

STA302 weeks 8–9

Mark Ebden 2018. Continuing Ch 5

With grateful acknowledgment to Alison Gibbs

What we're doing

- ▶ Midterms discussed on Thursday (not Tuesday)
- ▶ §5.2 (Estimation and Inference in MLR) is what we've begun, via the RMA
- ▶ Chapter 5's matrices



Fitted values ($\hat{\mathbf{Y}}$) in matrix form



Recall from Weeks 6–7 that our model is:

$$\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \mathbf{e}$$

Recalling that $\hat{\boldsymbol{\beta}}$ is unbiased and that $E(\mathbf{e}) = \mathbf{0}$, we have $\hat{\mathbf{Y}} = \mathbf{X}\hat{\boldsymbol{\beta}}$. So:

$$\hat{\mathbf{Y}} = \mathbf{X}\hat{\boldsymbol{\beta}} = \mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{Y} = \mathbf{H}\mathbf{Y}$$

where $\mathbf{H} = \mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'$ is the **hat matrix**, comprised of the h_{ij} values.

$$\begin{bmatrix} h_{11} & h_{12} & \cdots \\ & h_{22} & \cdots \\ & & \ddots & h_{nn} \end{bmatrix}$$

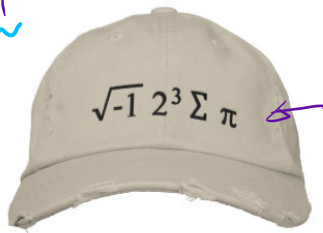
Re-“cap”

Recall from weeks 4-5 that h in $h_{ij} = \frac{1}{n} + \frac{(x_i - \bar{x})(x_j - \bar{x})}{S_{xx}}$ stands for “hat”. This is because, considering $\hat{y}_i = \sum_{j=1}^n \underbrace{h_{ij}}_{\text{weights}} y_j$, the h values show how to get from y_i 's to \hat{y}_i 's.

This is even more apparent in the matrix notation.

$$\hat{\underset{\sim}{Y}} = H \underset{\sim}{Y}$$

$$\hat{\underset{\sim}{y}} \leftarrow h \underset{\sim}{y}$$



Properties of H

$$A^{-1}A = I$$

$$H = H^2 = HH$$

↑
same

$H = X(X'X)^{-1}X'$ is an example of an idempotent matrix. **Exercise:** Show this.

$$HH = \underbrace{X(X'X)^{-1}X'}_A \underbrace{X(X'X)^{-1}X'}_B = X(X'X)^{-1}X' = H$$

H is symmetric. **Exercise:** Show this.

$$\begin{aligned} H' &= \left[\underbrace{X(X'X)^{-1}}_A \underbrace{X'}_B \right]' \\ &= \underbrace{X'}_{B'} \underbrace{(X(X'X)^{-1})'}_{A'} = H \end{aligned}$$

Remember

$$\underline{h_{ij} = h_{ji} ?}$$

Five facts about idempotent matrices

$$J = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix} \quad (n=3)$$

- 1. A square matrix \mathbf{A} is idempotent iff $\mathbf{A}^2 = \mathbf{A}$
- 2. If \mathbf{A} is idempotent then $\text{trace}(\mathbf{A}) = \text{rank}(\mathbf{A})$
- 3. \mathbf{A} is idempotent iff $\text{rank}(\mathbf{A}) + \text{rank}(\mathbf{I} - \mathbf{A}) = n$ where the dimensions of \mathbf{A} are $n \times n$ and \mathbf{I} is the $n \times n$ identity matrix
- 4. For hat matrix \mathbf{H} and matrix of all 1's \mathbf{J} , the following matrices are idempotent:

$$\mathbf{H}$$

$$\mathbf{I} - \mathbf{H}$$

$$\frac{1}{n}\mathbf{J}$$

$$\mathbf{H} - \frac{1}{n}\mathbf{J}$$

- 5. If \mathbf{A} , \mathbf{B} , and \mathbf{C} are idempotent and $\mathbf{A} = \mathbf{B} + \mathbf{C}$, then $\text{rank}(\mathbf{A}) = \text{rank}(\mathbf{B}) + \text{rank}(\mathbf{C})$

iff = "if and only if"

