

# HW 4

## Exercise 1

a.  $y_i = \beta_0 + \beta_1 x_i + \varepsilon$

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} = \underbrace{\begin{bmatrix} 1 & x_{11} \\ 1 & x_{21} \\ \vdots & \vdots \\ 1 & x_{n1} \end{bmatrix}}_{\underline{X}} \begin{bmatrix} \beta_0 \\ \beta_1 \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{bmatrix}$$

$$\underline{X}'\underline{X} = \begin{bmatrix} 1 & 1 & \dots & 1 \\ x_{11} & x_{21} & \dots & x_{n1} \end{bmatrix} \begin{bmatrix} 1 & x_{11} \\ 1 & x_{21} \\ \vdots & \vdots \\ 1 & x_{n1} \end{bmatrix} = \begin{bmatrix} n & \sum x_i \\ \sum x_i & \sum x_i^2 \end{bmatrix}$$

$$(\underline{X}'\underline{X})^{-1} = \frac{1}{n \sum x_i^2 - \sum x_i \sum x_i} \begin{bmatrix} \sum x_i^2 - \sum x_i \\ -\sum x_i & n \end{bmatrix}$$

$(\underline{X}'\underline{X})^{-1}$  forms part of the solution to finding  $\hat{\beta}_0, \hat{\beta}_1$  from the Normal Equations for simple regression

b. Find  $\hat{\beta}_0$  and  $\hat{\beta}_1$  using  $\hat{\beta} = (\underline{X}'\underline{X})^{-1} \underline{X}'\underline{Y}$

$$\hat{\beta} = \begin{bmatrix} \hat{\beta}_0 \\ \hat{\beta}_1 \end{bmatrix} \in \mathbb{R}^{2 \times 1} \quad \underline{Y} = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} \in \mathbb{R}^{n \times 1}$$

$$\underline{X}'\underline{Y} = \begin{bmatrix} 1 & 1 & \dots & 1 \\ x_{11} & x_{21} & \dots & x_{n1} \end{bmatrix} \begin{bmatrix} y_1 \\ y_n \\ \vdots \\ y_n \end{bmatrix} = \begin{bmatrix} \sum y_i \\ \sum x_i y_i \end{bmatrix}$$

using  $(\underline{X}'\underline{X})^{-1}$  we found in part a:

$$\hat{\beta} = \frac{1}{n \sum x_i^2 - \sum x_i \sum x_i} \begin{bmatrix} \sum x_i^2 - \sum x_i \\ -\sum x_i & n \end{bmatrix} \begin{bmatrix} \sum y_i \\ \sum x_i y_i \end{bmatrix}$$

$$= \frac{1}{n \sum x_i^2 - (\sum x_i)^2} \begin{bmatrix} \sum x_i^2 & -n\bar{x} \\ -n\bar{x} & n \end{bmatrix} \begin{bmatrix} \sum Y_i \\ \sum x_i Y_i \end{bmatrix}$$

$$= \frac{1}{n \sum (x_i - \bar{x})^2} \begin{bmatrix} (\sum Y_i)(\sum x_i^2) - n\bar{x} \sum x_i Y_i \\ -n\bar{x} \sum Y_i + n \sum x_i Y_i \end{bmatrix}$$

$$= \begin{bmatrix} \frac{\bar{y} \sum x_i^2}{\sum (x_i - \bar{x})^2} - \frac{\bar{x} \sum x_i Y_i}{\sum (x_i - \bar{x})^2} \\ \frac{-\bar{x} \sum Y_i + \sum x_i Y_i}{\sum (x_i - \bar{x})^2} \end{bmatrix} = \begin{bmatrix} \frac{\bar{y} \sum x_i^2}{\sum (x_i - \bar{x})^2} - \frac{\bar{x} \sum x_i Y_i}{\sum (x_i - \bar{x})^2} \\ \frac{\sum x_i Y_i - n\bar{x}\bar{y}}{\sum x_i^2 - \frac{(\sum x_i)^2}{n}} \end{bmatrix}$$

