

Properties of the LS estimates

ST552 Lecture 6

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The least squares estimates are unbiased

Go over last time's fill in the blanks.

The least squares estimates have variance-covariance matrix

$$\text{Var}(\hat{\beta}) =$$

We can pull out the variance of individual parameters from the diagonal, and covariances from the off diagonals:

$$\begin{aligned}\text{Var}(\hat{\beta}_j) &= \sigma^2 \left((X^T X)^{-1} \right)_{j,j} \\ \text{Cov}(\hat{\beta}_j, \hat{\beta}_k) &= \sigma^2 \left((X^T X)^{-1} \right)_{j,k}\end{aligned}$$

(Careful: the way I did the notation, the row and column indexing starts at 0 (i.e. for β_0))

Gauss Markov Theorem

You might wonder if we can find estimates with better properties. The Gauss-Markov theorem says the least squares estimates are BLUE.

Of all linear, unbiased estimates, the least squares estimates have the smallest variance.

Of course if you are willing to let go of linear and/or, unbiasedness you might be able to find an estimate with smaller variance.

Gauss Markov Theorem (proof)

Estimating σ

To make use of the variance-covariance results we need to be able to estimate σ^2 .

An unbiased estimate is:

$$\hat{\sigma}^2 = \frac{1}{n-p} \sum_{i=1}^n e_i^2 = \frac{\|e\|^2}{n-p}$$

Proof:

Standard errors

$$\sqrt{\widehat{\text{Var}}(\hat{\beta}_j)} = \text{SE}(\hat{\beta}_j) = \sqrt{\hat{\sigma}^2 (X^T X)^{-1}_{j,j}}$$

Summary

For the linear regression model

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

where $E(\epsilon) = 0_{n \times 1}$, $\text{Var}(\epsilon) = \sigma^2 I_n$, and the matrix $X_{n \times p}$ is fixed with rank p .

The least squares estimates are

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

Furthermore, the least squares estimates are BLUE, and

$$E(\hat{\beta}) = \beta, \quad \text{Var}(\hat{\beta}) = \sigma^2 (X^T X)^{-1}$$
$$E(\hat{\sigma}^2) = E\left(\frac{1}{n-p} \sum_{i=1}^n e_i^2\right) = \sigma^2$$

We have not used any Normality assumptions to show these properties.