

Stat 608 BLUE Notes

BLUE: Best Linear Unbiased Estimator

- The Gauss-Markov Theorem says that our parameter estimate vector is BLUE:
 - Best: Minimum Variance
 - Linear: A linear combination of Y's (we can write $\hat{\beta}$ as **a'y** for some vector a)
 - Unbiased: That is, $E[\hat{\beta}|X] = \beta$
 - Estimator: A statistic

For estimating the mean of the normal distribution, we like the sample mean better than the sample median because of the smaller variability.

Gauss-Markov Theorem

- lacktriangle Consider the linear model: $\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \mathbf{e}$
- Assume that the errors have mean and covariance 0, that the variance of the errors is constant, and that the design matrix X is full rank. Then:

For any
$$\tilde{\boldsymbol{\beta}}$$
 a linear combination of \mathbf{y} such that $E[\tilde{\boldsymbol{\beta}}] = \boldsymbol{\beta}$, $Var(\mathbf{c}'\tilde{\boldsymbol{\beta}}) \geq Var(\mathbf{c}'\hat{\boldsymbol{\beta}})$

That is, $\mathbf{c}'\hat{\boldsymbol{\beta}}$ is the Best Linear Unbiased Estimator of $\mathbf{c}'\boldsymbol{\beta}$

Note: we didn't assume independence of the errors or any particular distribution of the errors.

Gauss-Markov Theorem

■ Proof:

First note that the expected value and variance of $\mathbf{c}'\hat{\boldsymbol{\beta}}$ are:

$$E[\mathbf{c}'\hat{\boldsymbol{\beta}}] = \mathbf{c}'\boldsymbol{\beta}$$
 $Var(\mathbf{c}'\hat{\boldsymbol{\beta}}) = \sigma^2\mathbf{c}'(\mathbf{X}'\mathbf{X})^{-1}\mathbf{c}$

Next, since $\tilde{\beta}$ is another linear combination of y's, it can be written as:

$$\tilde{\boldsymbol{\beta}} = [(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}' + \mathbf{B}] \mathbf{y} + \mathbf{b}_0$$

where **B** and \mathbf{b}_0 are a constant p×n matrix and p×1 vector, respectively.

Gauss-Markov Theorem

■ Then:

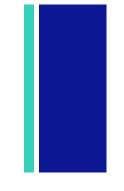
$$E[\tilde{\boldsymbol{\beta}}] = E[[(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}' + \mathbf{B}]\mathbf{y} + \mathbf{b}_0]$$
=

Note: Being the best linear unbiased estimator means we are only concerned with unbiased $\tilde{\beta}$ which implies both BX = 0 and $b_0 = 0$.

Gauss-Markov Theorem

■ The variance of $\tilde{\beta}$ is:

$$Var(\tilde{\boldsymbol{\beta}}) = Var([(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}' + \mathbf{B}]\mathbf{y})$$
$$= Var([(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}' + \mathbf{B}](\mathbf{X}\boldsymbol{\beta} + \mathbf{e}))$$



Gauss-Markov Theorem

■ So then, the variance of the new estimator is:

$$Var(\mathbf{c}'\hat{\boldsymbol{\beta}}) = \mathbf{c}' Var(\hat{\boldsymbol{\beta}}) \mathbf{c}$$

$$= \mathbf{c}' \left\{ \sigma^2 \left[(\mathbf{X}'\mathbf{X})^{-1} + \mathbf{B}\mathbf{B}' \right] \right\} \mathbf{c}$$

$$= Var(\mathbf{c}'\hat{\boldsymbol{\beta}}) + \mathbf{c}'\mathbf{B}\mathbf{B}'\mathbf{c}$$

■ But since **BB'** is positive semidefinite, **c'BB'c** ≥ 0.



UMVUE: Uniform Minimum Variance Unbiased Estimator

- 610/611: Uniform Minimum Variance Unbiased Estimators
 - Minimum variance for UMVUE is across all unbiased estimators, including non-linear estimators
 - Saying $\hat{\beta}$ is BLUE only means minimum variance across all unbiased linear estimators.
 - To prove an estimator is UMVUE, often the Cramer-Rao Lower Bound is used, which requires some distribution assumptions.
 - The Gauss-Markov Theorem doesn't require any distribution assumptions; β is BLUE whatever the distribution of the errors.



Example: Median

- Assume that we have iid errors with mean 0.
- For the linear model $y_i = \beta + e_i$ we might use the median as an estimator of our parameter β .
- Is the median the BLUE for parameter β ? Why or why not?

Example: Another Estimator



$$y_i = \beta + e_i$$

consider the estimator for β :

$$\frac{y_1 + y_2}{2}$$

Is the above estimator the BLUE for estimating β? Why or why not?