Gauss Markov & Predictive Distributions

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STA721 Linear Models

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Outline

Topics

- Gauss-Markov Theorem
- Estimability and Prediction

Readings: Christensen Chapter 2, Chapter 6.3, (Appendix A, and Appendix B as needed)

Gauss-Markov Theorem

Theorem

Under the assumptions:

$$\begin{aligned} E[\mathbf{Y}] &= \boldsymbol{\mu} \\ Cov(\mathbf{Y}) &= \sigma^2 \mathbf{I}_n \end{aligned}$$

every estimable function $\psi = \boldsymbol{\lambda}^T \boldsymbol{\beta}$ *has a unique unbiased linear estimator* $\hat{\psi}$ *which has minimum variance in the class of all unbiased linear estimators.* $\hat{\psi} = \boldsymbol{\lambda}^T \hat{\boldsymbol{\beta}}$ *where* $\hat{\boldsymbol{\beta}}$ *is any set of ordinary least squares estimators.*

Unique Unbiased Estimator

Lemma

- If $\psi = \boldsymbol{\lambda}^T \beta$ is estimable, there exists a unique linear unbiased estimator of $\psi = \mathbf{a}^{*T}\mathbf{Y}$ with $a^* \in C(\mathbf{X})$.
- If $\mathbf{a}^T\mathbf{Y}$ is any unbiased linear estimator of ψ then a^* is the projection of $\mathbf{a}$ onto $C(\mathbf{X})$, i.e. $\mathbf{a}^* = \mathrm{P}_{\mathbf{X}}\mathbf{a}$.

Unique Unbiased Estimator

Proof

- Since ψ is estimable, there exists an $\mathbf{a} \in \mathbb{R}^n$ for which $\mathsf{E}[\mathbf{a}^T\mathbf{Y}] = \boldsymbol{\lambda}^T\boldsymbol{\beta} = \psi$ with $\mathbf{a}^T = \lambda^T\mathbf{X}$
- Let $\mathbf{a} = \mathbf{a}^* + \mathbf{u}$ where $\mathbf{a}^* \in C(\mathbf{X})$ and $\mathbf{u} \in C(\mathbf{X})^\perp$
- Then

$$\begin{aligned} \psi = \mathsf{E}[\mathbf{a}^T\mathbf{Y}] &= \mathsf{E}[\mathbf{a}^{*T}\mathbf{Y}] + {\color{red}\mathsf{E}[\mathbf{u}^T\mathbf{Y}]} \\ &= \mathsf{E}[\mathbf{a}^{*T}\mathbf{Y}] + {\color{red}0} \end{aligned}$$

$$\mathsf{E}[\mathbf{u}^T\mathbf{Y}] = \mathbf{u}^T\mathbf{X}\boldsymbol{\beta}$$

since $\mathbf{u} \perp C(\mathbf{X})$ (i.e. $\mathbf{u} \in C(\mathbf{X})^\perp$) $\mathsf{E}[\mathbf{u}^T\mathbf{Y}] = 0$

- Thus $\mathbf{a}^{*T}\mathbf{Y}$ is also an unbiased linear estimator of ψ with $\mathbf{a}^* \in C(\mathbf{X})$

Uniqueness

Proof.

Suppose that there is another $\mathbf{v} \in C(\mathbf{X})$ such that $\mathsf{E}[\mathbf{v}^T\mathbf{Y}] = \psi$. Then for all $\boldsymbol{\beta}$

$$\begin{aligned} 0 &= \mathsf{E}[\mathbf{a}^{*T}\mathbf{Y}] - \mathsf{E}[\mathbf{v}^T\mathbf{Y}] \\ &= (\mathbf{a}^* - \mathbf{v})^T\mathbf{X}\boldsymbol{\beta} \\ \text{So } (\mathbf{a}^* - \mathbf{v})^T\mathbf{X} &= 0 \quad \text{for all } \boldsymbol{\beta} \end{aligned}$$

- Implies $(\mathbf{a}^* - \mathbf{v}) \in C(\mathbf{X})^\perp$
- but by assumption $(\mathbf{a}^* - \mathbf{v}) \in C(\mathbf{X})$ ($C(\mathbf{X})$ is a vector space)
- the only vector in BOTH is $\mathbf{0}$, so $\mathbf{a}^* = \mathbf{v}$

Therefore $\mathbf{a}^{*T}\mathbf{Y}$ is the unique linear unbiased estimator of ψ with $\mathbf{a}^* \in C(\mathbf{X})$. $\square$

Proof of Minimum Variance (G-M)

- Let ${\mathbf{a}^*}^T\mathbf{Y}$ be the unique unbiased linear estimator of ψ with $\mathbf{a}^* \in C(\mathbf{X})$.
- Let $\mathbf{a}^T\mathbf{Y}$ be any unbiased estimate of ψ; $\mathbf{a} = \mathbf{a}^* + \mathbf{u}$ with $\mathbf{a}^* \in C(\mathbf{X})$ and $\mathbf{u} \in C(\mathbf{X})^\perp$

$$
\begin{aligned}
\mathrm{Var}(\mathbf{a}^T\mathbf{Y}) &= \mathbf{a}^T \mathrm{Cov}(\mathbf{Y})\mathbf{a} \\
&= \sigma^2\|\mathbf{a}\|^2 \\
&= \sigma^2(\|\mathbf{a}^*\|^2 + \|\mathbf{u}\|^2 + 2{\mathbf{a}^*}^T\mathbf{u}) \\
&= \sigma^2(\|\mathbf{a}^*\|^2 + \|\mathbf{u}\|^2) + 0 \\
&= \mathrm{Var}({\mathbf{a}^*}^T\mathbf{Y}) + \sigma^2\|\mathbf{u}\|^2 \\
&\geq \mathrm{Var}({\mathbf{a}^*}^T\mathbf{Y})
\end{aligned}
$$

with equality if and only if $\mathbf{a} = \mathbf{a}^*$

Hence ${\mathbf{a}^*}^T\mathbf{Y}$ is the unique linear unbiased estimator of ψ with minimum variance "BLUE" = Best Linear Unbiased Estimator

Continued

Proof.

