

4) A square + symmetric \Rightarrow
 \exists at least one symmetric A^{-1}

P_X is sometimes called "the hat matrix" and written H

Properties of projection

$P_X' = P_X$ (P_X is symmetric)

and $P_X P_X = P_X$ (P_X is idempotent)
 This makes sense because

A bit more matrix/linear algebra background

- Two vectors \underline{u} and \underline{v} are perpendicular provided $\underline{u}'\underline{v} = 0$

often people write $\underline{u} \perp \underline{v}$ day 3

- There is a subspace of \mathbb{R}^n that consists of all vectors perpendicular to all elements of $C(X)$ i.e.

$C(X)^\perp = \{ \underline{u} \mid \underline{u}'\underline{v} = 0 \ \forall \ \underline{v} \in C(X) \}$

$P_X \underline{y} \in C(X)$ and thus

$P_X (P_X \underline{y}) = P_X \underline{y} \quad \forall \ \underline{y}$

Notice

$\underline{e} = \underline{Y} - \hat{\underline{Y}} = (\mathbf{I} - P_X) \underline{Y}$

vector of residuals

and we need to think about this matrix $\mathbf{I} - P_X$, what it's doing and more about the geometry of least squares

$= \{ \underline{u} \mid \underline{u}'\underline{z}_i = 0 \ \forall \ \underline{z}_i \text{ a column of } X \}$

- $\mathbf{I} - P_X$ is an orthogonal projection matrix (it's symmetric and idempotent)

- $C(\mathbf{I} - P_X) = C(X)^\perp$

- $\text{rank}(X) = \text{rank}(P_X) = \text{dimension of } C(X)$

$\text{trace}(P_X)$

Thm 2.13D page 50 of Rencher (also top of page 414 Christensen)

$$\text{rank}(I - P_X) = \text{dimension of } C(X)^\perp$$

trace $(I - P_X)$ $\xrightarrow{\text{again see page 50 of Rencher}}$

$$\text{trace } I \stackrel{\text{Thm 2.11A page 40 Rencher}}{=} \text{trace}(P_X) + \text{trace}(I - P_X)$$

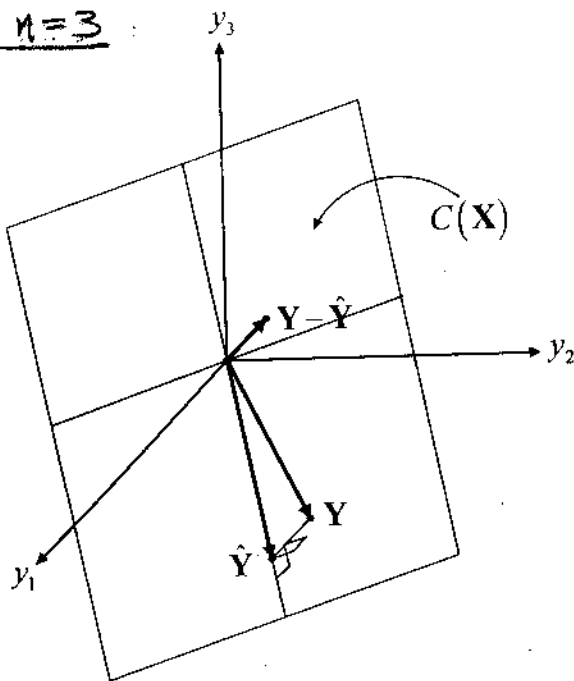
$\stackrel{\text{Thm 2.11A page 40 Rencher}}{=} n$

\uparrow
rank(X)

\uparrow
rank(I - P_X)

$$\text{So } \text{rank}(I - P_X) = \dim C(X)^\perp = n - \text{rank}(X)$$

Geometry $n=3$



and note

$$\begin{aligned} Y'Y &= ((P_X + (I - P_X))Y)'Y \\ &= Y'P_X'Y + Y'(I - P_X)'Y \\ &= Y'P_XY + Y'(I - P_X)Y \\ &= Y'P_X'P_XY + Y'(I - P_X)'(I - P_X)Y \\ &= (P_XY)'P_XY + ((I - P_X)Y)'(I - P_X)Y \end{aligned}$$

that is, the squared length of Y is the sum of squared lengths of P_XY and $(I - P_X)Y$ - this is an ANOVA identity / a Pythagorean Thm

(Ordinary) Least Squares Estimation of β
in Full Rank Cases

When $\text{rank}(X) = k$ X has k linearly independent columns and every $w \in C(X)$ has a unique representation as a linear combination of columns of X -

$$\begin{aligned} X\tilde{b}_1 &= X\tilde{b}_2 \Rightarrow X(\tilde{b}_1 - \tilde{b}_2) = \tilde{0} \\ &\Rightarrow \tilde{b}_1 - \tilde{b}_2 = \tilde{0} \\ &\tilde{b}_1 = \tilde{b}_2 \end{aligned}$$

(otherwise the columns of X are linearly dependent)

So in this case \exists a unique \underline{b} that solves

$$X \underline{b} = P_X Y \Leftrightarrow \hat{Y} = X \hat{\beta}$$

We can call this \underline{b} the ordinary least squares estimate of $\underline{\beta}$ — notice that

$$X \underline{b}_{OLS} = P_X Y = X(X'X)^{-1} X' Y$$

$$(X'X) \underline{b}_{OLS} = X'X(X'X)^{-1} X' Y$$

$k \times k$ with the same rank as X , namely k , so $X'X$ is non-singular, $(X'X)^{-1} = (X'X)^{-1}$

