

Definition:

Let A be a square matrix. A generalised inverse (G -inv) of A is any matrix A^{\dagger} such that:

$$A A^{\dagger} A = A$$

Properties: Let $G = A^{\dagger} = (X^T X)^{-1}$

(P1) G is also squared

(P2) G^T is also a G -inv of $A = X^T X$

(P3) Let $H_X := X G X^T$ projection matrix (hat matrix). projection onto column space of X .

$$\Rightarrow H_X \bar{X} = \bar{X}$$

(P4) $H_X = X G X^T$ is invariant to the choice of G

(P5) $H_X = X G X^T$ is symmetric

now!

(P6) $\text{rank}(H_X) = \text{rank}(X G X^T) = \text{rank}(X)$

$$\text{Now } \underline{y} - \underline{x}\tilde{\beta} = \underline{y} - \underline{x}(x^T x)^{-1} x^T \underline{y} = \underline{y} - \underline{x} G \underline{x}^T \underline{y} = \underline{y} - H_x \underline{y} = (I - H_x) \underline{y}$$

$$\Rightarrow \text{SSE} = (\underline{y} - \underline{x}\tilde{\beta})^T (\underline{y} - \underline{x}\tilde{\beta}) = \underline{y}^T (I - H_x)^T (I - H_x) \underline{y}$$

But $(I - H_x)^T = I - H_x^T = I - H_x$ since H_x is symmetric by (PS)

$$\text{Also } H_x H_x = \boxed{H_x \underline{x}} \underline{x}^T = \underline{x} \underline{x}^T = H_x , \quad H_x \text{ is idempotent}$$

$$\Rightarrow (I - H_x)(I - H_x) = I - H_x - H_x + H_x H_x = I - H_x - H_x + H_x = I - H_x \Rightarrow I - H_x \text{ is also idempotent}$$

$$\Rightarrow \boxed{\text{SSE} = \underline{y}^T (I - H_x)(I - H_x) \underline{y} = \underline{y}^T (I - H_x) \underline{y}}$$

and is invariant
to the choice $g = G$

invariant to
choice of G

ANOVA

$$\beta = \begin{pmatrix} \beta_0 \\ \vdots \\ \beta_k \end{pmatrix} \quad X = \begin{pmatrix} \cdot & \cdots & \cdot \end{pmatrix}$$

CRD

Effects Model

$$y_{ij} = \mu + \gamma_i + \epsilon_{ij}$$

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

$$SSE = (\underline{y} - X\tilde{\beta})^T (\underline{y} - X\tilde{\beta})$$

measures quality of fit

$\tilde{\beta}$ solution to normal eq's

Reduced model

$$Test H_0: \gamma_1 = \gamma_2 = \dots = \gamma_t \Rightarrow \underline{y}_{ij} = \mu + \epsilon_{ij}$$

$$\underline{y} = X_0\beta + \underline{\epsilon} \quad \text{where } X_0 = \begin{pmatrix} 1 & & \\ & \ddots & \\ & & 1 \end{pmatrix} \quad \beta = \mu$$

$$= \begin{pmatrix} 1 \\ \vdots \\ 1 \end{pmatrix} \mu + \underline{\epsilon}$$

$$\Rightarrow SSE_0 = (\underline{y} - X_0\hat{\mu})^T (\underline{y} - X_0\hat{\mu}) = (\underline{y} - \underline{1}\hat{\mu})^T (\underline{y} - \underline{1}\hat{\mu}) = \sum_i \sum_j (y_{ij} - \hat{\mu})^2$$

Called
 SST_{Total}

$$= (\underline{y} - \bar{y}\mathbf{1})^T (\underline{y} - \bar{y}\mathbf{1}) = (\underline{y} - \frac{1}{n}\mathbf{1}\mathbf{1}^T \underline{y})^T (\underline{y} - \frac{1}{n}\mathbf{1}\mathbf{1}^T \underline{y})$$

$$= \underline{y}^T (\mathbf{I} - \frac{1}{n}\mathbf{1}\mathbf{1}^T)(\mathbf{I} - \frac{1}{n}\mathbf{1}\mathbf{1}^T)\underline{y}$$

dump

$$Take A = \mathbf{I} - \frac{1}{n}\mathbf{1}\mathbf{1}^T \Rightarrow A^T = \mathbf{I} - \frac{1}{n}\mathbf{1}\mathbf{1}^T \quad \text{symmetric} \quad = \underline{y}^T A \underline{y} = \underline{y}^T A \underline{y}$$

$$\Rightarrow AA = (\mathbf{I} - \frac{1}{n}\mathbf{1}\mathbf{1}^T)(\mathbf{I} - \frac{1}{n}\mathbf{1}\mathbf{1}^T) = \mathbf{I} - \frac{1}{n}\mathbf{1}\mathbf{1}^T - \frac{1}{n}\mathbf{1}\mathbf{1}^T + \frac{1}{n^2}\mathbf{1}\mathbf{1}^T\mathbf{1}\mathbf{1}^T = \mathbf{I} - \frac{2}{n}\mathbf{1}\mathbf{1}^T + \frac{1}{n^2}\mathbf{1}\mathbf{1}^T$$

