

# **ONE-FACTOR ANALYSIS: PART 2**

Chapter 3-5, 8

# LEARNING OBJECTIVES

- Define a sampling distribution for a statistic
- Write null and alternative hypotheses for two-sample tests and simple linear regression
- Understand relationship between null and alternative distributions
- Explain how to calculate Type 1 error and power

# BREAD YEAST AND TIME TO RISE

- Yeast is added to bread to make it “rise”
  - Contacts warm water and feeds on sugars in the flour
  - Releases carbon dioxide at some rate
- Bread dough rests for a period of time to allow this process to happen
- Compare **two different rise times** to see if there is a significant difference in dough height
  - 35 and 45 minutes (quantitative or categorical?)
- **Large batch of dough partitioned into  $N$  loaf pans**

# TWO SAMPLE HYPOTHESIS TESTING

- Have  $r_1$  and  $r_2$  loaf pans for 35 and 45 minutes
  - Conclude there are differences in rise time if the mean dough heights are different
- Write effects model for this data (as in R)
- **Hypothesis test:**
  - Assume opposite of what you want to show (**null hypothesis**)
$$H_0: \mu_1 = \mu_2 \Leftrightarrow \mu_1 - \mu_2 = 0$$
  - Choose **test statistic** whose **distribution changes** depending on whether the null or or alternative hypothesis is true
  - Statistic distribution is called **sampling distribution**
  - If the observed test statistic is **unlikely to come from null distribution**, we reject the null hypothesis

# COMMENTS ABOUT HYPOTHESIS TESTING

- Prefer to write null hypothesis in terms of **estimable functions** when we can
  - Can only test hypotheses that can be written this way
- Need to know the null and alternative distributions
- Always chance we falsely reject null (Type I error) but we can control this error rate with  $\alpha$
- If we fail to reject the null **we cannot conclude the null hypothesis is true**

# TWO SAMPLE HYPOTHESIS TESTING

- Unbiased estimator for  $\mu_1 - \mu_2$  is  $\bar{Y}_1 - \bar{Y}_2$ .
- Sampling distribution:  
$$N\left(\mu_1 - \mu_2, \sigma^2 \left(\frac{1}{r_1} + \frac{1}{r_2}\right)\right)$$
- **Basic idea:** if  $\bar{Y}_1 - \bar{Y}_2$  “far” from 0 then we reject null,
- What does it mean to be far?
  - Take into account **expected variability**
  - Cutoff for unlikely values controls Type 1 error

# TWO-SAMPLE Z-STATISTIC

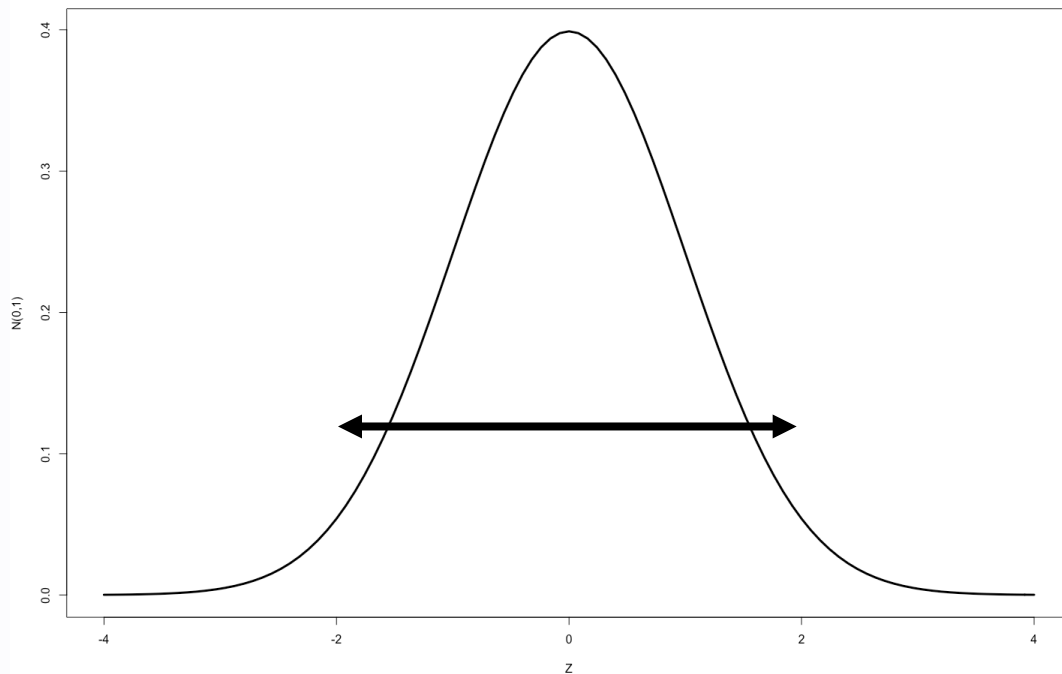
- A related test statistic we could use is

