

6. ANalysis Of VAriance (ANOVA)

Setup and Notation

corresponds to intercept only
model (averaging all y -values)

GHMNE

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\epsilon}, \boldsymbol{\epsilon} \sim \mathcal{N}(\mathbf{0}, \sigma^2 \mathbf{I})$$

Sequence of
model
matrices

Let $\mathbf{X}_1 = \mathbf{1}$, $\mathbf{X}_m = \mathbf{X}$, and $\mathbf{X}_{m+1} = \mathbf{I}$.

$n \times n$

Suppose $\mathbf{X}_2, \dots, \mathbf{X}_m$ are matrices satisfying

$$\mathcal{C}(\mathbf{X}_1) \subset \mathcal{C}(\mathbf{X}_2) \subset \dots \subset \mathcal{C}(\mathbf{X}_{m-1}) \subset \mathcal{C}(\mathbf{X}_m).$$

Let $\mathbf{P}_j = \mathbf{P}_{\mathbf{X}_j}$ and $r_j = \text{rank}(\mathbf{X}_j) \forall j = 1, \dots, m+1$.

The Total Sum of Squares

The *total sum of squares* (also known as the *corrected total sum of squares*) is

$$\begin{aligned} \sum_{i=1}^n (y_i - \bar{y}_.)^2 &= \begin{bmatrix} \frac{y_1 - \bar{y}_.}{\vdots} \\ \frac{y_n - \bar{y}_.}{\vdots} \end{bmatrix}^\top \begin{bmatrix} y_1 - \bar{y}_. \\ \vdots \\ y_n - \bar{y}_. \end{bmatrix} = [\mathbf{y} - \boxed{\bar{y}_. \mathbf{1}}]^\top [\mathbf{y} - \bar{y}_. \mathbf{1}] \\ &= [\mathbf{y} - \mathbf{P}_1 \mathbf{y}]^\top [\mathbf{y} - \mathbf{P}_1 \mathbf{y}] = [\mathbf{I} \mathbf{y} - \mathbf{P}_1 \mathbf{y}]^\top [\mathbf{I} \mathbf{y} - \mathbf{P}_1 \mathbf{y}] \\ &= [(\mathbf{I} - \mathbf{P}_1) \mathbf{y}]^\top [(\mathbf{I} - \mathbf{P}_1) \mathbf{y}] \\ &= \mathbf{y}^\top (\mathbf{I} - \mathbf{P}_1)^\top (\mathbf{I} - \mathbf{P}_1) \mathbf{y} \\ &= \mathbf{y}^\top \underbrace{(\mathbf{I} - \mathbf{P}_1)}_{\text{Symmetric}} (\mathbf{I} - \mathbf{P}_1) \mathbf{y} \quad (\mathbf{I} - \mathbf{P}_1) \text{ is also idem. pote.} \\ &= \mathbf{y}^\top (\mathbf{I} - \mathbf{P}_1) \mathbf{y}. \end{aligned}$$

Partitioning the Total Sum of Squares

Slide 1: $X_{m+1} = \underline{\underline{I}}$

$$P_{m+1} = \underline{\underline{I}}$$

$$\sum_{i=1}^n (y_i - \bar{y}_.)^2 = \underline{\underline{y}^\top (I - P_1)y} = \underline{\underline{y}^\top (P_{m+1} - P_1)y}$$

$$\begin{aligned} &= \underline{\underline{y}^\top \left(\sum_{j=2}^{m+1} P_j - \sum_{j=1}^m P_j \right) y} \\ &= \underline{\underline{y}^\top (P_{m+1} - P_m + P_m - P_{m-1} + \dots + P_2 - P_1)y} \end{aligned}$$

*partition into
disjoint sums
of squares*

$$= \underline{\underline{y}^\top (P_{m+1} - P_m)y} + \dots + \underline{\underline{y}^\top (P_2 - P_1)y}$$

$$= \sum_{j=1}^m \underline{\underline{y}^\top (P_{j+1} - P_j)y}.$$

The sums of squares in the equation

$$\mathbf{y}^\top (\mathbf{I} - \mathbf{P}_1) \mathbf{y} = \sum_{j=1}^m \mathbf{y}^\top (\mathbf{P}_{j+1} - \mathbf{P}_j) \mathbf{y}$$

are often arranged in an ANOVA table.

