

Prediction:

^{True model}
we fit the model $\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \varepsilon$ and estimate \mathbf{b} of $\boldsymbol{\beta}$. Using OLS.

Let $\mathbf{x}'_0 = [1, x_{01}, \dots, x_{0k}]$ represent a set

of explanatory-variable scores for which a prediction is desired

- a) If we use $\hat{Y}_0 = \mathbf{x}'_0 \mathbf{b}$ to estimate $E(Y_0)$, then the error in estimation is $\delta \equiv \hat{Y}_0 - E(Y_0)$. Show that if the model is correct, then $E(\delta) = 0$ (i.e. \hat{Y}_0 is an unbiased estimator of $E(Y_0)$) and that $V(\delta) = \sigma_\varepsilon^2 \mathbf{x}'_0 (\mathbf{X}'\mathbf{X})^{-1} \mathbf{x}_0$.

$$\begin{aligned} E(\delta) &= E[\hat{Y}_0 - E(Y_0)] \\ &= E(\hat{Y}_0) - E(E(Y_0)) \quad \text{linearity of } E \\ &= \mathbf{x}'_0 E(\mathbf{b}) - E(\mathbf{x}'_0 \boldsymbol{\beta} + \varepsilon_0) \\ &= \mathbf{x}'_0 E(\hat{\boldsymbol{\beta}}) - \mathbf{x}'_0 \boldsymbol{\beta} \\ &= (\mathbf{x}'_0 - \mathbf{x}_0) \boldsymbol{\beta} = 0 \end{aligned}$$

$$\begin{aligned} V(\delta) &= V(\hat{Y}_0 - E(Y_0)) \\ &= V(\hat{Y}_0) \\ &= \mathbf{x}'_0{}^T V(\hat{\boldsymbol{\beta}}) \mathbf{x}_0 \\ &= \mathbf{x}'_0{}^T \left[\sigma^2 (\mathbf{X}'\mathbf{X})^{-1} \right] \mathbf{x}_0 \\ &= \sigma^2 \mathbf{x}'_0 (\mathbf{X}'\mathbf{X})^{-1} \mathbf{x}_0 \end{aligned}$$

Since $\mathbf{x}'_0 = \mathbf{x}_0$ True

- b) We may be interested not in estimating the ^{$E(Y_0)$} *expected* value of Y_0 but in predicting or forecasting the *actual* value of $Y_0 = \mathbf{x}'_0 \boldsymbol{\beta} + \varepsilon_0$ that will be observed. The (error in the forecast) is then



$$D \equiv \hat{Y}_0 - Y_0 = \mathbf{x}'_0 \mathbf{b} - (\mathbf{x}'_0 \boldsymbol{\beta} + \varepsilon_0) = \mathbf{x}'_0 (\mathbf{b} - \boldsymbol{\beta}) - \varepsilon_0$$

Show that $E(D) = 0$ and that $V(D) = \sigma_\varepsilon^2 [1 + \mathbf{x}'_0 (\mathbf{X}'\mathbf{X})^{-1} \mathbf{x}_0]$. Why is the forecast error D greater than the variance of δ found in part (a)?

$$\begin{aligned} E(D) &= E(\hat{Y}_0 - Y_0) \\ &= E(\mathbf{x}'_0 (\mathbf{b} - \boldsymbol{\beta}) - \varepsilon_0) \\ &= 0 \end{aligned}$$

$$\begin{aligned} V(D) &= V(\hat{Y}_0 - Y_0) \\ &= V(\mathbf{x}'_0 (\mathbf{b} - \boldsymbol{\beta}) - \varepsilon_0) \\ &= \mathbf{x}'_0{}^T V(\mathbf{b} - \boldsymbol{\beta}) \mathbf{x}_0 + V(\varepsilon_0) \\ &= \sigma^2 \mathbf{x}'_0 (\mathbf{X}'\mathbf{X})^{-1} \mathbf{x}_0 + \sigma^2 \end{aligned}$$

[2 Pts.] *TRUE / FALSE Under the assumptions $E(Y) = X\beta$ and $Cov(Y) = \sigma^2 I$, all the fitted values have the same variance.*

FALSE. The variance-covariance matrix of the fitted values is $\sigma^2 H$ where H is the projection matrix $X(X^T X)^{-1} X^T$. The variances of the fitted values are the diagonal terms of this matrix, which need not all be the same.

5. [2 Pts.] *TRUE/FALSE If m is a submodel of a full model M , then $ErrSS(m) - ErrSS(M)$ and $ErrSS(M)$ are statistically independent under the assumption of normality.*

TRUE. $ErrSS(m) - ErrSS(M) = y^T[(I - H_m) - (I - H_M)]y = y^T(H_M - H_m)y$, while $ErrSS(M) = y^T(I - H_M)y$. Since $(I - H_M)y$ and $(H_M - H_m)y$ are both multivariate normal functions of y under the normality assumption, and since they are also orthogonal, their quadratic forms must be independent.