1 dominant *n* $= \mathbf{I} - \frac{1}{n}\mathbf{1}\mathbf{1}^T = A$

Result ① If A is idempotent then $\text{rank}(A) = \text{trace}(A) = \text{sum diagonal}$

② $H_x X = X \Rightarrow H_x \mathbf{1} = \mathbf{1}$ (since $\mathbf{1}$ is a column of X !) elements.

$$\text{rank}\left(I - \frac{1}{n} \mathbf{1} \mathbf{1}^T\right) = \text{trace}\left(I - \frac{1}{n} \mathbf{1} \mathbf{1}^T\right) = \text{trace}(I) - \frac{1}{n} \text{trace}(\mathbf{1} \mathbf{1}^T) = n - \frac{1}{n} n = n-1$$

use $H_{\perp} = \frac{1}{n} \mathbf{1} \mathbf{1}^T$

$$\begin{pmatrix} 1 & 1 & \dots & 1 \\ 1 & 1 & \dots & 1 \\ \vdots & \vdots & \ddots & \vdots \\ 1 & 1 & \dots & 1 \end{pmatrix}$$

Always $SSE_0 > SSE$ (F.t is always worse
if less parameters)

$$\Rightarrow SSE_0 - SSE > 0$$

$$-\mathbf{y}^T (I - X_0 X^T) \mathbf{y} + \mathbf{y}^T (I - \frac{1}{n} \mathbf{1} \mathbf{1}^T) \mathbf{y} = \mathbf{y}^T \underbrace{\left(X_0 X^T - \frac{1}{n} \mathbf{1} \mathbf{1}^T \right)}_{H_x - H_{\perp}} \mathbf{y}$$

$$B = \left(X_0 X^T - \frac{1}{n} \mathbf{1} \mathbf{1}^T \right) \left(X_0 X^T - \frac{1}{n} \mathbf{1} \mathbf{1}^T \right)$$

$$= X_0 X^T - \frac{1}{n} \underbrace{X_0 X^T \mathbf{1} \mathbf{1}^T}_{\text{② projection}} - \frac{1}{n} \mathbf{1} \mathbf{1}^T X_0 X^T + \frac{1}{n} \mathbf{1} \mathbf{1}^T$$

$$= X_0 X^T - \frac{1}{n} \mathbf{1} \mathbf{1}^T - \cancel{\frac{1}{n} \mathbf{1} \mathbf{1}^T} + \cancel{\frac{1}{n} \mathbf{1} \mathbf{1}^T} = B \text{ idempotent}$$

$$\begin{aligned} \text{rank}(B) &= \\ \text{trace}(B) &= \text{trace}(H_x) \\ -\frac{1}{n} \text{trace}(\mathbf{1} \mathbf{1}^T) &= \textcircled{P6} \\ \text{trace}(X^T G) - 1 &= \text{rank}(B) - 1 \end{aligned}$$

Theorem

$$\underline{y} \sim N(\underline{\mu}, \sigma^2 I)$$

Defining Central
non-central $\begin{matrix} x \\ x' \end{matrix}$

Warning

$\frac{1}{2}$ (a R is just)

Then

$$\frac{\underline{y}^T A \underline{y}}{\sigma^2} \sim \chi^2_{(n-t), \lambda}, \lambda = \frac{1}{\sigma^2} \underline{\mu}^T A \underline{\mu}$$