Note:  $\sum (x_i - \bar{x})^2 =$   
 $\sum (x_i^2 - 2x_i\bar{x} + \bar{x}^2) =$   
 $\sum x_i^2 - 2\bar{x} \sum x_i + \sum \bar{x}^2 =$   
 $\sum x_i^2 - 2n\bar{x}\bar{x} + n\bar{x}^2 =$   
 $\sum x_i^2 - n\bar{x}^2 =$   
 $= \sum x_i^2 - \frac{1}{n} (\sum x_i)^2$

$\Rightarrow n \sum (x_i - \bar{x})^2 =$   
 $n \sum x_i^2 - (\sum x_i)^2$

$\Rightarrow \sum x_i^2 = \sum (x_i - \bar{x})^2 + n\bar{x}^2$

From the  
normal eq.  
we know:

$$\hat{\beta}_0 = \frac{\sum x_i Y_i - n\bar{x}\bar{y}}{\sum x_i^2 - \frac{(\sum x_i)^2}{n}}$$

using  $\sum x_i^2 = \sum (x_i - \bar{x})^2 + n\bar{x}^2$ :

$$= \begin{bmatrix} \frac{\bar{y} \sum (x_i - \bar{x})^2}{\sum (x_i - \bar{x})^2} + \frac{\bar{y} n \bar{x}^2}{\sum (x_i - \bar{x})^2} - \frac{\bar{x} \sum (x_i Y_i)}{\sum (x_i Y_i)} \\ \hat{\beta}_1 \end{bmatrix} = \begin{bmatrix} \bar{y} + \frac{\bar{y} n [\bar{x}]^2}{\sum (x_i - \bar{x})^2} - \frac{\bar{x} \sum (x_i Y_i)}{\sum (x_i - \bar{x})^2} \\ \hat{\beta}_1 \end{bmatrix}$$

$$= \begin{bmatrix} \bar{y} - \bar{x} \left[ \frac{-n\bar{y}\bar{x} + \sum x_i Y_i}{\sum (x_i - \bar{x})^2} \right] \\ \hat{\beta}_1 \end{bmatrix} = \begin{bmatrix} \bar{y} - \bar{x} \left[ \frac{-\sum \bar{x} Y_i + \sum x_i Y_i}{\sum (x_i - \bar{x})^2} \right] \\ \hat{\beta}_1 \end{bmatrix}$$

$$= \begin{bmatrix} \bar{y} - \bar{x} \left[ \frac{\sum (x_i - \bar{x}) Y_i}{\sum (x_i - \bar{x})^2} \right] \\ \hat{\beta}_1 \end{bmatrix}$$

using the normal equations:

$$\hat{\beta}_1 = \frac{\sum (x_i - \bar{x}) Y_i}{\sum (x_i - \bar{x})^2}$$

$$= \begin{bmatrix} \bar{y} - \hat{\beta}_1 \bar{x} \\ \hat{\beta}_1 \end{bmatrix} = \begin{bmatrix} \hat{\beta}_0 \\ \hat{\beta}_1 \end{bmatrix} = \hat{\beta}$$

using the normal equations

$$\hat{\beta}_0 = \bar{y} - \hat{\beta}_1 \bar{x}$$

## Exercise 2

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \beta_3 x_{i3} + \epsilon_i$$

$$\tilde{y} = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix}$$

$$\tilde{X} = \begin{bmatrix} 1 & x_{11} & x_{12} & x_{13} \\ 1 & x_{21} & x_{22} & x_{23} \\ \vdots & \vdots & \vdots & \vdots \\ 1 & x_{n1} & x_{n2} & x_{n3} \end{bmatrix} \in \mathbb{R}^{n \times 4}$$

$$\tilde{X}' = \begin{bmatrix} 1 & 1 & \dots & 1 \\ x_{11} & x_{21} & \dots & x_{n1} \\ x_{12} & x_{22} & \dots & x_{n2} \\ x_{13} & x_{23} & \dots & x_{n3} \end{bmatrix} \in \mathbb{R}^{4 \times n}$$

