

Homework 03

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1- First of all, let's consider:

$$S_{xx} = \sum_{i=1}^n (x_i - \bar{x})^2$$

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

$$S_{xy} = \sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})$$

$$\text{Var}(y_i) = \sigma^2$$

$$\beta_1 = \frac{\sum_{i=1}^n (x_i - \bar{x})y_i}{S_{xx}}$$

a) Let's find out $\text{Var}(\beta_1)$ first:

$$\text{Var}(\beta_1) = \text{Var}\left(\frac{S_{xy}}{S_{xx}}\right)$$

$$\text{Var}(\beta_1) = \text{Var}\left(\frac{\sum_{i=1}^n (x_i - \bar{x})y_i}{S_{xx}}\right)$$

$$\text{Var}(\beta_1) = \frac{\text{Var}(y_i)}{(S_{xx})^2} \sum_{i=1}^n (x_i - \bar{x})^2$$

$$\text{Var}(\beta_1) = \frac{\sigma^2}{S_{xx}}$$

$$\text{cov}(\beta_1) = \frac{\sigma^2}{S_{xx}}$$

$$\text{cov}(\hat{\beta}_0, \hat{\beta}_1) = \text{cov}(\bar{y} - \hat{\beta}_1 \bar{x}, \hat{\beta}_1)$$

$$= \text{cov}\left(\sum_{i=1}^n y_i - \sum_{i=1}^n \frac{(x_i - \bar{x})\bar{x}}{S_{xx}} y_i, \sum_{i=1}^n \frac{(x_i - \bar{x})y_i}{S_{xx}}\right)$$

$$= \sum_{i=1}^n \left(\frac{1}{n} - \frac{x_i - \bar{x}}{S_{xx}} \bar{x}\right) \frac{x_i - \bar{x}}{S_{xx}} \sigma^2$$

$$= -\frac{\bar{x}}{S_{xx}} \sigma^2$$

b)

$$\text{cov}(\bar{y}, \hat{\beta}_1) = \text{cov}\left(\frac{\sum_{i=1}^n y_i}{n}, \frac{\sum (x_i - \bar{X})y_i}{S_{xx}}\right)$$

$$\begin{aligned}
&= \frac{1}{nS_{xx}} \text{cov}\left(\sum_{i=1}^n y_i, \sum (x_i - \bar{X})y_i\right) \\
&= \frac{1}{nS_{xx}} \text{cov}(y_1 + \dots + y_n, (x_1 - \bar{X})y_1 + \dots + (x_n - \bar{X})y_n) \\
&= \frac{1}{nS_{xx}} [\text{cov}(y_1, (x_1 - \bar{X})y_1) + \dots + \text{cov}(y_n, (x_n - \bar{X})y_n)] \\
&= \frac{\sum_{i=1}^n \text{cov}(y_i - \bar{X}y_i)}{nS_{xx}} \\
&= \frac{\sum_{i=1}^n (x_i - \bar{X})\text{cov}(y_i, y_i)}{nS_{xx}} \\
&= \frac{(n\bar{X} - x\bar{X})\sigma^2}{nS_{xx}} = 0
\end{aligned}$$

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$$\begin{aligned}
SS_r &= \sum_{i=1}^n (\hat{y}_i - \bar{y})^2 \\
&= \sum_{i=1}^n (\hat{y}_i^2 - 2\hat{y}_i\bar{y} + \bar{y}^2) \\
&= \sum_{i=1}^n (\hat{y}_i^2) - 2 \sum_{i=1}^n (\hat{y}_i\bar{y}) + \sum_{i=1}^n (\bar{y}^2) \\
&= \sum_{i=1}^n (\hat{y}_i^2) - 2\bar{y} \sum_{i=1}^n (\hat{y}_i) + n\bar{y}^2 \\
&= \sum_{i=1}^n (\hat{y}_i^2) - 2\bar{y}(n\bar{y}) + n\bar{y}^2 \\
&= \sum_{i=1}^n (\hat{y}_i^2) - 2(n\bar{y}^2) + n\bar{y}^2 \\
&= \sum_{i=1}^n (\hat{y}_i^2) - (n\bar{y}^2)
\end{aligned}$$

3 - Considering $H = X(X^T X)^{-1} X^T$

a) \mathbf{H} is idempotent: it means that any power of itself is itself.

$$H^2 = (X(X^T X)^{-1} X^T)(X(X^T X)^{-1} X^T)$$

$$H^2 = (X(X^T X)^{-1} X^T)(X(X^T X)^{-1} X^T)$$

And,

$$I = (X^T X)^{-1} (X^T X)$$

Thus,

$$H^2 = X(X^T X)^{-1} X^T$$

$$H^2 = H$$

Now considering:

$$(H - I)(I - H) = I - H$$

$$I - H - H + H^2 = I - H$$

$$I - 2H + H^2 = I - H$$

And,

$$H^2 = H$$

Thus,

$$I - 2H + H = I - H$$

$$I - H = I - H$$

b)

$$\hat{Y} = X(X^T X)^{-1} X^T Y = HY$$

$$Var(\hat{Y}) = Var(HY)$$

$$Var(\hat{Y}) = HVar(Y)H^T$$

$$Var(\hat{Y}) = \sigma^2 HH^T$$

Considering that:

$$H^T = H$$

So,

$$Var(\hat{Y}) = \sigma^2 HH$$

Also considering that:

$$H^2 = H$$

Therefore,

$$Var(\hat{Y}) = \sigma^2 H$$

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$$R^2 \equiv 1 - \frac{SS_{res}}{SS_{tot}}$$

For R^2 be larger than 1 or smaller than 0, $SS_{res} \leq SS_{tot}$, SS_{res} and SS_{tot} be both positive or both negative.

$$SS_{res} = \sum_i (y_i - f_i)^2$$

$$SS_{tot} = \sum_i (y_i - \bar{y})^2$$

SS_{tot} is the gaps between the y observed values and their mean.

At the end we can get two different scenarios:

1 $y = \bar{y}$, the model minimises the residual. Thus, $SS_{res} = SS_{tot}$;

2 The regression results in a different model, since the regression is producing a model that minimises residuals, the residuals of this model must be smaller than y, so $SS_{res} < SS_{tot}$.

Also, SS_{tot} and SS_{res} are given by the sum of squares, thus they are always positive.