\Leftarrow non-central

$$\Rightarrow SST_{Total} = \frac{\underline{y}^T (I - \frac{1}{n} \underline{1} \underline{1}^T) \underline{y}}{\sigma^2} \sim \chi^2_{(n-t), 0}$$

$$\text{rank } K(I - \frac{1}{n} \underline{1} \underline{1}^T) = n-1$$

$$\text{where } \underline{\mu} = \mu \underline{1} \Rightarrow \lambda = \frac{1}{\sigma^2} \mu^2 \underline{1}^T (I - \frac{1}{n} \underline{1} \underline{1}^T) \underline{1}$$

$$\lambda = \frac{1}{\sigma^2} \mu^2 (1^T \underline{1} - \frac{1}{n} n^2) \\ \underline{n} - n = 0$$

$$\Rightarrow SSE = \frac{\underline{y}^T (I - X \beta X^T) \underline{y}}{\sigma^2} \sim \chi^2_{(n-t), 0}$$

$$\text{rank } K(I - X \beta X^T) = \text{rank } K(I) - \text{rank } K(X \beta X^T) \\ = n-t$$

$$\text{where } \underline{\mu} = X \beta$$

$$\lambda = \frac{1}{\sigma^2} \beta^T \underline{X}^T (I - X \beta X^T) \underline{X} \beta$$

$$= \frac{1}{\sigma^2} \beta^T (\underline{X}^T \underline{X} - \underline{X}^T X \underline{X}^T) \beta$$

$$= \frac{1}{\sigma^2} \beta^T \underbrace{(\underline{X}^T \underline{X} - \underline{X}^T \underline{X})}_{0} \beta = 0$$

$$SST = \frac{y^T (x_0 x^T - \frac{1}{n} \mathbb{1} \mathbb{1}^T) y}{\sigma^2} \sim \chi^2_{(t-1, \lambda)}$$

$$\text{rank } k(x_0 x^T - \frac{1}{n} \mathbb{1} \mathbb{1}^T) = t-1$$

hence

$$\underline{\mu} = x \beta$$

note $\lambda = 0$ if true
 $\underline{\mu} = \underline{\mu} \mathbb{1}$

$$\begin{aligned} SStotal &= SSE \\ SSE &= \end{aligned}$$

$$\lambda = \frac{1}{2\sigma^2} \beta^T \mathbb{X}^T (x_0 x^T - \frac{1}{n} \mathbb{1} \mathbb{1}^T) \mathbb{X} \beta$$

$$= \beta^T (x_0 x^T x - \frac{1}{n} \mathbb{X}^T \mathbb{1} \mathbb{1}^T x) \beta$$

$$= \beta^T (\mathbb{X}^T \mathbb{X} - \frac{1}{n} \mathbb{X}^T \mathbb{1} \mathbb{1}^T x) \beta$$

otherwise is weighted avg

$$= \beta^T \mathbb{X}^T (\mathbb{I} - \frac{1}{n} \mathbb{1} \mathbb{1}^T) x \beta$$

$$\text{note (if balanced)} \quad \bar{\mu} = \frac{v_1 \mu_1 + v_2 \mu_2 + \dots + v_n \mu_n}{v_1 + v_2 + \dots + v_n} = \frac{\mu_1 + \mu_2 + \dots + \mu_n}{t}$$

$$= \beta^T (\mathbb{I} - \frac{1}{n} \mathbb{1} \mathbb{1}^T) \beta = \beta^T \beta - n \bar{\mu}^2$$

$$\underline{\mu} = \begin{pmatrix} \mu_1 \\ \mu_2 \\ \vdots \\ \mu_t \end{pmatrix} \begin{matrix} \\ \vdots \\ \\ \end{matrix} \begin{matrix} v_1 \\ v_2 \\ \vdots \\ v_t \end{matrix} \begin{matrix} \\ \vdots \\ \\ \end{matrix} \begin{matrix} r_1 \\ r_2 \\ \vdots \\ r_t \end{matrix}$$

$$\Rightarrow \lambda = \frac{1}{\sigma^2} \sum_{i=1}^t v_i (\mu_i - \bar{\mu})^2 = \frac{v}{\sigma^2} \sum_{i=1}^t (\mu_i - \bar{\mu})^2$$

balanced

$$\sum \mu_i^2 - n \bar{\mu}^2$$

$$\frac{\sum (\mu_i - \bar{\mu})^2}{\sigma^2}$$

ANOVA table

Source	df	Sum of Squares	Mean Squares	F
Treatment	t-1	SST	$MS_T = \frac{SST}{t-1}$	$F = \frac{MS_T}{MS_E} = \frac{SST/t-1}{SSE/u-t}$
Error	u-t	SSE	$MS_E = \frac{SSE}{u-t}$	
Total	u-1	SSTotal		

Under $H_0: \mu_1 = \mu_2 = \dots = \mu_t$

$$SST \sim \chi^2_{(t-1, 0)} \xrightarrow{\text{indep}} F = \frac{SST/t-1}{SSE/u-t} \sim F_{(t-1, u-t)}$$

central F

$$SSE \sim \chi^2_{(u-t, 0)}$$

(balanced design)