$$\tilde{X}'\tilde{X} = \begin{bmatrix} 1 & 1 & \dots & 1 \\ x_{11} & x_{21} & \dots & x_{n1} \\ x_{12} & x_{22} & \dots & x_{n2} \\ x_{13} & x_{23} & \dots & x_{n3} \end{bmatrix} \begin{bmatrix} 1 & x_{11} & x_{12} & x_{13} \\ 1 & x_{21} & x_{22} & x_{23} \\ \vdots & \vdots & \vdots & \vdots \\ 1 & x_{n1} & x_{n2} & x_{n3} \end{bmatrix} = \begin{bmatrix} n & \sum x_{i1} & \sum x_{i2} & \sum x_{i3} \\ \sum x_{i1} & \sum x_{i1}^2 & \sum x_{i1}x_{i2} & \sum x_{i1}x_{i3} \\ \sum x_{i2} & \sum x_{i2}x_{i1} & \sum x_{i2}^2 & \sum x_{i2}x_{i3} \\ \sum x_{i3} & \sum x_{i3}x_{i1} & \sum x_{i3}x_{i2} & \sum x_{i3}^2 \end{bmatrix} \in \mathbb{R}^{4 \times 4}$$

$$\tilde{X}'\tilde{y} = \begin{bmatrix} 1 & 1 & \dots & 1 \\ x_{11} & x_{21} & \dots & x_{n1} \\ x_{12} & x_{22} & \dots & x_{n2} \\ x_{13} & x_{23} & \dots & x_{n3} \end{bmatrix} \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} = \begin{bmatrix} \sum y_i \\ \sum x_{i1} y_i \\ \sum x_{i2} y_i \\ \sum x_{i3} y_i \end{bmatrix} \in \mathbb{R}^{4 \times 1}$$

### Exercise 3

- a.  $y = X\beta + \epsilon \rightarrow$  Gauss-Markov conditions hold  
 show  $\hat{\beta} = \beta + A\epsilon$   
 then show  $\hat{y} = X\hat{\beta} + B\epsilon$  } find  $A, B$

$$\begin{aligned} \hat{\beta} &= (X'X)^{-1} X'Y \rightarrow \hat{\beta} = (X'X)^{-1} X' (X\beta + \epsilon) \quad \downarrow \text{Plug in given value of } Y \\ &= (X'X)^{-1} X'X\beta + (X'X)^{-1} X'\epsilon \\ &= \beta + (X'X)^{-1} X'\epsilon \\ &= \beta + A\epsilon \Rightarrow A = (X'X)^{-1} X' \end{aligned}$$

$$\begin{aligned} \hat{y} &= X\hat{\beta} \quad \text{using the definition of } \hat{y} \\ &= X(\beta + A\epsilon) \\ &= X\beta + \underline{XA}\epsilon \\ &= X\beta + B\epsilon = B = XA = X(X'X)^{-1} X' \end{aligned}$$

- b. Show  $e'x = 0$  where  $e = Y - X\hat{\beta}$  using the definition of  $e$   
 $= Y - \hat{y} \in \mathbb{R}^n$

$$e = Y - \hat{y} = Y - HY = (I_n - H)Y \quad \text{using the definition of } \hat{y}$$

$$\begin{aligned} \text{so } e'x &= Y'(I - H)'x = Y'(I' - H')x \stackrel{\text{both symmetric}}{=} Y'(I - H)x \\ &= Y'(x - Hx) = Y'(x - \underbrace{X(X'X)^{-1}X'x})_x \\ &= Y'(x - x) = 0 \end{aligned}$$

