Yet Another Proof of the Gauss-Markov Theorem Statistics 215

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Suppose X is fixed (not random), $n \times p$, of full rank p. Suppose

(1)
$$Y = X\beta + \epsilon$$

where

(2)
$$E(\epsilon) = 0_{n \times 1}, \quad \operatorname{cov}(\epsilon) = \sigma^2 I_{n \times n}.$$

THEOREM. GAUSS-MARKOV. The OLS estimator is BLUE.

The acronym BLUE stands for Best Linear Unbiased Estimator, i.e., the one with the smallest variance. Let $\gamma = c'\beta$, where c is $p \times 1$: the parameter γ is a linear combination of the components of β . Examples would include β_1 , or $\beta_2 - \beta_3$. The OLS estimator for γ is $\hat{\gamma} = c'\hat{\beta} = c'(X'X)^{-1}X'Y$. This is unbiased by (2), and $\operatorname{var}(\hat{\gamma}) = \sigma^2 c'(X'X)^{-1}c$. Let $\tilde{\gamma}$ be another linear unbiased estimator for γ . Then $\operatorname{var}(\tilde{\gamma}) \ge \operatorname{var}(\hat{\gamma})$, and $\operatorname{var}(\tilde{\gamma}) = \operatorname{var}(\hat{\gamma})$ entails $\tilde{\gamma} = \hat{\gamma}$. That is what the theorem says.

Proof. Recall that X is fixed. Since $\tilde{\gamma}$ is by assumption a linear function of Y, there is an $n \times 1$ vector d with $\tilde{\gamma} = d'Y = d'X\beta + d'\epsilon$. Then $E(\tilde{\gamma}) = d'X\beta$ by (2). Since $\tilde{\gamma}$ is unbiased, $d'X\beta = c'\beta$ for all β . Therefore,

$$d'X = c'.$$

Caution: *c* is $p \times 1$ but *d* is $n \times 1$

It will help to have another formula for $var(\hat{\gamma})$. Since

$$\hat{\gamma} = c'\beta + c'(X'X)^{-1}X'\epsilon,$$

we have

$$var(\hat{\gamma}) = \sigma^{2} \|c'(X'X)^{-1}X'\|^{2}$$

= $\sigma^{2} \|X(X'X)^{-1}c\|^{2}$
= $\sigma^{2} \|X(X'X)^{-1}X'd\|^{2}$
= $\sigma^{2} \|Hd\|^{2}$

where *H* is the hat matrix. On the other hand, $\tilde{\gamma} = d'X\beta + d'\epsilon$, so $\operatorname{var}(\tilde{\gamma}) = \sigma^2 ||d||^2$. But

$$d = Hd + (I - H)d,$$

the summands being orthogonal since *H* is symmetric and idempotent. In particular, $||d||^2 = ||Hd||^2 + ||(I - H)d||^2$ and $||d||^2 \ge ||Hd||^2$, the inequality being strict unless

$$d = Hd = X(X'X)^{-1}X'd = X(X'X)^{-1}c,$$

i.e., $\tilde{\gamma} = \hat{\gamma}$.