$$Z = \frac{(\bar{y}_{1\cdot} - \bar{y}_{2\cdot})}{\sigma \sqrt{\frac{1}{r_1} + \frac{1}{r_2}}}$$

- If  $\mu_1 - \mu_2 = 0$  and we knew  $\sigma$  then  $Z$  would be  $N(0, 1)$ 
  - Call this **null distribution**
  - **Unlikely** for  $|z| > 2$  (absolute value of  $z$ )
- If  $\mu_1 - \mu_2 \neq 0$ ,  $Z$  does not follow  $N(0,1)$  distribution
  - Call this **alternative distribution**
  - **More likely** for  $|z| > 2$

# TWO-SAMPLE Z-STATISTIC NULL DISTRIBUTION

## ■ Plot of null distribution



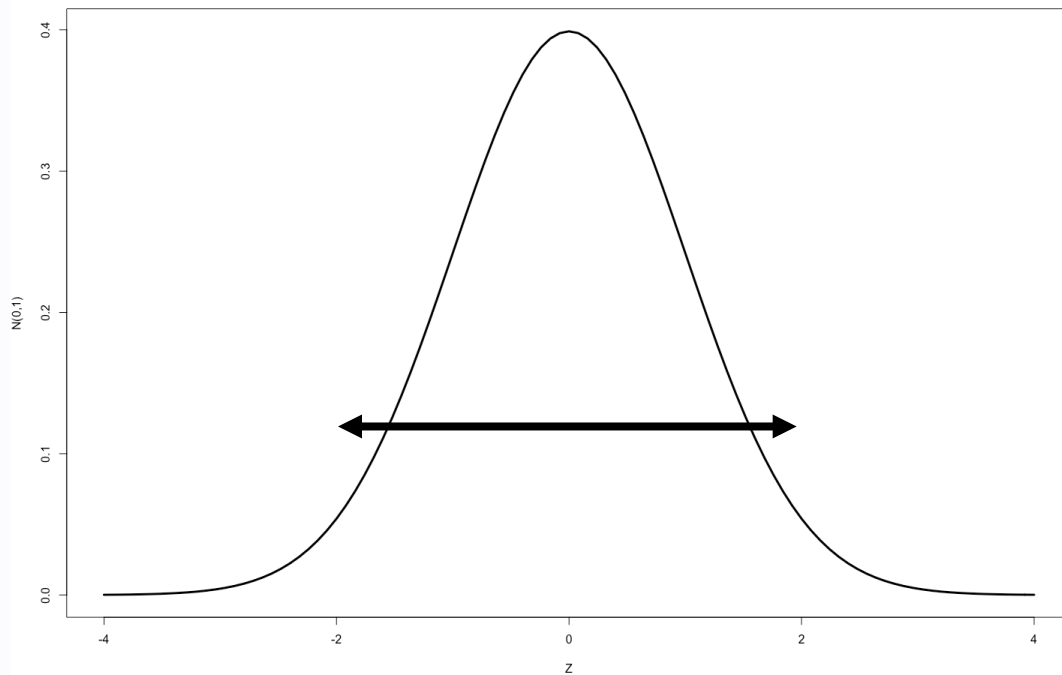
If null true, then 95% chance observed  $Z$  is between  $-1.96$  and  $1.96$