- c. Show  $e'\hat{y} = 0$

$$e'\hat{y} = e'X\hat{\beta} = (e'X)\hat{\beta} = 0\hat{\beta} = 0$$

# Exercise 4

$$E[Y_i] = \beta_0 + \beta_1 x_i + \beta_2 (3x_i^2 - 2) \quad i=1,2,3$$

$$E[Y] = E[X\beta + \varepsilon] = X\beta$$

$$\begin{matrix} \begin{bmatrix} 1 & -1 & 1 \\ 1 & 0 & -2 \\ 1 & 1 & 1 \end{bmatrix} & \begin{bmatrix} \beta_0 \\ \beta_1 \\ \beta_2 \end{bmatrix} & = & \begin{bmatrix} \beta_0 - \beta_1 + \beta_2 \\ \beta_0 - 2\beta_2 \\ \beta_0 + \beta_1 + \beta_2 \end{bmatrix} & X_1 = -1 & X_2 = 0 & X_3 = 1 & \underline{Y} = \begin{bmatrix} Y_1 \\ Y_2 \\ Y_3 \end{bmatrix} \\ \underline{X} & \underline{\beta} & & E[Y] \end{matrix}$$

→ solved for  $\underline{X}$

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

$$\underline{X}'\underline{X} = \begin{bmatrix} 1 & 1 & 1 \\ -1 & 0 & 1 \\ 1 & -2 & 1 \end{bmatrix} \begin{bmatrix} 1 & -1 & 1 \\ 1 & 0 & -2 \\ 1 & 1 & 1 \end{bmatrix} = \begin{bmatrix} 3 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 6 \end{bmatrix} \rightarrow (\underline{X}'\underline{X})^{-1} = \begin{bmatrix} \frac{1}{3} & 0 & 0 \\ 0 & \frac{1}{2} & 0 \\ 0 & 0 & \frac{1}{6} \end{bmatrix}$$

$$\underline{X}'\underline{Y} = \begin{bmatrix} 1 & 1 & 1 \\ -1 & 0 & 1 \\ 1 & -2 & 1 \end{bmatrix} \begin{bmatrix} Y_1 \\ Y_2 \\ Y_3 \end{bmatrix} = \begin{bmatrix} Y_1 + Y_2 + Y_3 \\ Y_3 - Y_1 \\ Y_1 - 2Y_2 + Y_3 \end{bmatrix}$$

$$\hat{\beta} = \begin{bmatrix} \frac{1}{3}(Y_1 + Y_2 + Y_3) \\ \frac{1}{2}(Y_3 - Y_1) \\ \frac{1}{6}(Y_1 - 2Y_2 + Y_3) \end{bmatrix} = \begin{bmatrix} \hat{\beta}_0 \\ \hat{\beta}_1 \\ \hat{\beta}_2 \end{bmatrix}$$

$$\text{var}(\hat{\beta}) = \sigma^2 (\underline{X}'\underline{X})^{-1} = \sigma^2 \begin{bmatrix} \frac{1}{3} & 0 & 0 \\ 0 & \frac{1}{2} & 0 \\ 0 & 0 & \frac{1}{6} \end{bmatrix} = \begin{bmatrix} \frac{\sigma^2}{3} & 0 & 0 \\ 0 & \frac{\sigma^2}{2} & 0 \\ 0 & 0 & \frac{\sigma^2}{6} \end{bmatrix}$$

$$* = \text{new} \quad \hat{\beta} = \begin{bmatrix} \hat{\beta}_0 \\ \hat{\beta}_1 \\ \hat{\beta}_2 \end{bmatrix} = (\underline{X}'\underline{X})^{-1} \underline{X}'\underline{Y} \quad \hat{\beta}^* = \begin{bmatrix} \hat{\beta}_0^* \\ \hat{\beta}_1^* \\ \hat{\beta}_2^* \end{bmatrix} = (\underline{X}^{*'}\underline{X}^*)^{-1} \underline{X}^{*'}\underline{Y}$$

we want to show:  $\hat{\beta}_0 = \hat{\beta}_0^*$  and  $\hat{\beta}_1 = \hat{\beta}_1^*$

