MBI} = 330$
M				M	
M				M	
C	$\bar{y}_{obs}$	$\begin{bmatrix} 390 \\ 260 \end{bmatrix}$	$\begin{bmatrix} 325 \\ 260 \end{bmatrix}$	C	$\bar{y}_{CBI}$
C				C	

Let's say  
Test statistic =  $|\bar{y}_c - \bar{y}_m| = EST$

p-value will be  $= \frac{\# \text{BS test-statistic} \geq \text{Obs. test-stat}}{\text{total B}}$

$$EST = \bar{y}_c - \bar{y}_m = 349.25 - 316 = 33.25$$

$$EST_{B1} = 352 - 330 = 22$$

$$EST_{B2} = 379 - 315 = 64 \leftarrow \text{of 2 BS only one is } \geq 33.25 \leftarrow \text{total B} = 2$$

x

Permutation approaches to hypothesis testing:

When - Small sample

- Parametric approaches not suitable
- test something other than mean/median eg. Range

From above  $EST_{mean} = 33.25$

$$g. |\text{Med}_c - \text{Med}_m| \neq EST_{median} = 58.5$$

Permutation - all possible permutation of data independent of feed type

\* Bootstrap is with replacement  
Permutation is shuffling, obs. not repeated

$$p\text{-Value} = \frac{\# \text{Permutation Test stat} > \text{obs. test stat (EST)}}{P \rightarrow (\text{no. of permutation})}$$

P → (no. of permutation)