4 is the only one we prove here

Residuals ($\hat{\mathbf{e}}$) in matrix form

$$e_i = y_i - \hat{y}_i$$

The residuals are given by

$$\hat{\mathbf{e}} = \begin{pmatrix} \hat{e}_1 \\ \vdots \\ \hat{e}_n \end{pmatrix} = \mathbf{Y} - \hat{\mathbf{Y}} = \mathbf{Y} - \mathbf{X}\hat{\boldsymbol{\beta}}$$

Handwritten annotations: Arrows point from \hat{e}_1 and \hat{e}_n to the vector $\hat{\mathbf{e}}$. An arrow points from $\hat{\mathbf{Y}}$ to $\mathbf{H}\mathbf{Y}$. Another arrow points from $\mathbf{X}\hat{\boldsymbol{\beta}}$ to $\mathbf{X}\hat{\boldsymbol{\beta}}$.

Donning our new hat matrix, this can be rewritten as $\hat{\mathbf{e}} = \mathbf{Y} - \mathbf{H}\mathbf{Y}$ before determining $\mathbf{E}(\hat{\mathbf{e}})$ and $\text{var}(\hat{\mathbf{e}})$.

To begin, how could we factorize $\hat{\mathbf{e}} = \mathbf{Y} - \mathbf{H}\mathbf{Y}$?

$$\begin{aligned} &= \mathbf{I}\mathbf{Y} - \mathbf{H}\mathbf{Y} \\ &= (\mathbf{I} - \mathbf{H})\mathbf{Y} \end{aligned}$$

Handwritten annotations: Arrows point from \mathbf{I} and \mathbf{H} to $(\mathbf{I} - \mathbf{H})$. An arrow points from \mathbf{Y} to \mathbf{Y} .

Properties of $I - H$

Is $I - H$ idempotent?

$$\begin{aligned}(I - H)(I - H) &= II - IH - HI + HH \\ &= I - H - H + H \\ &= I - H\end{aligned}$$

Is $I - H$ symmetric?

$$\begin{aligned}(I - H)' &= I' - H' \\ &= I - H\end{aligned}$$

Re-d5 H:

$$\hat{e}_i = y_i - \hat{y}_i$$

$$\hat{y}_i = \dots$$

$$b_0 = \dots$$

$$b_1 = \dots$$

$$S_{xy} = \dots, S_{xx}$$

$$\sum \hat{e}_i = 0 \rightarrow$$

$$\sum \hat{e}_i \hat{y}_i = 0 \rightarrow$$

vars
cov's
etc

Matrices:

$$\hat{e} = (I - H)\tilde{y}$$

$$\hat{y} = H\tilde{y} = X\hat{\beta}$$

$$H = X(X'X)^{-1}X'$$

$$\hat{\beta} = (X'X)^{-1}X'\tilde{y}$$

$$\begin{matrix} 1 \times n & n \times 2 & 1 \times 2 \\ \hat{e}' & \tilde{X} & = \tilde{0} \end{matrix}$$

$$\begin{matrix} & & 1 \times 1 \\ \hat{e}' & \hat{y} & = 0 \end{matrix}$$

Continuing:

$$= E(Y - X\hat{\beta}) = E(Y) - E(X\hat{\beta})$$

$$\searrow \quad = X\beta - X E(\hat{\beta})$$

$E(\hat{e}) =$

$$= X\beta - X\beta$$

$$= 0$$

$\text{var}(\hat{e}) =$

$$\text{var}[(I-H)Y] = (I-H) \text{var}(Y) (I-H)'$$

$$= (I-H) \sigma^2 I (I-H)$$

$$= \sigma^2 (I-H)(I-H)$$

$$= \sigma^2 (I-H) \quad \leftarrow$$

Recap of our recent studies

The SLR model in matrix form is $\mathbf{Y} = \mathbf{X}\beta + \mathbf{e}$, in which:

$$\mathbf{Y} = \begin{pmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_n \end{pmatrix}, \quad \mathbf{X} = \begin{pmatrix} 1 & X_1 \\ 1 & X_2 \\ \vdots & \vdots \\ 1 & X_n \end{pmatrix}, \quad \beta = \begin{pmatrix} \beta_0 \\ \beta_1 \end{pmatrix}, \quad \mathbf{e} = \begin{pmatrix} e_1 \\ e_2 \\ \vdots \\ e_n \end{pmatrix}$$