$$X = \begin{bmatrix} 1 & x_1 & 3x_1^2 - 2 \\ 1 & x_2 & 3x_2^2 - 2 \\ 1 & x_3 & 3x_3^2 - 2 \end{bmatrix} = \begin{bmatrix} 1 & -1 & 1 \\ 1 & 0 & -2 \\ 1 & 1 & 1 \end{bmatrix} \quad X^* = \begin{bmatrix} 1 & x_1 \\ 1 & x_2 \\ 1 & x_3 \end{bmatrix} = \begin{bmatrix} 1 & -1 \\ 1 & 0 \\ 1 & 1 \end{bmatrix} \in \mathbb{R}^{3 \times 2}$$

$$X^{*T} X^* = \begin{bmatrix} 1 & 1 & 1 \\ -1 & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & -1 \\ 1 & 0 \\ 1 & 1 \end{bmatrix} = \begin{bmatrix} 3 & 0 \\ 0 & 2 \end{bmatrix} \rightarrow (X^{*T} X^*)^{-1} = \begin{bmatrix} 1/3 & 0 \\ 0 & 1/2 \end{bmatrix}$$

$$X^{*T} Y = \begin{bmatrix} 1 & 1 & 1 \\ -1 & 0 & 1 \end{bmatrix} \begin{bmatrix} Y_1 \\ Y_2 \\ Y_3 \end{bmatrix} = \begin{bmatrix} Y_1 + Y_2 + Y_3 \\ Y_3 - Y_1 \end{bmatrix}$$

$$\hat{\beta}^* = \begin{bmatrix} 1/3 & 0 \\ 0 & 1/2 \end{bmatrix} \begin{bmatrix} Y_1 + Y_2 + Y_3 \\ Y_3 - Y_1 \end{bmatrix} = \begin{bmatrix} \frac{1}{3}(Y_1 + Y_2 + Y_3) \\ \frac{1}{2}(Y_3 - Y_1) \end{bmatrix} = \begin{bmatrix} \hat{\beta}_0^* \\ \hat{\beta}_1^* \end{bmatrix}$$

$$\hat{\beta}_0 = \frac{1}{3}(Y_1 + Y_2 + Y_3) = \hat{\beta}_0^*$$

$$\hat{\beta}_1 = \frac{1}{2}(Y_3 - Y_1) = \hat{\beta}_1^*$$

## Exercise 5

$$Y = X\beta + \epsilon$$

Gauss-Markov Conditions hold

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

Let  $a$  be some column vector where the  $i$ th row is one and all other values are 0

$$a = \begin{bmatrix} 0 \\ \vdots \\ 1 \\ \vdots \\ 0 \end{bmatrix} \leftarrow \text{ith row}$$

Therefore:

$$Ha = \underbrace{\begin{bmatrix} & & & & \\ & & & & \\ & & & & \\ & & & & \\ & & & & \end{bmatrix}}_{\text{hat matrix}} \begin{bmatrix} 0 \\ \vdots \\ 1 \\ \vdots \\ 0 \end{bmatrix} = H_{\cdot i}$$

This means  $Ha$  will be equivalent to the  $i$ th column of  $H$

In order to sum up the  $i$ th column we write:

$$1' H_{\cdot i} = \sum_{j=1}^n H_{ji}$$

We can generalize this to sum any column  $i$  (of matrix  $H$ ) where  $i = 1, 2, \dots, n$

$$1' H_{\cdot i} = 1' Ha \quad \text{due to the fact } H_{\cdot i} = Ha \quad (\text{shown above})$$

$$1' Ha = (H1)'a \quad \text{due to the fact } H = H' : (H1)'a = 1'H'a = 1'Ha$$

We know that  $H1 = 1$  due to the properties of  $H$ , therefore:

$$(H1)'a = (1)'a = 1'a$$

$$\text{We also know } 1'a = \sum_{i=1}^n a_i$$

as shown above,  $a$  is a column vector where only the  $i$ th row is one and all other rows are 0

$$\text{Therefore: } \sum_{i=1}^n a_i = 0 + \dots + 1 + \dots + 0 = 1$$

Therefore, the sum of any column of  $H$  must equal 1.