Some Additional Sum of Squares Notation

reduction in the overall/total sums of squares
when using X_2 as a model matrix instead of X_1

Sum of Squares	Sum of Squares	intercept - only model
$y^\top (P_2 - P_1)y$	$SS(2 1)$	intercept only model
$y^\top (P_3 - P_2)y$	$SS(3 2)$	
\vdots	\vdots	
$y^\top (P_m - P_{m-1})y$	$SS(m m - 1)$	
$y^\top (P_{m+1} - P_m)y$	$SSE = y^\top (I - P_X)y$	

amount of variability
that remains unexplained

Note that

$$\begin{aligned}\underline{SS(j+1 \mid j)} &= \underline{\mathbf{y}^\top (\mathbf{P}_{j+1} - \mathbf{P}_j) \mathbf{y}} \\ &= \mathbf{y}^\top (\mathbf{P}_{j+1} - \mathbf{P}_j \boxed{+ \mathbf{I} - \mathbf{I}}) \mathbf{y} \\ &= \mathbf{y}^\top (\mathbf{I} - \mathbf{P}_j - \mathbf{I} + \mathbf{P}_{j+1}) \mathbf{y} \\ &= \mathbf{y}^\top (\mathbf{I} - \mathbf{P}_j) \mathbf{y} - \mathbf{y}^\top (\mathbf{I} - \mathbf{P}_{j+1}) \mathbf{y} \\ &= SSE_j - \underline{SSE_{j+1}} \text{ reduction in} \\ &\text{sums of squares moving from} \\ &\text{model matrix } X_j \text{ to } X_{j+1}\end{aligned}$$

Thus, $SS(j+1 | j)$ is the amount the error sum of square decreases when y is projected onto $\mathcal{C}(X_{j+1})$ instead of $\mathcal{C}(X_j)$.

$SS(j+1 | j)$, $j = 1, \dots, m-1$ are called Sequential Sums of Squares.

SAS calls these *Type I Sums of Squares*.

Type II, Type III, Type IV

Properties of the Matrices of the Quadratic Forms

The matrices of the quadratic forms in the ANOVA table have several useful properties:

- Symmetry ✓
- Idempotency ✓
- $\text{rank}(P_{j+1} - P_j) = r_{j+1} - r_j$ ✓
- Zero Cross-Products ✓

Symmetry and Idempotency

Note that $\forall j = 1, \dots, m$

$$(\mathbf{P}_{j+1} - \mathbf{P}_j)^\top = \mathbf{P}_{j+1}^\top - \mathbf{P}_j^\top = \mathbf{P}_{j+1} - \mathbf{P}_j$$

and

$$\begin{aligned} (\mathbf{P}_{j+1} - \mathbf{P}_j)(\mathbf{P}_{j+1} - \mathbf{P}_j) &= \mathbf{P}_{j+1}\mathbf{P}_{j+1} - \mathbf{P}_{j+1}\mathbf{P}_j - \mathbf{P}_j\mathbf{P}_{j+1} \\ &\quad + \mathbf{P}_j\mathbf{P}_j \\ &= \mathbf{P}_{j+1} - \mathbf{P}_j - \mathbf{P}_j + \mathbf{P}_j \\ &= \mathbf{P}_{j+1} - \mathbf{P}_j. \end{aligned}$$

