

Analysis of Variance

Recall: TWO independent sample t-test

Pop 1:  $N(\mu_1, \sigma^2) \Rightarrow$  Random Sample  $Y_1^1, \dots, Y_n^1 \stackrel{iid}{\sim} N(\mu_1, \sigma^2)$

Pop 2:  $N(\mu_2, \sigma^2) \Rightarrow$  Random Sample  $Y_1^2, \dots, Y_n^2 \stackrel{iid}{\sim} N(\mu_2, \sigma^2)$

Let  $\delta = \mu_2 - \mu_1$  and its estimate  $\hat{\delta} = \bar{Y}_2 - \bar{Y}_1$ .

Observe that  $\hat{\delta} \sim N(E(\hat{\delta}) = \mu_2 - \mu_1 = \delta, \text{Var}(\hat{\delta}) = \frac{\sigma^2}{n_2} + \frac{\sigma^2}{n_1} = \sigma^2(\frac{1}{n_1} + \frac{1}{n_2}))$

Thus,  

$$\frac{\hat{\delta} - \delta}{\sqrt{\sigma^2(\frac{1}{n_1} + \frac{1}{n_2})}} \sim N(0, 1)$$

*Unknown, so estimate*

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

*weights sum to 1.*

$$\therefore \frac{(n_1+n_2-2) S_p^2}{\sigma^2} = \frac{\sum_{i=1}^{n_1} (Y_i^1 - \bar{Y})^2}{\sigma^2} + \frac{\sum_{i=1}^{n_2} (Y_i^2 - \bar{Y})^2}{\sigma^2} \sim \chi^2_{(n_1+n_2-2)}$$

So,  

$$\frac{\hat{\delta} - \delta}{\sqrt{S_p^2(\frac{1}{n_1} + \frac{1}{n_2})}} \sim t_{(n_1+n_2-2)}$$

And under  $H_0$ ,

$$T = \frac{\hat{\delta}}{\sqrt{S_p^2(\frac{1}{n_1} + \frac{1}{n_2})}} \stackrel{H_0}{\sim} t_{(n_1+n_2-2)}$$

Decision Rule:

Reject  $H_0$   
if

$$|T| > t_{(0.975, n_1+n_2-2)}$$

## Linear Regression Framework

$$\left. \begin{array}{l} Y_i^1 = \mu_1 + \epsilon_i \quad \epsilon_i \stackrel{iid}{\sim} N(0, \sigma^2) \\ Y_j^2 = \mu_2 + \epsilon_j \quad \epsilon_j \stackrel{iid}{\sim} N(0, \sigma^2) \end{array} \right\} \text{Model Assumption}$$

$$Y = X \underline{\beta} + \underline{\epsilon}$$

$$\underline{\beta} = \begin{pmatrix} \mu_1 \\ \mu_2 \end{pmatrix}$$

$$\begin{bmatrix} Y_1^1 \\ \vdots \\ Y_{n_1}^1 \\ \dots \\ Y_{n_1+n_2}^2 \\ \vdots \\ Y_{n_1+n_2}^2 \end{bmatrix} = \begin{bmatrix} M_1 \\ \vdots \\ M_1 \\ \dots \\ M_2 \\ \vdots \\ M_2 \end{bmatrix} + \begin{bmatrix} \epsilon_1 \\ \vdots \\ \epsilon_{n_1} \\ \dots \\ \epsilon_{n_1+n_2} \\ \vdots \\ \epsilon_{n_1+n_2} \end{bmatrix} \quad \text{where } \underline{\epsilon} \sim N(0, I_n \otimes \sigma^2)$$

Note:

$$\begin{bmatrix} M_1 \\ \vdots \\ M_1 \\ M_2 \\ \vdots \\ M_2 \end{bmatrix} = \underbrace{\begin{bmatrix} 1 & 0 \\ \vdots & \vdots \\ 0 & 1 \end{bmatrix}}_{X} \underbrace{\begin{pmatrix} M_1 \\ M_2 \end{pmatrix}}_{\underline{\beta}}$$

$$Y = X \underline{\beta} + \underline{\epsilon}$$

And by construction of  $X$  ( $X$  is full column rank - actually orthogonal),  $(X^T X)^{-1}$  exists.