Setting the derivative of $RSS(\beta)$ to zero yielded $\hat{\beta} = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{Y}$ when $\text{rank}(\mathbf{X}) = 2$. This plus the fact that $E(\mathbf{e}) = \mathbf{0}$ gives

$$\hat{\mathbf{Y}} = \mathbf{X}\hat{\beta} = \mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{Y} = \mathbf{H}\mathbf{Y}$$

We can write the residuals in terms of idempotent matrix $\mathbf{I} - \mathbf{H}$ as

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

We found $E(\hat{\mathbf{e}}) = \mathbf{0}$ and ~~were about to try~~ $\text{var}(\hat{\mathbf{e}})$ requiring the notion of a covariance matrix: $\text{var}(\mathbf{X}) = E[(\mathbf{X} - E(\mathbf{X}))(\mathbf{X} - E(\mathbf{X}))']$.


Variance of the residuals, in matrix form

$$\begin{aligned}\text{var}(\hat{\mathbf{e}}) &= E \left\{ \overbrace{[\hat{\mathbf{e}} - E(\hat{\mathbf{e}})] [\hat{\mathbf{e}} - E(\hat{\mathbf{e}})]'} \right\} \\ &= E \left\{ (\mathbf{I} - \mathbf{H}) \mathbf{Y} \mathbf{Y}' (\mathbf{I} - \mathbf{H}) \right\} \\ &= (\mathbf{I} - \mathbf{H}) \underbrace{E(\mathbf{Y} \mathbf{Y}')} (\mathbf{I} - \mathbf{H})\end{aligned}$$

Compare to our previous work: $\text{var}(\hat{e}_i) = \sigma^2(1 - h_{ii})$. Does the above match?

NB: As before, the “ \mathbf{X} ” is implicit — e.g. $\text{var}(\hat{\mathbf{e}}|\mathbf{X})$ is abbreviated as $\text{var}(\hat{\mathbf{e}})$.

Variance of the residuals, in matrix form


$$\begin{aligned}\text{The middle factor is } E(\mathbf{Y}\mathbf{Y}') &= E\{(\mathbf{X}\boldsymbol{\beta} + \mathbf{e})(\mathbf{X}\boldsymbol{\beta} + \mathbf{e})'\} \\ &= E\{(\mathbf{X}\boldsymbol{\beta} + \mathbf{e})(\boldsymbol{\beta}'\mathbf{X}' + \mathbf{e}')\} \\ &= E\{\mathbf{X}\boldsymbol{\beta}\boldsymbol{\beta}'\mathbf{X}' + \mathbf{X}\boldsymbol{\beta}\mathbf{e}' + \mathbf{e}\boldsymbol{\beta}'\mathbf{X}' + \mathbf{e}\mathbf{e}'\} \\ &= E\{\mathbf{X}\boldsymbol{\beta}\boldsymbol{\beta}'\mathbf{X}'\} + \mathbf{0} + \mathbf{0} + E(\mathbf{e}\mathbf{e}')\end{aligned}$$

$$E(\mathbf{Y}\mathbf{Y}') = \mathbf{X}\boldsymbol{\beta}\boldsymbol{\beta}'\mathbf{X}' + \sigma^2\mathbf{I}$$

Inserting the above into $\text{var}(\hat{\mathbf{e}})$ gives

$$\begin{aligned}\text{var}(\hat{\mathbf{e}}) &= (\mathbf{I} - \mathbf{H})(\mathbf{X}\boldsymbol{\beta}\boldsymbol{\beta}'\mathbf{X}' + \sigma^2\mathbf{I})(\mathbf{I} - \mathbf{H}) \\ &= [\mathbf{I}(\mathbf{X}\boldsymbol{\beta}\boldsymbol{\beta}'\mathbf{X}' + \sigma^2\mathbf{I}) - \mathbf{H}(\mathbf{X}\boldsymbol{\beta}\boldsymbol{\beta}'\mathbf{X}' + \sigma^2\mathbf{I})](\mathbf{I} - \mathbf{H}) \\ &= [\mathbf{X}\boldsymbol{\beta}\boldsymbol{\beta}'\mathbf{X}' + \sigma^2\mathbf{I} - \mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'(\mathbf{X}\boldsymbol{\beta}\boldsymbol{\beta}'\mathbf{X}') - \sigma^2\mathbf{H}](\mathbf{I} - \mathbf{H}) \\ &= \sigma^2(\mathbf{I} - \mathbf{H})(\mathbf{I} - \mathbf{H})\end{aligned}$$

$$\text{var}(\hat{\mathbf{e}}) = \sigma^2(\mathbf{I} - \mathbf{H})$$

$E(\mathbf{X}\boldsymbol{\beta}\mathbf{e}') = 0$
const

Gauss-Markov cond'n:
 $E(\mathbf{e}) = \mathbf{0}$

What's the rank of $\text{var}(\hat{\mathbf{e}})$? = $\underbrace{\sigma^2}_{\text{green}} \underbrace{(\mathbf{I} - \mathbf{H})}_{\text{green}}$