If observed  $Z$  is **outside this range**, makes sense to **reject null**



# TWO-SAMPLE Z-STATISTIC CRITICAL VALUE REJECTION

## ■ Plot of null distribution

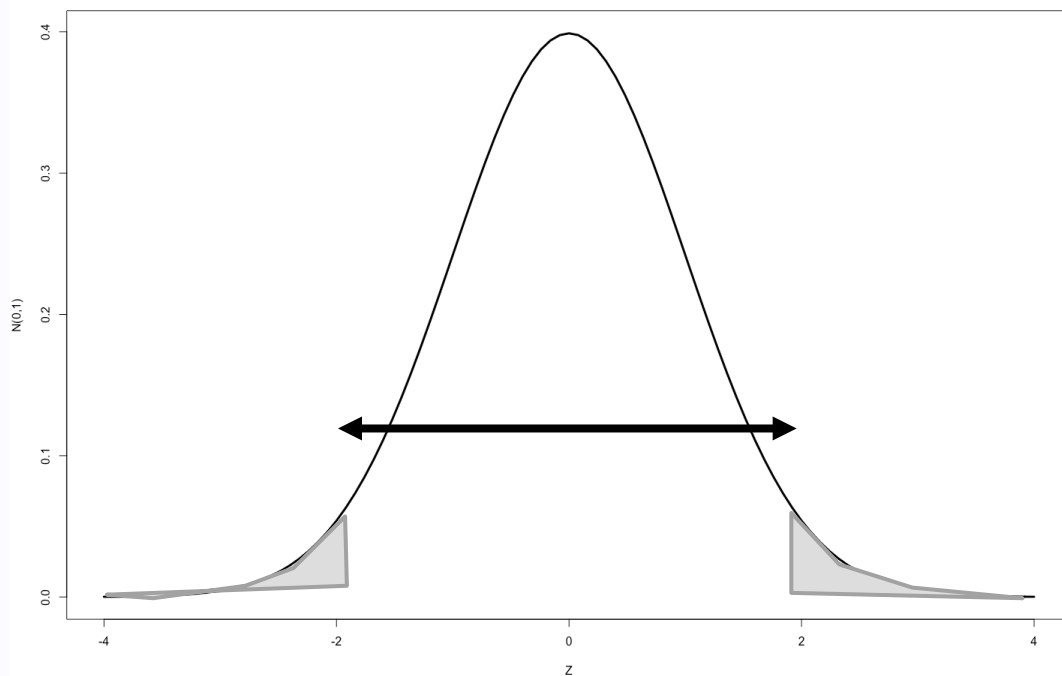


**Rejection rule:** if  $|Z_{obs}| > 1.96$  then reject null hypothesis

Call 1.96 the **critical value**

# TYPE 1 ERROR

- **Type 1 error:** reject when null is true (false reject)