By idempotency and symmetry,

$$\begin{aligned}\mathbf{y}^\top (\mathbf{P}_{j+1} - \mathbf{P}_j) \mathbf{y} &= \mathbf{y}^\top (\mathbf{P}_{j+1} - \mathbf{P}_j) (\mathbf{P}_{j+1} - \mathbf{P}_j) \mathbf{y} \\ &= \mathbf{y}^\top (\mathbf{P}_{j+1} - \mathbf{P}_j)^\top (\mathbf{P}_{j+1} - \mathbf{P}_j) \mathbf{y} \\ &= [(\mathbf{P}_{j+1} - \mathbf{P}_j) \mathbf{y}]^\top [(\mathbf{P}_{j+1} - \mathbf{P}_j) \mathbf{y}] \\ &= \|(\mathbf{P}_{j+1} - \mathbf{P}_j) \mathbf{y}\|^2 \\ &= \|\mathbf{P}_{j+1} \mathbf{y} - \mathbf{P}_j \mathbf{y}\|^2 \\ &\equiv \|\hat{\mathbf{y}}^{(j+1)} - \hat{\mathbf{y}}^{(j)}\|^2 \\ &= \sum_{i=1}^n \left(\hat{y}_i^{(j+1)} - \hat{y}_i^{(j)} \right)^2,\end{aligned}$$

which is why we call $\mathbf{y}^\top (\mathbf{P}_{j+1} - \mathbf{P}_j) \mathbf{y}$ a “sum of squares.”

$$\text{rank}(P_{j+1} - P_j) = r_{j+1} - r_j$$

Because rank is equal to trace for idempotent matrices, we have

$$\begin{aligned}\text{rank}(\mathbf{P}_{j+1} - \mathbf{P}_j) &= \text{tr}(\mathbf{P}_{j+1} - \mathbf{P}_j) = \text{tr}(\mathbf{P}_{j+1}) - \text{tr}(\mathbf{P}_j) \\ &= \text{rank}(\mathbf{P}_{j+1}) - \text{rank}(\mathbf{P}_j) \\ &= \text{rank}(\mathbf{X}_{j+1}) - \text{rank}(\mathbf{X}_j) \\ &= r_{j+1} - r_j.\end{aligned}$$

Zero Cross-Products

$\forall j < \ell$

$$\begin{aligned} (\mathbf{P}_{j+1} - \mathbf{P}_j)(\mathbf{P}_{\ell+1} - \mathbf{P}_\ell) &= \mathbf{P}_{j+1}\mathbf{P}_{\ell+1} - \mathbf{P}_{j+1}\mathbf{P}_\ell - \mathbf{P}_j\mathbf{P}_{\ell+1} \\ &\quad + \mathbf{P}_j\mathbf{P}_\ell \\ &= \mathbf{P}_{j+1} - \mathbf{P}_{j+1} - \mathbf{P}_j + \mathbf{P}_j \\ &= \mathbf{0}. \end{aligned}$$

Transposing both sides and using symmetry gives

$$(\mathbf{P}_{\ell+1} - \mathbf{P}_\ell)(\mathbf{P}_{j+1} - \mathbf{P}_j) = \mathbf{0}.$$

Distribution of Scaled ANOVA Sums of Squares

$A\Sigma$ is idempotent $\Rightarrow y^\top A y \sim \chi^2$

Because

$$\left(\frac{\mathbf{P}_{j+1} - \mathbf{P}_j}{\sigma^2} \right) \left(\sigma^2 \mathbf{I} \right) = \mathbf{P}_{j+1} - \mathbf{P}_j$$

$= A$ $= \Sigma$ *ACP*

is idempotent,

$$\frac{\mathbf{y}^\top (\mathbf{P}_{j+1} - \mathbf{P}_j) \mathbf{y}}{\sigma^2} \sim \chi^2_{r_{j+1} - r_j} \left(\frac{\boldsymbol{\beta}^\top \mathbf{X}^\top (\mathbf{P}_{j+1} - \mathbf{P}_j) \mathbf{X} \boldsymbol{\beta}}{2\sigma^2} \right)$$

for all $j = 1, \dots, m.$

Scaled sums of squares

Lecture 13

2-19-25