Recall the fifth of our *Five facts about idempotent matrices*:

If $\mathbf{A} = \mathbf{B} + \mathbf{C}$, then $\text{rank}(\mathbf{A}) = \text{rank}(\mathbf{B}) + \text{rank}(\mathbf{C})$.

Put another way, $\text{rank}(\mathbf{B}) = \text{rank}(\mathbf{A}) - \text{rank}(\mathbf{C})$.

Therefore, for example $\text{rank}(\mathbf{I} - \mathbf{H}) = \text{rank}(\mathbf{I}) - \text{rank}(\mathbf{H}) = n - 2$. We'll do other similar calculations when considering ANOVA in matrix terms.

ANOVA in matrix terms

Recall from Week 3 that

$$\boxed{SST = SS_{\text{Reg}} + RSS}$$

where

$$SST = \sum_{i=1}^n (y_i - \bar{y})^2 = \sum_{i=1}^n y_i^2 - n\bar{y}^2$$

Exercise: Show that SST can be re-expressed as

$$SST = \mathbf{Y}'\mathbf{Y} - \frac{1}{n}\mathbf{Y}'\mathbf{J}\mathbf{Y}$$

where \mathbf{J} is an $n \times n$ matrix of 1's. This means we can also write

$$n=3: \begin{pmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{pmatrix} = \mathbf{J}$$

$$SST = \mathbf{Y}' \left(\mathbf{I} - \frac{1}{n}\mathbf{J} \right) \mathbf{Y}$$

$$\sum (y_i - \bar{y})^2 = \sum (y_i - \hat{y}_i)^2 + \sum (\hat{y}_i - \bar{y})^2$$

$$= \sum (y_i - \hat{y}_i)^2 + \sum (b_1^2 (x_i - \bar{x})^2)$$

Some properties of $\mathbf{I} - \frac{1}{n}\mathbf{J}$

$$\frac{\mathbf{Y}'(\mathbf{I} - \frac{1}{n}\mathbf{J})\mathbf{Y}}{\text{SST}}$$

1. Note that $\mathbf{I} - \frac{1}{n}\mathbf{J}$ is symmetric. For a vector \mathbf{Y} and symmetric matrix \mathbf{A} , you may recall from other courses that $\mathbf{Y}'\mathbf{A}\mathbf{Y}$ is a quadratic form (second-degree polynomial).

q. form in 1 variable: ay_1^2

2 vars: $ay_1^2 + by_2^2 + cy_1y_2$

\vdots

n vars: $a_1y_1^2 + \dots + a_ny_n^2 + b_1y_1y_2 + b_2y_1y_3 + \dots$

entirely

2. ~~Symmetric~~ \mathbf{I} is idempotent and $\frac{1}{n}\mathbf{J}$ is idempotent (from the five facts), $\mathbf{I} - \frac{1}{n}\mathbf{J}$ is also idempotent.

3. The rank of $\mathbf{I} - \frac{1}{n}\mathbf{J}$ is $\text{rank}(\mathbf{I}) - \text{rank}(\frac{1}{n}\mathbf{J}) = n - 1$.

► This is the number of degrees of freedom for SST

Decomposing SST $y_i - \hat{y}_i + \hat{y}_i$

Taking the first term of SST = $\mathbf{Y}'\mathbf{Y} - \frac{1}{n}\mathbf{Y}'\mathbf{J}\mathbf{Y}$,