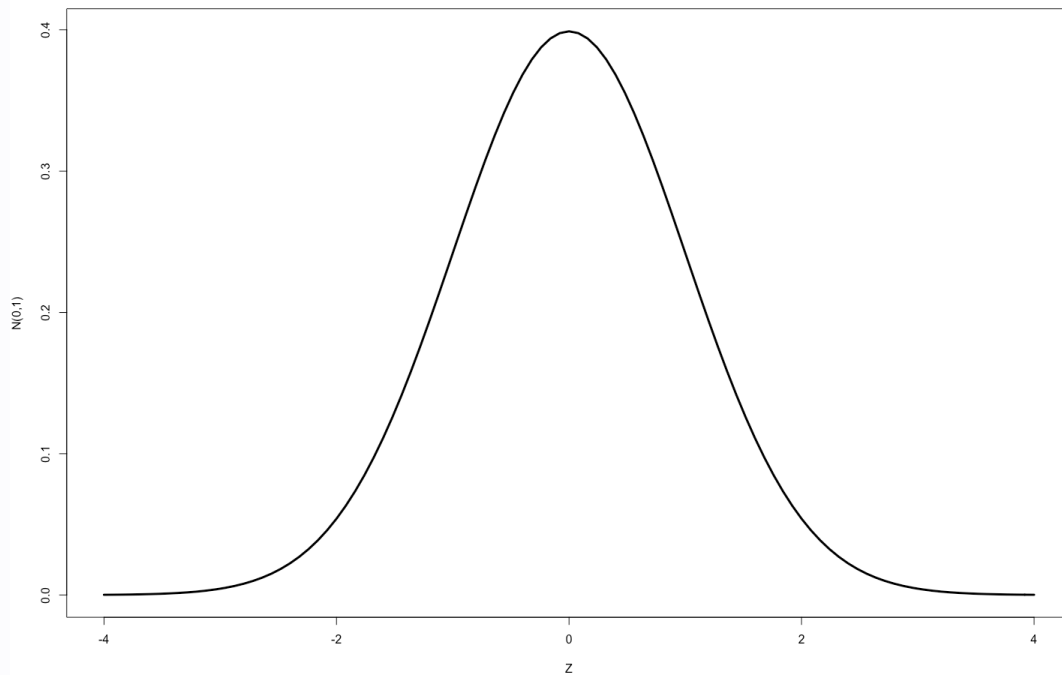


$$P(\text{Type 1 error}) = P_{H_0}(|Z| > 1.96) = 0.05 = \alpha$$

Assuming  $H_0$  is true

# TWO-SAMPLE Z-STATISTIC P-VALUE REJECTION

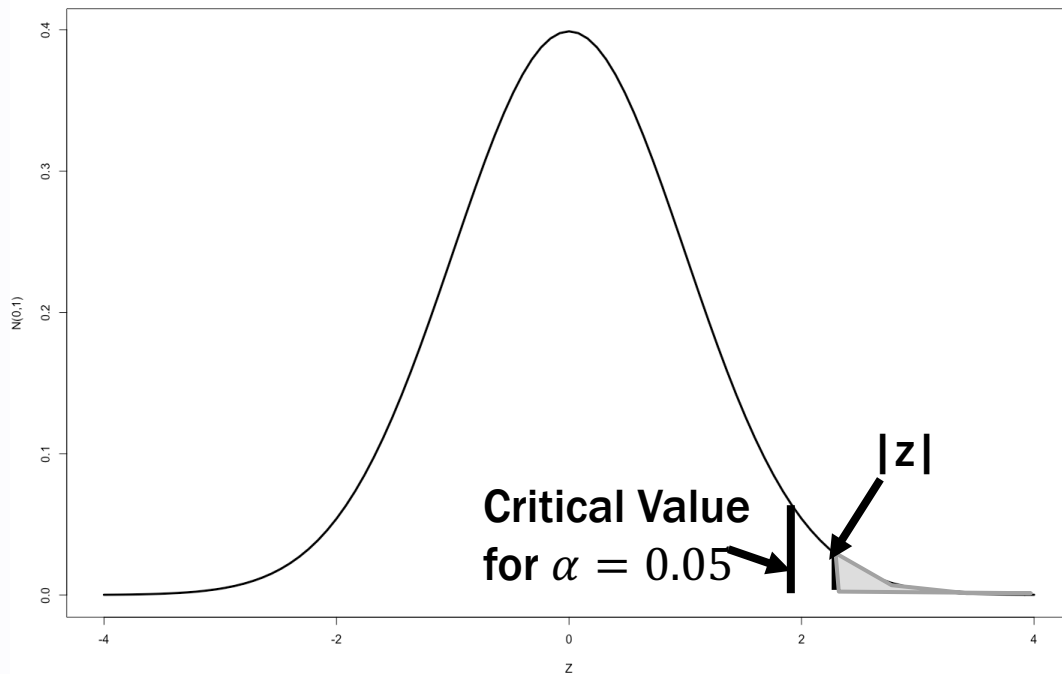
- An alternative rejection rule



Calculate **probability of observed statistic ( $z$ ) or more extreme value** assuming the null is true