(Ordinary) Least Squares Estimation of

$$\underline{c}' \underline{\beta}$$

~~day 4~~

When X is of full rank the obvious OLS estimate of $\underline{c}' \underline{\beta}$ is

$$\hat{\underline{c}' \underline{\beta}}_{OLS} = \underline{c}' \underline{b}_{OLS}$$

When X is not of full rank $\underline{c}' \underline{\beta}$ can be unambiguous (even though $\underline{\beta}$ is ambiguous)

$$(X'X) \underline{b}_{OLS} = X' Y$$

so called "normal equations"

$$\underline{b}_{OLS} = (X'X)^{-1} X' Y$$

When X is not of full rank, there are multiple \underline{b} 's that will solve

$$X \underline{b} = P_X Y$$

and multiple $\underline{\beta}$'s that could be used to represent $EY \in C(X) \dots \gg \gg \gg$ — so there is no sensible unique "least squares estimator of $\underline{\beta}$ "

Example b) 1 way ANOVA model

Version 1 $y_{ij} = \mu_i + \epsilon_{ij}$

Version 2 $y_{ij} = \mu + \tau_i + \epsilon_{ij}$

will typically give full rank X and meaningful \underline{b}_{OLS}

This gives a less than full rank X

— clearly $\mu_1 = \mu + \tau_1$

and "clearly" we should call \hat{y}_i the OLS estimate of μ_i

$$\begin{pmatrix} 1 & 1 & 0 & 0 \end{pmatrix} \begin{pmatrix} \mu \\ \tau_1 \\ \tau_2 \\ \tau_3 \end{pmatrix} = \mu + \tau_1$$

?? What is "special" about \underline{c} in this example version 2 that makes $\underline{c}'\beta$ unambiguous even though β is ambiguous?

Result: The following are equivalent regarding $\underline{c} \in \mathbb{R}^k$

- 1) $\exists \underline{a} \in \mathbb{R}^n$ such that $\underline{a}'X\beta = \underline{c}'\beta \quad \forall \beta$
- 2) $\underline{c} \in C(X')$ (\underline{c}' is a l.c. of rows of X)
- 3) $X\beta_1 = X\beta_2 \Rightarrow \underline{c}'\beta_1 = \underline{c}'\beta_2$
(This last one is a condition about lack of

so for this \underline{a} , $\underline{c}'\beta = \underline{a}'X\beta \quad \forall \beta$
and 1) holds

Now suppose 1) holds i.e. $\exists \underline{a}$ s.t.
 $\underline{a}'X\beta = \underline{c}'\beta \quad \forall \beta$. Suppose $X\beta_1 = X\beta_2$
then for this \underline{a} , $\underline{a}'X\beta_1 = \underline{a}'X\beta_2$

$$\begin{array}{ccc} \text{"} & & \text{"} \\ \underline{c}'\beta_1 & & \underline{c}'\beta_2 \end{array}$$

and 3) holds

Now suppose that 3) holds -

ambiguity for $\underline{c}'\beta$)

condition 1) is

$$\begin{array}{l} \underline{a}'X\beta = \underline{a}'EY = E\underline{a}'Y \\ \text{"} \\ \underline{c}'\beta \end{array}$$

i.e. $\underline{a}'Y$ can be used to estimate $\underline{c}'\beta$ in an unbiased fashion

Pf: Suppose 2) holds
 $\underline{c} \in C(X') \Rightarrow \exists \underline{a}$ s.t. $\underline{c}' = \underline{a}'X$

it is "obviously" equivalent to write

$$X(\beta_1 - \beta_2) = \underline{0} \Rightarrow \underline{c}'(\beta_1 - \beta_2) = 0 \quad \forall \beta_1, \beta_2$$

i.e. its equivalent to write

$$X\underline{d} = \underline{0} \Rightarrow \underline{c}'\underline{d} = 0 \quad \forall \underline{d}$$

claim that 3) \Rightarrow 2) is the claim that

$$\{\underline{c} \mid \forall \text{ holds}\} \subset C(X')$$

suppose that \underline{c} is such that \square holds

Write
$$\underline{c} = P_{X'}\underline{c} + (I - P_{X'})\underline{c}$$

and let $\underline{d}^* = (I - P_{X'})\underline{c}$ - I'll argue $\underline{d}^* = \underline{0}$ 10

clearly $\underline{d}^* \in C(X')^\perp$ so it must
be that

$$\underline{c}' \underline{d}^* = 0$$

from condition but

$$\begin{aligned}\underline{c}' \underline{d}^* &= \underline{c}' (\mathbf{I} - \mathbf{P}_{X'}) \underline{c} \\ &= \underline{c}' \underline{c} - \underline{c}' \mathbf{P}_{X'} \underline{c}\end{aligned}$$

So $\underline{c}' \underline{c} = \underline{c}' \mathbf{P}_{X'} \underline{c}$. But

$$\begin{aligned}\underline{c}' \underline{c} &= \underline{c}' (\mathbf{P}_{X'} + (\mathbf{I} - \mathbf{P}_{X'})) \underline{c} \\ &= \underline{c}' \mathbf{P}_{X'} \underline{c} + \underline{c}' (\mathbf{I} - \mathbf{P}_{X'}) \underline{c}\end{aligned}$$

$$= \underline{c}' \mathbf{P}_{X'} \underline{c} + \underbrace{\underline{c}' (\mathbf{I} - \mathbf{P}_{X'}) (\mathbf{I} - \mathbf{P}_{X'}) \underline{c}}_{\underline{d}^{*'} \underline{d}}$$

$$\begin{aligned}\underline{d}^{*'} \underline{d} &= 0 \text{ so } \underline{d}^* = \underline{0} \text{ and } \underline{c} = \mathbf{P}_{X'} \underline{c} \\ \text{and } \underline{c} &\in C(X')\end{aligned}$$

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