$$\therefore \hat{\underline{\beta}} = (X^T X)^{-1} X^T Y = \begin{bmatrix} \bar{Y}_1 \\ \bar{Y}_2 \end{bmatrix}$$

$$\delta = \mu_2 - \mu_1 = \underbrace{\begin{pmatrix} -1 & 1 \end{pmatrix}}_{C} \underline{\beta}$$

$$\hat{\delta} = \bar{Y}_2 - \bar{Y}_1 = \underbrace{C}_{\hat{\underline{\beta}}} \quad ,$$

$$\hat{\underline{\beta}} = \underbrace{(X^T X)^{-1} X^T Y}_{\text{constant}} \sim N(E \hat{\underline{\beta}} = (X^T X)^{-1} X^T EY = \underline{\beta}, \text{Var}(\hat{\underline{\beta}}) = [(X^T X)^{-1} X^T] \text{cov}(Y) [X^T (X^T X)^{-1}] = (X^T X)^{-1} \otimes \sigma^2)$$

utilized  $\text{Var}(aY) = a^2 \text{Var}(Y)$   
 $\text{Cov}(AY) = A \text{Cov}(Y) A^T$

$$\text{Thus, } \hat{\delta} = C \hat{\underline{\beta}} \sim N(E \hat{\delta} = C \underline{\beta} = \delta, \text{Var}(\hat{\delta}) = C \text{Var}(\hat{\underline{\beta}}) C^T = (-1 \ 1) (X^T X)^{-1} \otimes \sigma^2 \begin{pmatrix} 1 \\ -1 \end{pmatrix})$$

$$= \sigma^2 \left( \frac{1}{n_1} + \frac{1}{n_2} \right) \quad (X^T X)^{-1} = \begin{bmatrix} \frac{1}{n_1} & 0 \\ 0 & \frac{1}{n_2} \end{bmatrix}$$

$$\therefore \hat{\delta} \sim N(\delta, \sigma^2 (\frac{1}{n_1} + \frac{1}{n_2}))$$

So,

$$\hat{Y} = \begin{bmatrix} Y_1 \\ \vdots \\ Y_{n_1} \\ \vdots \\ Y_{n_1+n_2} \end{bmatrix} = X\hat{\beta} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}_{(n_1+n_2) \times 2} \begin{pmatrix} \bar{Y}_1 \\ \bar{Y}_2 \end{pmatrix} = \begin{bmatrix} \bar{Y}_1 \\ \vdots \\ \bar{Y}_1 \\ \bar{Y}_2 \\ \vdots \\ \bar{Y}_2 \end{bmatrix}$$

Our Model:  $\underline{Y} = X\beta + \epsilon$ , where  $X\beta = \begin{bmatrix} \mu_1 \\ \mu_1 \\ \mu_2 \\ \mu_2 \end{bmatrix}$

$$\hat{Y} = X\hat{\beta} = \begin{bmatrix} \bar{Y}_1 \\ \bar{Y}_1 \\ \bar{Y}_2 \\ \bar{Y}_2 \end{bmatrix}$$

$$R = \underline{Y} - \hat{Y} = \begin{bmatrix} Y_1 \\ Y_1 \\ Y_2 \\ \vdots \\ Y_2 \end{bmatrix} - \begin{bmatrix} \bar{Y}_1 \\ \bar{Y}_1 \\ \bar{Y}_2 \\ \vdots \\ \bar{Y}_2 \end{bmatrix} = \begin{bmatrix} Y_1 - \bar{Y}_1 \\ \vdots \\ Y_1 - \bar{Y}_1 \\ Y_2 - \bar{Y}_2 \\ \vdots \\ Y_2 - \bar{Y}_2 \end{bmatrix}$$

Note:

$$\epsilon = \underline{Y} - X\hat{\beta}$$

$$E \|\epsilon\|_2 = E \sum_{k=1}^{n_1+n_2} \epsilon_k^2 = (n_1+n_2)\sigma^2$$

$$\text{so, } E \left\{ \frac{\|\epsilon\|_2}{n_1+n_2} \right\} = \sigma^2$$

The data analog is:

$$\hat{\sigma}^2 = \frac{\|R\|_2}{n_1+n_2-2} = \frac{\sum_{i=1}^{n_1} (Y_i - \bar{Y}_1)^2 + \sum_{j=1}^{n_2} (Y_j - \bar{Y}_2)^2}{n_1+n_2-2}$$

$$\uparrow = \frac{(n_1-1)S_1^2 + (n_2-1)S_2^2}{n_1+n_2-2}, \text{ where } (n_1-1)S_1^2 = \sum_{i=1}^{n_1} (Y_i - \bar{Y}_1)^2$$

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$$(n_2-1)S_2^2 = \sum_{j=1}^{n_2} (Y_j - \bar{Y}_2)^2$$

## ANOVA

An approach for comparing nested models

General Model

FULL  $\mathcal{M}_1 : \beta = \begin{pmatrix} \mu_1 \\ \mu_2 \end{pmatrix} \in \mathbb{R}^2 = p1$

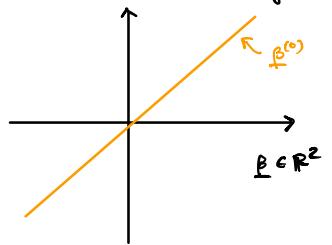
$$\underline{Y} = X\beta + \epsilon$$

$$X = \begin{bmatrix} 1 & 0 \\ \vdots & \vdots \\ 0 & 1 \end{bmatrix}, \epsilon = \begin{bmatrix} \epsilon_1 \\ \vdots \\ \epsilon_{n_1+n_2} \end{bmatrix}$$