# TWO-SAMPLE Z-STATISTIC P-VALUE REJECTION

- An alternative rejection rule



$$2 \times P_{H_0}(Z > |z|) = p - value$$

Reject null if  $p - value < \alpha$

# POWER

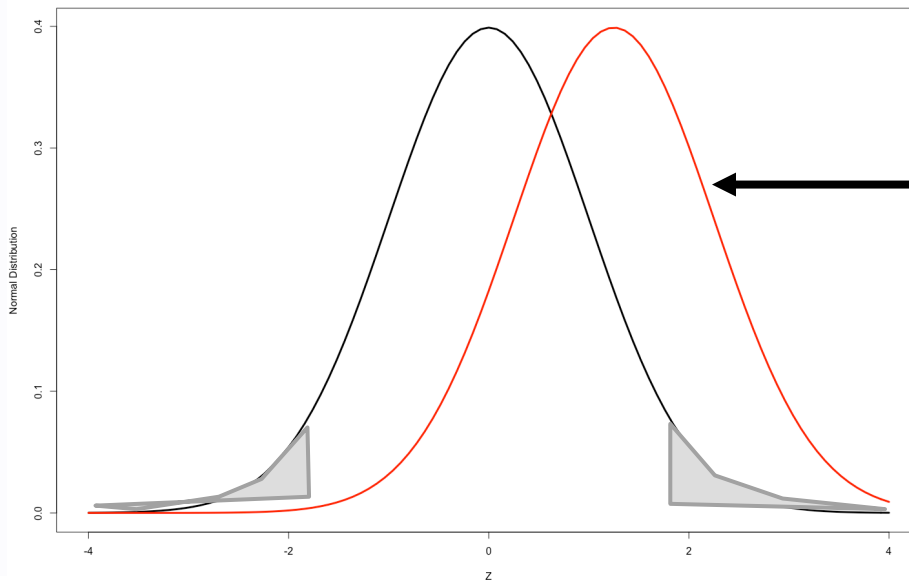
- **Power:** probability of rejecting **assuming fixed alternative hypothesis is true**
- For given data set, power depends on:
  - Alternative hypothesis (**specific**  $|\mu_1 - \mu_2| > 0$ )
  - Critical level for desired significance level
  - Sample sizes
  - $\sigma$
- Use power to determine "optimal" relative sample sizes after fixing alternative, critical value, and  $\sigma$

# TWO-SAMPLE Z-STATISTIC POWER

- If  $\mu_1 - \mu_2 \neq 0$  then alternative distribution of  $Z$  is

$$Z \sim N\left(\frac{\mu_1 - \mu_2}{\sigma \sqrt{\frac{1}{r_1} + \frac{1}{r_2}}}, 1\right) \quad \text{Noncentrality parameter}$$

- The larger this mean is, the more likely we observe “extreme” values



$$P_{H_0}(|Z| > 1.96) = 0.05 = \alpha$$

$$\sigma = 1 \quad \mu_1 - \mu_2 = 0.25 \\ r_1 = 10 \quad r_2 = 10$$

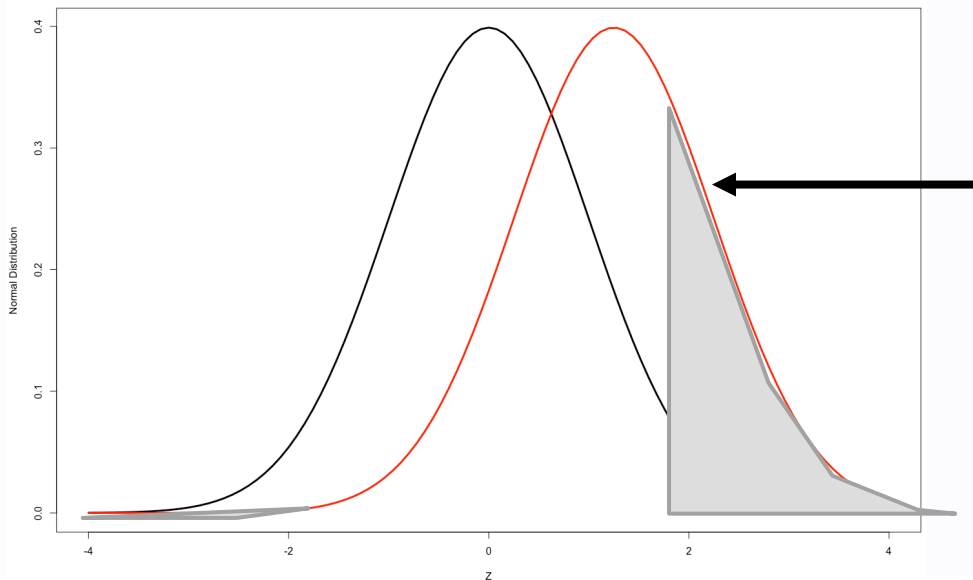
$$\frac{\mu_1 - \mu_2}{\sigma \sqrt{\frac{1}{r_1} + \frac{1}{r_2}}} = 1.25$$