When we remove the intercept from the model, the definition of  $H$  does not change, however the first column of  $X$  is no longer a column of 1s and the property  $H1=1$  is no longer true. This puts a fault in the logic used above and means we are no longer able to know that the sum of the columns of  $H$  are equal to 1.



# Question 5

With Intercept:

```
#Create the X matrix
X <- cbind(c(1,1,1), c(-1,0,1), c(1,-2,1))

#find the H (hat) matrix
H <- X %*% solve(t(X) %*% X) %*% t(X)

#find the column sums of H
colSums(H)
```

```
## [1] 1 1 1
```

Without Intercept:

```
#Create the X matrix
X <- cbind(c(-1,0,1), c(1,-2,1))

#find the H (hat) matrix
H <- X %*% solve(t(X) %*% X) %*% t(X)

#find the column sums of H
colSums(H)
```

```
## [1] -5.551115e-17  0.000000e+00 -5.551115e-17
```

# Exercise 6

a.  $H \in \mathbb{R}^{n \times n}$  s.t.  $\hat{Y} = HY \in \mathbb{R}^{n \times 1}$

need to show:  $\sum_j H_{ij}^2 = H_{ii}$

Recall:  $\hat{Y} = X\hat{\beta} = X(X'X)^{-1}X'Y$

so  $H = X(X'X)^{-1}X' \in \mathbb{R}^{n \times n}$

Note (Properties of H):

1. H is symmetric:  $H' = H$
2. H is idempotent:  $H^2 = HH = H$

Note:

Let  $A \in \mathbb{R}^{m \times d}$ ,  $B \in \mathbb{R}^{d \times k}$

1.  $[AB]_{ij} = A_{i \cdot} B_{\cdot j}$    
  $\uparrow$    
  $i$ th row  $j$ th column

2.  $[AB]_{i \cdot} = A_{i \cdot} B$

3.  $[AB]_{\cdot j} = AB_{\cdot j}$

Inner Product

$$\langle v, v \rangle = \sum_{j=1}^d v_j^2 \quad \text{for } v \in \mathbb{R}^d$$

$$H_{ii} = [HH]_{ii} = \underbrace{H_{i \cdot}}_{\mathbb{R}^{1 \times n}} \underbrace{H_{\cdot i}}_{\mathbb{R}^{n \times 1}} = H_{i \cdot} (H_{i \cdot})' = \langle H_{i \cdot}, H_{i \cdot} \rangle$$

$$= \sum_{j=1}^n H_{ij}^2$$

b. show  $SSE = Y'Y - \hat{\beta}'X'X\hat{\beta} = Y'Y - \hat{\beta}'X'Y = Y'Y - \hat{\beta}'X'\hat{Y}$

$SSE = e'e$

$= Y'(I-H)'(I-H)Y$

$= Y'(I-H)(I-H)Y$

$= Y'(I-H)Y$

$= Y'Y - Y'H Y$

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

$= Y'Y - \hat{\beta}'X'Y$

Note:  $e = (I-H)Y$

Note:  $(I-H)' = (I-H)$

Note:  $(I-H)(I-H) = (I-H)$

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

Note:  $\hat{\beta}' = Y'X(X'X)^{-1}$

$$\begin{aligned}
 &= Y'Y - \hat{\beta}' \overbrace{x'x}^{I_n} (x'x)^{-1} x'Y \\
 &= Y'Y - \hat{\beta}' x'x \hat{\beta} \\
 &= Y'Y - \hat{\beta}' x' \hat{Y}
 \end{aligned}$$