$$\begin{aligned}\mathbf{Y}'\mathbf{Y} &= (\mathbf{Y} - \mathbf{X}\mathbf{b} + \mathbf{X}\mathbf{b})'(\mathbf{Y} - \mathbf{X}\mathbf{b} + \mathbf{X}\mathbf{b}) \\ &= (\mathbf{Y} - \mathbf{X}\mathbf{b})'(\mathbf{Y} - \mathbf{X}\mathbf{b}) + (\mathbf{Y} - \mathbf{X}\mathbf{b})'\mathbf{X}\mathbf{b} + (\mathbf{X}\mathbf{b})'(\mathbf{Y} - \mathbf{X}\mathbf{b}) + (\mathbf{X}\mathbf{b})'(\mathbf{X}\mathbf{b}) \\ &= \hat{\mathbf{e}}'\hat{\mathbf{e}} + \underbrace{\hat{\mathbf{e}}'\mathbf{X}\mathbf{b} + (\mathbf{X}\mathbf{b})'\hat{\mathbf{e}}}_{\text{equal scalars, both 0}} + \mathbf{b}'\mathbf{X}'\mathbf{X}\mathbf{b} \\ &\stackrel{RSS}{=} \boxed{\hat{\mathbf{e}}'\hat{\mathbf{e}}} + \mathbf{b}'\mathbf{X}'\mathbf{X}\mathbf{b}\end{aligned}$$

The middle terms were zero because

$$\mathbf{X}'\hat{\mathbf{e}} = \mathbf{X}'(\mathbf{I} - \mathbf{H})\mathbf{Y} = \mathbf{X}'\mathbf{Y} - \mathbf{X}'\mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{Y} = \mathbf{0}$$

So,

$$\text{SST} = \mathbf{Y}'\mathbf{Y} - \frac{1}{n}\mathbf{Y}'\mathbf{J}\mathbf{Y}$$

$$\text{SST} = \underbrace{\hat{\mathbf{e}}'\hat{\mathbf{e}}}_{\text{RSS}} + \underbrace{\mathbf{b}'\mathbf{X}'\mathbf{X}\mathbf{b} - \frac{1}{n}\mathbf{Y}'\mathbf{J}\mathbf{Y}}_{\text{SSReg}}$$

A closer look at RSS

$$\boxed{\text{SST} = \text{SSReg} + \text{RSS}}$$

Making use of our expression $\hat{\mathbf{e}} = (\mathbf{I} - \mathbf{H})\mathbf{Y}$, we have

$$\begin{aligned}\text{RSS} &= \hat{\mathbf{e}}'\hat{\mathbf{e}} \\ &= \mathbf{Y}'(\mathbf{I} - \mathbf{H})'(\mathbf{I} - \mathbf{H})\mathbf{Y} \\ &= \mathbf{Y}'(\mathbf{I} - \mathbf{H})\mathbf{Y}\end{aligned}$$

This is another quadratic form in \mathbf{Y} . Also, $\text{rank}(\mathbf{I} - \mathbf{H}) = n - 2$ from earlier, the number of degrees of freedom for the error.

A closer look at SSReg

$$\boxed{\text{SST} = \text{SSReg} + \text{RSS}}$$

Making use of $\hat{\beta} = \mathbf{b} = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{Y}$, and slide 16

$$\begin{aligned}\text{SSReg} &= \mathbf{b}'\mathbf{X}'\mathbf{X}\mathbf{b} - \mathbf{Y}'\frac{1}{n}\mathbf{J}\mathbf{Y} \quad \leftarrow \\ &= \mathbf{Y}'\underbrace{\mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'}_{\mathbf{H}}\mathbf{Y} - \mathbf{Y}'\frac{1}{n}\mathbf{J}\mathbf{Y} \\ &= \mathbf{Y}'\underbrace{\mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'}_{\mathbf{H}}\mathbf{Y} - \mathbf{Y}'\frac{1}{n}\mathbf{J}\mathbf{Y} \\ &= \mathbf{Y}'\left(\mathbf{H} - \frac{1}{n}\mathbf{J}\right)\mathbf{Y}\end{aligned}$$

This is again a quadratic form in \mathbf{Y} , since the middle matrix is symmetric. Also, $\text{rank}(\mathbf{H} - \frac{1}{n}\mathbf{J}) = \text{rank}(\mathbf{H}) - \text{rank}(\frac{1}{n}\mathbf{J}) = 2 - 1 = 1$, the number of degrees of freedom for SSReg.