# TWO-SAMPLE Z-STATISTIC POWER

- If  $\mu_1 - \mu_2 \neq 0$  then true distribution of  $Z$  is

$$Z \sim N\left(\frac{\mu_1 - \mu_2}{\sigma \sqrt{\frac{1}{r_1} + \frac{1}{r_2}}}, 1\right)$$

- The larger this mean is, the more likely we observe “extreme” values



$$P_{H_A}(|Z| > 1.96) = 0.2395 > 0.05$$

Assuming  $H_A$  is true

$$\begin{aligned} \sigma &= 1 & \mu_1 - \mu_2 &= 0.25 \\ r_1 &= 10 & r_2 &= 10 \end{aligned}$$

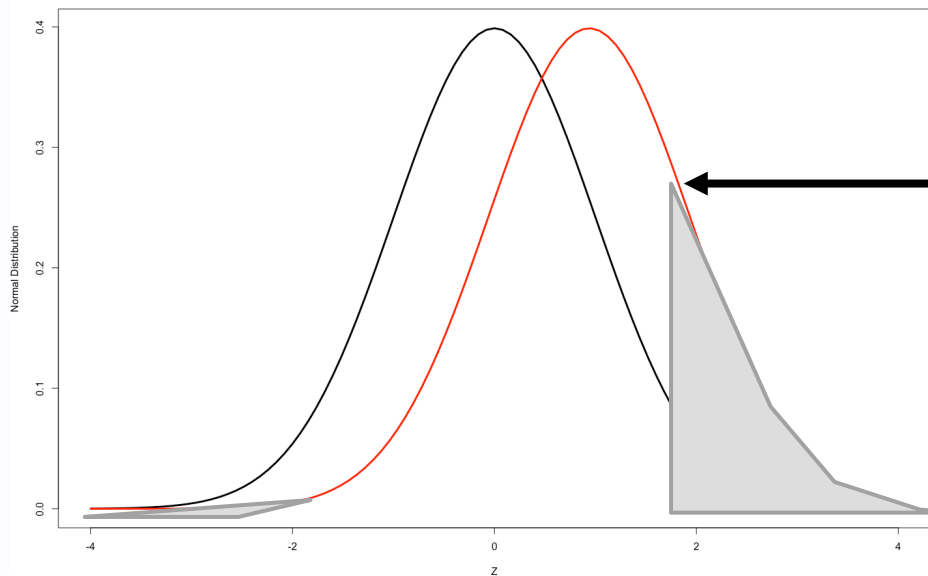
$$\frac{\mu_1 - \mu_2}{\sigma \sqrt{\frac{1}{r_1} + \frac{1}{r_2}}} = 1.25$$

# TWO-SAMPLE Z-STATISTIC POWER

- If  $\mu_1 - \mu_2 \neq 0$  then true distribution of  $Z$  is

$$Z \sim N\left(\frac{\mu_1 - \mu_2}{\sigma \sqrt{\frac{1}{r_1} + \frac{1}{r_2}}}, 1\right)$$