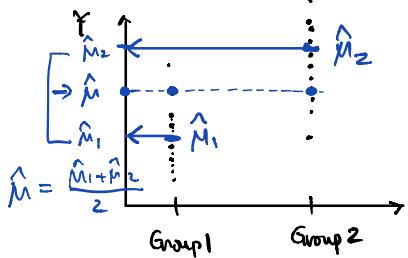
Note:

$$H_0 : \beta = 0 \Leftrightarrow \mu_1 = \mu_2 := \mu$$

Reduced Model  $M_0$   $\hat{\beta}^{(0)} = \begin{pmatrix} M \\ M \end{pmatrix} = p^0 \in P^1$  where we have the following subspace



Suppose:



We Consider Two Models:  
 $M_1 : \hat{\mu}_1, \hat{\mu}_2 \}$   
 $M_0 : \hat{\mu}$

In this case,  $M_1$  seems to have a smaller overall variance than model  $M_0$ .

Under  $M_1$  :  $\hat{\beta} = \begin{pmatrix} \bar{Y}_1 \\ \bar{Y}_2 \end{pmatrix}$

$$\bar{Y} = X\hat{\beta} = \begin{pmatrix} \bar{Y}_1 \\ \bar{Y}_2 \\ \vdots \\ \bar{Y}_n \end{pmatrix}$$

$$SSE = \| Y - \bar{Y} \|_2$$

$$= \sum_{i=1}^{n_1} (Y_i - \bar{Y}_1)^2 + \sum_{j=1}^{n_2} (Y_j - \bar{Y}_2)^2$$

Under  $M_0$  :  $Y = X\hat{\beta}^{(0)} + \epsilon$

$$= \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} \begin{pmatrix} M \\ M \end{pmatrix} + \epsilon$$

$$= \begin{pmatrix} 1 & M \\ 1 & M \end{pmatrix} + \epsilon$$

$$= \underbrace{\mathbf{1}}_{X^0} \underbrace{M}_{\beta^0} + \epsilon$$

Note:  $\hat{\beta}^0 = (X^0 X^0)^{-1} X^0 Y = \frac{1}{n_1+n_2} \sum_{i=1}^{n_1+n_2} Y_i = \bar{Y}$

$$= \frac{1}{n_1+n_2} \left[ \sum_{i=1}^{n_1} Y_i + \sum_{i=n_1+1}^{n_1+n_2} Y_i \right]$$

$$= \frac{n_1}{n_1+n_2} \bar{Y}_1 + \frac{n_2}{n_1+n_2} \bar{Y}_2$$

$$\therefore \hat{Y}^o = X^o \hat{\beta}^o = \begin{pmatrix} \bar{Y} \\ \vdots \\ \bar{Y} \end{pmatrix}$$

$$\begin{aligned} SSE^o &= \| Y - \hat{Y}^o \|_2 \\ &= \sum_{i=1}^{n_1} (Y_i^1 - \bar{Y})^2 + \sum_{j=1}^{n_2} (Y_j^2 - \bar{Y})^2 \end{aligned}$$

Summary:

$$\begin{array}{lll} M_1 & Y = X \beta + \epsilon & \\ (\text{Full}) & \beta = \begin{pmatrix} M_1 \\ M_2 \end{pmatrix} & SSE^1 = \sum_{i=1}^{n_1} (Y_i^1 - \bar{Y}_1)^2 + \sum_{j=1}^{n_2} (Y_j^2 - \bar{Y}_2)^2 \\ & & df = n_1 + n_2 - 2 \end{array}$$

$$\begin{array}{lll} M_0 & Y = X^o \beta^o + \epsilon & \\ (\text{Reduced}) & X^o = 1, \beta^o = \mu & SSE^0 = \sum_{i=1}^{n_1} (Y_i^1 - \bar{Y})^2 + \sum_{j=1}^{n_2} (Y_j^2 - \bar{Y})^2 \\ & & df = n_1 + n_2 - 1 \end{array}$$

\*  $SSE^o \geq SSE^1$  (Reduced Model will be at least as large as the Full Model)

Compare  $M_1$  and  $M_0$  via  $SSE(1)$  and  $SSE(0)$  by examining:

$$F = \frac{\frac{SSE(0) - SSE(1)}{df_0 - df_1}}{\frac{SSE(1)}{df_1}} \stackrel{H_0}{\sim} F \quad (df = \text{numerator}, df = \text{denominator})$$

$F$  is the test statistic

Decision: Reject  $H_0$  if  $F$  is large.  
Choose Full Model