$$\text{Note: } \hat{\beta} = (x'x)^{-1} x'Y$$

$$\text{Note: } \hat{Y} = x\hat{\beta}$$

$$c. \text{ Show } (Y - x\beta)'(Y - x\beta) = (Y - x\hat{\beta})'(Y - x\hat{\beta}) + (\hat{\beta} - \beta)'x'x(\hat{\beta} - \beta)$$

$$Y - x\beta = Y - x\hat{\beta} + x(\hat{\beta} - \beta) = e + x(\hat{\beta} - \beta)$$

$$\begin{aligned}
 (Y - x\beta)'(Y - x\beta) &= (e + x(\hat{\beta} - \beta))'(e + x(\hat{\beta} - \beta)) \\
 &= (e' + (\hat{\beta} - \beta)'x')(e + x(\hat{\beta} - \beta)) \\
 &= (e' + \hat{\beta}'x' - \beta'x')(e + x\hat{\beta} - x\beta) \\
 &= \underbrace{e'e}_{0} + \underbrace{e'x\hat{\beta}}_{0} - \underbrace{e'x\beta}_{0} + \underbrace{\hat{\beta}'x'e}_{0} + \hat{\beta}'x'x\hat{\beta} - \hat{\beta}'x'x\beta - \underbrace{\beta'x'e}_{0} - \beta'x'x\hat{\beta} + \beta'x'x\beta
 \end{aligned}$$

$$\text{Note: } e'x = 0 \text{ and } x'e = 0$$

$$= e'e + \hat{\beta}'x'x\hat{\beta} - \hat{\beta}'x'x\beta - \beta'x'x\hat{\beta} + \beta'x'x\beta$$

$$\text{Note: } e = Y - x\hat{\beta}$$

$$\text{Note: } (\hat{\beta} - \beta)'x'x(\hat{\beta} - \beta)$$

$$= (\hat{\beta}' - \beta')x'x(\hat{\beta} - \beta)$$

$$= (\hat{\beta}'x'x - \beta'x'x)(\hat{\beta} - \beta)$$

$$= \hat{\beta}'x'x\hat{\beta} - \hat{\beta}'x'x\beta - \beta'x'x\hat{\beta} + \beta'x'x\beta$$

$$= (Y - x\hat{\beta})'(Y - x\hat{\beta}) + (\hat{\beta} - \beta)'x'x(\hat{\beta} - \beta)$$

# Exercise 7

Load data and see the first 6 rows

```
a <- read.table("http://www.stat.ucla.edu/~nchristo/statistics100C/jura.txt", header=TRUE)
```

```
#See the first six rows of the data:  
head(a)
```

```
##           x           y Landuse Rock      Cd      Co      Cr      Cu      Ni      Pb      Zn  
## 1 2.672 3.558           3      5 1.570  8.28 37.12 18.60 18.60 38.20 65.2  
## 2 3.589 4.443           3      1 2.045 10.80 40.80 11.48 21.52 33.36 112.8  
## 3 4.010 4.713           2      1 1.203 12.00 53.20 13.04 23.92 26.56 91.6  
## 4 2.942 3.137           2      5 0.490 10.92 23.40  5.64 14.60 25.88 41.2  
## 5 1.409 2.748           3      3 0.692  8.12 27.16 10.32 14.64 31.16 50.4  
## 6 3.978 2.910           1      2 1.750  9.12 35.48  8.36 26.40 37.72 63.2
```

Create the X and Y matrices (assuming an intercept):

```
X <- as.matrix(cbind(rep(1, nrow(a)), a$Cd, a$Cu, a$Zn))  
Y <- as.matrix(cbind(a$Pb))
```

## 1a. Compute $(X'X)$

```
xx <- t(X) %*% X  
xx
```

```
##           [,1]           [,2]           [,3]           [,4]  
## [1,] 359.000 462.4770 8467.184 27241.60  
## [2,] 462.477 860.0015 11922.631 40964.38  
## [3,] 8467.184 11922.6310 377220.935 803949.53  
## [4,] 27241.600 40964.3842 803949.534 2407169.16
```