- The larger this mean is, the more likely we observe “extreme” values



$$P_{H_A}(|Z| > 1.96) = 0.1552 > 0.05$$

$$\sigma = 1 \quad \mu_1 - \mu_2 = 0.25$$
$$r_1 = 5 \quad r_2 = 15$$

$$\frac{\mu_1 - \mu_2}{\sigma \sqrt{\frac{1}{r_1} + \frac{1}{r_2}}} = 0.9375$$

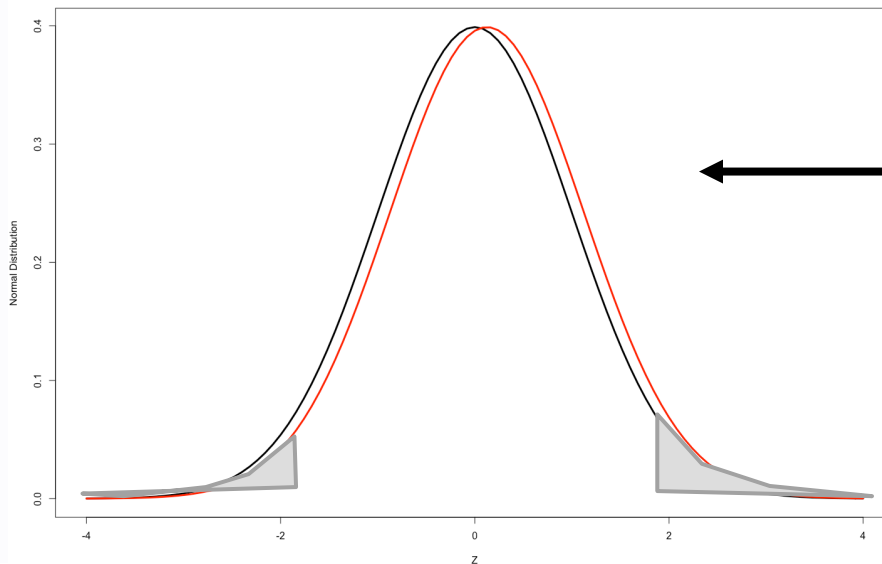


# TWO-SAMPLE Z-STATISTIC POWER

- If  $\mu_1 - \mu_2 \neq 0$  then true distribution of  $Z$  is

$$Z \sim N\left(\frac{\mu_1 - \mu_2}{\sigma \sqrt{\frac{1}{r_1} + \frac{1}{r_2}}}, 1\right)$$

- The larger this mean is, the more likely we observe “extreme” values



$$P_{H_A}(|Z| > 1.96) = 0.0518 > 0.05$$

$$\sigma = 10 \quad \mu_1 - \mu_2 = 0.25$$
$$r_1 = 10 \quad r_2 = 10$$

$$\frac{\mu_1 - \mu_2}{\sigma \sqrt{\frac{1}{r_1} + \frac{1}{r_2}}} = 0.125$$

# LESSONS FROM POWER

- **Achieving high power is a delicate balance between**
  - Alternative hypothesis (specific  $|\mu_1 - \mu_2| > 0$ )
  - Critical level for desired significance level
  - Sample sizes
  - $\sigma$
- Equal sample sizes maximize power when the two populations have equal variance
- Minimizing  $\sigma$  maximizes power (local error control)
- Power can only be calculated for guesses of the true parameters
- If the alternative is true, may have low power which is why we never accept the null, only fail to reject

# TWO-SAMPLE CONFIDENCE INTERVALS

- If we reject the null we should provide estimate of what the difference truly is
- Use a  $100(1 - \alpha)\%$  confidence interval centered at estimate

$$(\bar{Y}_{1\cdot} - \bar{Y}_{2\cdot}) \pm t_{n-2, \alpha/2} \hat{\sigma} \sqrt{\frac{1}{r_1} + \frac{1}{r_2}}$$

The diagram shows the formula for a two-sample confidence interval. Below the formula, three horizontal brackets are used to group parts of the expression. The first bracket is under  $(\bar{Y}_{1\cdot} - \bar{Y}_{2\cdot})$  and is labeled 'Estimator'. The second bracket is under  $\pm t_{n-2, \alpha/2}$  and is labeled 'Critical value from T-distribution with df'. The third bracket is under  $\hat{\sigma} \sqrt{\frac{1}{r_1} + \frac{1}{r_2}}$  and is labeled 'Standard error of estimate'. Arrows point from each label to its corresponding bracket.

- Like “inverting” hypothesis test

# LEARNING OBJECTIVES REVIEW

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