Result:- Rank(X) is generally 2. And from LMA, 26 : $\text{rank}(\mathbf{H}) = \dots = 2$

Using RSS to estimate σ^2

In $S^2 = \text{RSS}/(n-2)$, we have an unbiased estimator for σ^2 . We can show it's unbiased using matrices by showing that $E(\text{RSS}) = (n-2)\sigma^2$ as we did without matrices — i.e. when we considered $E(\text{RSS}) = E(\sum_{i=1}^n \hat{e}_i^2)$.

$$E(\text{RSS}) = E(\hat{\mathbf{e}}' \hat{\mathbf{e}})$$

trace(scalar) = itself

$$= E\{\mathbf{Y}'(\mathbf{I} - \mathbf{H})\mathbf{Y}\}$$

from slide 17

$$= E\{\text{trace}[\mathbf{Y}'(\mathbf{I} - \mathbf{H})\mathbf{Y}]\}$$

since $\mathbf{Y}'(\mathbf{I} - \mathbf{H})\mathbf{Y}$ is a scalar

$$= E\{\text{trace}[(\mathbf{I} - \mathbf{H})\mathbf{Y}\mathbf{Y}']\}$$

since $\text{trace}(\mathbf{AB}) = \text{trace}(\mathbf{BA})$ ★

$$= \text{trace}[(\mathbf{I} - \mathbf{H})E(\mathbf{Y}\mathbf{Y}')] \quad \leftarrow$$

$$= \text{trace}[(\mathbf{I} - \mathbf{H})(\sigma^2\mathbf{I} + \mathbf{X}\beta\beta'\mathbf{X}')] \quad \text{from slide 12}$$

$$= \text{trace}[(\mathbf{I} - \mathbf{H})\sigma^2 + \underbrace{\mathbf{X}\beta\beta'\mathbf{X}'}_{=0} - \underbrace{\mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{X}\beta\beta'\mathbf{X}'}_{=0}]$$

$$= \text{trace}(\mathbf{I} - \mathbf{H})\sigma^2$$

$$E(\text{RSS}) = (n-2)\sigma^2$$

where we have used $\text{trace}(\mathbf{A} + \mathbf{B}) = \text{trace}(\mathbf{A}) + \text{trace}(\mathbf{B})$ ★

$$\text{trace}(\mathbf{I} - \mathbf{H}) = \text{trace}(\mathbf{I}) - \text{trace}(\mathbf{H}) = n - \sum_{i=1}^n h_{ii} = n - 2.$$

~ Week 4

The big picture

We have expressed the ANOVA identity in matrix form:

$$\underbrace{\mathbf{Y}' \left(\mathbf{I} - \frac{1}{n} \mathbf{J} \right) \mathbf{Y}}_{\text{SST}} = \underbrace{\mathbf{Y}' \left(\mathbf{H} - \frac{1}{n} \mathbf{J} \right) \mathbf{Y}}_{\text{SSReg}} + \underbrace{\mathbf{Y}' (\mathbf{I} - \mathbf{H}) \mathbf{Y}}_{\text{RSS}}$$

y_i \bar{y} \hat{y}_i \bar{y} y_i \hat{y}_i



What does R have to say about this?

ANOVA in R

$$y = \beta_0 + \beta_1 x + e$$

PPC ←

SS_{ky} :
 RSS :
 SST :

The `anova` command is one way in R to produce an ANOVA table (of the sort we saw in Week 3), in addition to analysing it. For example, for a 654-point SLR problem:

→ `a2 = read.table("Data2.txt", sep=" ", header=T) # Load the data set`
 → `fev <- a2$fev; age <- a2$age`
 → `mod1 = lm(fev~age)`
 → `anova(mod1)`

Analysis of Variance Table

##

Response: fev

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
age	1	280.92	280.919	872.18	< 2.2e-16 ***
Residuals	652	210.00	0.322		

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

estimate of σ^2
 (if $H_0: \beta_1 = 0$ is true)



ANOVA in R

The p -value will match that obtained from the `summary(lm...)` command:

```
summary(mod1)
```

```
##
## Call:
## lm(formula = fev ~ age)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1.57539 -0.34567 -0.04989  0.32124  2.12786
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.431648   0.077895   5.541 4.36e-08 ***
## age          0.222041   0.007518  29.533 < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.5675 on 652 degrees of freedom
## Multiple R-squared:  0.5722, Adjusted R-squared:  0.5716
## F-statistic: 872.2 on 1 and 652 DF,  p-value: < 2.2e-16
```

β_0
 β_1

We hope you have an enjoyable week

- ▶ Remember that for the Study Break of 5-9 November, there will be a pause in lectures, TA office hours, and instructor office hours
- ▶ No pause in the New College Stats Aid Centre