## 1b. Compute $(X'X)^{-1}$

```
xx_inverse <- solve(xx)  
xx_inverse
```

```
##           [,1]           [,2]           [,3]           [,4]  
## [1,] 0.0216942476 0.0018266062 1.554642e-04 -3.285175e-04  
## [2,] 0.0018266062 0.0075924443 1.334245e-04 -1.944384e-04  
## [3,] 0.0001554642 0.0001334245 1.225894e-05 -8.124196e-06  
## [4,] -0.0003285175 -0.0001944384 -8.124196e-06 1.015543e-05
```

## 1c. Compute $(X'Y)$

```
xy <- t(X) %*% Y
xy
```

```
##           [,1]
## [1,] 19612.52
## [2,] 27548.77
## [3,] 680026.00
## [4,] 1731176.69
```

## 2. Compute B Hat (the beta\_hat vector)

```
beta_hat <- solve(t(X) %*% X) %*% t(X) %*% Y
beta_hat
```

```
##           [,1]
## [1,] 12.7974915
## [2,] -0.8881627
## [3,] 0.9967046
## [4,] 0.2565816
```

## 3. Compute H (the hat matrix)

```
hat <- X %*% solve(t(X) %*% X) %*% t(X)
head(hat[,1])
```

```
## [1] 0.0047820244 0.0001749063 -0.0001138486 0.0030733254 0.0029572837
## [6] 0.0050189629
```

## 4. Compute Y hat (the fitted values)

```
Yhat <- X %*% beta_hat
head(Yhat)
```

```
##           [,1]
## [1,] 46.67090
## [2,] 51.36578
## [3,] 48.22894
## [4,] 28.55487
## [5,] 35.40059
## [6,] 35.79162
```

## 5. Compute e (the residuals)

```
e <- Y - Yhat
head(e)
```

```
##          [,1]
## [1,]  -8.470904
## [2,] -18.005776
## [3,] -21.668938
## [4,]  -2.674869
## [5,]  -4.240589
## [6,]   1.928383
```

# Exercise 8

$$SSE = e'e = (Y - X\hat{\beta})'(Y - X\hat{\beta}) = \sum (y_i - x_i'\hat{\beta})^2$$

$$SSE_1 = (Y - Xc)'(Y - Xc)$$

$$\text{want to show: } SSE_1 - SSE = (\hat{\beta} - c)' X'X (\hat{\beta} - c)^*$$

Recall: if  $A \in \mathbb{R}^{m \times m}$  is positive, definite, then for all  $v \in \mathbb{R}^{m \times 1}$   $v'Av \geq 0$   
 and  $v \in \mathbb{R}^{m \times 1} \setminus \{0\}$   $v'Av > 0$   
 ↑ excluding 0

claim:  $X'X$  is positive, definite

Therefore \* is showing that  $SSE \leq SSE_1$  for any  $c \in \mathbb{R}^p$

$$\begin{aligned} SSE_1 &= (Y - Xc)'(Y - Xc) = (Y - X\hat{\beta} + X\hat{\beta} - Xc)'(Y - X\hat{\beta} + X\hat{\beta} - Xc) \\ &= (e + X(\hat{\beta} - c))'(e + X(\hat{\beta} - c)) \\ &= \underbrace{e'e}_{SSE} + \underbrace{e'X(\hat{\beta} - c)}_{// 0} + (\hat{\beta} - c)'X'e + \underbrace{(\hat{\beta} - c)'X'X(\hat{\beta} - c)}_{// 0} \\ &= SSE + (\hat{\beta} - c)'X'X(\hat{\beta} - c) \\ &\Rightarrow SSE_1 - SSE = (\hat{\beta} - c)'X'X(\hat{\beta} - c) \geq 0 \end{aligned}$$

Recall HW1 Exercise 5

$X'X \in \mathbb{R}^{p \times p}$  and is symmetric if columns are independent  
 when  $X$  is full-column rank and is symmetric  $\Rightarrow X$  is positive definite

transpose of 0 is 0