In general

$$SST \sim \chi^2_{(t-1, \lambda)} \xrightarrow{\text{indep}} F = \frac{SST/(t-1)}{SSE/u-t} \sim F_{(t-1, u-t, \lambda)}$$

non central F

$$SSE \sim \chi^2_{(u-t, 0)}$$

non centrality parameter

$$\lambda = \frac{u}{\sum_{i=1}^t} (m_i - \bar{m})^2$$

$$\text{ANOVA} \quad \text{Factorial design} \quad Y_{ijk} = \mu + \gamma_i + \alpha_j + \delta_{ij} + \epsilon_{ijk}$$

$$= (1 \bar{x}_1, \bar{x}_2, \bar{x}_{\text{int}})$$

$$SSE = \underline{y^T(I-H_x)y} \quad \text{stays the same! Just different } \bar{x} \text{ and } \Rightarrow \text{different } H_x$$

Test null hypothesis $H_0: \delta_{ij} = 0 \quad \forall i, j$ (no interactions)

$$\Rightarrow \bar{X}_0 = (1 \bar{x}_1, \bar{x}_2) \Rightarrow SSE_0 = \underline{y^T(I-H_{\bar{X}_0})y} \quad \text{since clearly } H_{\bar{X}_0} \text{ is also}\text{ (dominant) } \Rightarrow I - H_{\bar{X}_0} \text{ is dominant too!}$$

$$\text{Also } SSE_0 - SSE > 0$$

$$\Rightarrow SSE_0 - SSE = \underline{y^T(H_x - H_{\bar{X}_0})y} \quad \text{rank}(H_x - H_{\bar{X}_0}) = \text{trace}(H_x - H_{\bar{X}_0})$$

"sum of squares
due to the
interactions"

$$= \text{trace}(H_x) - \text{trace}(H_{\bar{X}_0}) = \text{rank}(x) - \text{rank}(\bar{X}_0)$$

$$= (t-1) + (s-1) + (t-1)(s-1) - (1 + (t-1) + (s-1))$$

$$SS_{\text{Int}}$$

$$= (t-1)(s-1)$$

Theorem

$$\Rightarrow \frac{\underline{q}^T (Hx - Hx_0) \underline{q}}{s^2} \sim \chi^2_{(t-1)(s-1), \lambda} \quad \text{where } \lambda = \sum_{j=1}^s \underline{\beta}_j^T (Hx - Hx_0) \underline{\beta}_j$$

under $H_0 : \underline{\beta}_{ij} = 0$

$$\Rightarrow \underline{\beta} = \underline{X}_0 \underline{\beta}_0$$

$$\Rightarrow \lambda = \sum_{j=1}^s \underline{\beta}_j^T \underline{X}_0^T (Hx - Hx_0) \underline{X}_0 \underline{\beta}_j$$

$$= \sum_{j=1}^s \underline{\beta}_j^T \underline{X}_0^T \left(\underbrace{H_x \underline{X}_0}_{\underline{X}_0} - \underbrace{H_{\underline{X}_0} \underline{X}_0}_{\underline{X}_0} \right) \underline{\beta}_j$$

$$\Rightarrow \lambda = 0$$

otherwise

$$\begin{aligned} \lambda &= \sum_{j=1}^s \underline{\beta}^T \underline{X}^T (Hx - Hx_0) \underline{\beta} \\ &= \sum_{j=1}^s \underline{\beta}^T \underline{X}^T (\underline{X} - H_{\underline{X}_0} \underline{X}) \underline{\beta} \\ &= \sum_{j=1}^s \underline{\beta}^T \underline{X}^T (I - H_{\underline{X}_0}) \underline{X} \underline{\beta} \end{aligned}$$

ANOVA Table for factorial $H_0: \delta_{ij} = 0$ $\forall i, j$

Balanced design

Source	df	Sum of Squares	Mean Squares	F
Interaction	$(t-1)(s-1)$	SS_{Int}	$SS_{\text{Int}} / (t-1)(s-1)$	$SS_{\text{Int}} / (t-1)(s-1)$
Error	$st(v-1)$	SS_E	$SSE / st(v-1)$	$SSE / st(v-1)$

under H_0

$$F \sim F_{(s-1)(t-1), st(v-1), 0}$$

in general

$$F \sim F'_{(s-1)(t-1), st(v-1), \lambda}$$

↳ previous page

$$\begin{aligned} s - t &= str - \left(1 + \frac{1}{t-1} + \frac{1}{s-1} + \frac{1}{(t-1)(s-1)} \right) \\ &\cancel{+} \cancel{s-1} + \cancel{t-1} - \cancel{s} + \cancel{t} \\ &= str - st = st(v-1) \end{aligned}$$