Show that $\hat{\psi} = \mathbf{a}^{*T}\mathbf{Y} = \boldsymbol{\lambda}^T\hat{\beta}$

Since $\mathbf{a}^* \in C(\mathbf{X})$ we have $\mathbf{a}^* = \mathrm{P}_{\mathbf{X}}\mathbf{a}^*$

$$\begin{aligned}
\mathbf{a}^{*T}\mathbf{Y} &= \mathbf{a}^{*T}\mathrm{P}_X^T\mathbf{Y} \\
&= \mathbf{a}^{*T}\mathrm{P}_x\mathbf{Y} \\
&= \mathbf{a}^{*T}\mathbf{X}\hat{\beta} \\
&= \boldsymbol{\lambda}^T\hat{\beta}
\end{aligned}$$

for $\boldsymbol{\lambda}^T = \mathbf{a}^{*T}\mathbf{X}$ or $\mathbf{a} = \mathbf{X}^T\lambda$ $\square$

MVUE

- Gauss-Markov Theorem says that OLS has minimum variance in the class of all Linear Unbiased estimators
- Requires just first and second moments
- Additional assumption of normality, OLS $=$ MLEs have minimum variance out of ALL unbiased estimators; not just linear estimators (requires Completeness and Rao-Blackwell Theorem - next semester)

Prediction

- For predicting at new $\mathbf{x}_*$ is there always a unique unbiased estimator of $E[\mathbf{Y} \mid \mathbf{x}_*]$?
- If so how do we determine it?

Existence

- $\mathbf{x}_* \beta$ has a unique unbiased estimator if $\mathbf{x}_* = \boldsymbol{\lambda} = \mathbf{X}^T \mathbf{a}$
- Clearly if $\mathbf{x}_* = \mathbf{x}_i$ (ith row of observed data) then it is estimable with $\mathbf{a}$ equal to the vector with a 1 in the ith position even if $\mathbf{X}$ is not full rank!
- What about out of sample prediction?

Example

```
> x1 = -4:4
> x2 = c(-2, 1, -1, 2, 0, 2, -1, 1, -2)
> x3 = 3*x1  -2*x2
> x4 = x2 - x1 + 4
> Y = 1+x1+x2+x3+x4 + c(-.5,.5,.5,-.5,0,.5,-.5,-.5,.5)
> dev.set = data.frame(Y, x1, x2, x3, x4)
> lm1234 = lm(Y ~ x1 + x2 + x3 + x4, data=dev.set)
> coefficients(lm1234)
 (Intercept)    x1     x2      x3      x4
5.000000e+00     3 v    0      NA      NA

> lm3412 = lm(Y ~ x3 + x4 + x1 + x2, data = dev.set)
> coefficients(lm3412)
(Intercept)     x3     x4      x1      x2
        -19      3      6      NA      NA
```

In Sample Predictions

```
> cbind(dev.set, predict(lm1234), predict(lm3412))
     Y x1 x2  x3 x4    predict(lm1234)    predict(lm3412)
1 -7.5 -4 -2  -8  6                 -7                 -7
2 -3.5 -3  1 -11  8                 -4                 -4
3 -0.5 -2 -1  -4  5                 -1                 -1
4  1.5 -1  2  -7  7                  2                  2
5  5.0  0  0   0  4                  5                  5
6  8.5  1  2  -1  5                  8                  8
7 10.5  2 -1   8  1                 11                 11
8 13.5  3  1   7  2                 14                 14
9 17.5  4 -2  16 -2                 17                 17
```

Both models agree!

Out of Sample

```
> out = data.frame(test.set,
                   Y1234=predict(lm1234, new=test.set),
                   Y3412=predict(lm3412, new=test.set))
> out
  x1 x2 x3 x4 Y1234 Y3412
1  3  1  7  2    14    14
2  6  2 14  4    23    47
3  6  2 14  0    23    23
4  0  0  0  4     5     5
5  0  0  0  0     5   -19
6  1  2  3  4     8    14
```

Agreement for cases 1, 3, and 4 only! Can we determine that without finding the predictions and comparing?

Determining Estimable $\boldsymbol{\lambda}$

- Estimable means that $\boldsymbol{\lambda} = \mathbf{X}^T\mathbf{a}$ for $\mathbf{a} \in C(\mathbf{X})$
- $\boldsymbol{\lambda} \in C(\mathbf{X}^T)$ ($\boldsymbol{\lambda} \in R(\mathbf{X})$)
- $\boldsymbol{\lambda} \perp C(\mathbf{X}^T)^\perp$
- $C(\mathbf{X}^T)^\perp$ is the null space of $\mathbf{X}$

$$\mathbf{v} \perp C(\mathbf{X}^T): \ \mathbf{X}\mathbf{v} = 0 \Leftrightarrow \mathbf{v} \in N(\mathbf{X})$$

- $\boldsymbol{\lambda} \perp N(\mathbf{X})$
- if P is a projection onto $C(\mathbf{X}^T)$ then $\mathbf{I} - \mathrm{P}$ is a projection onto $N(X)$ and therefore $(\mathbf{I} - \mathrm{P})\boldsymbol{\lambda} = \mathbf{0}$ if $\boldsymbol{\lambda}$ is estimable

Take $\mathrm{P}_{\mathbf{X}^T} = (\mathbf{X}^T\mathbf{X})(\mathbf{X}^T\mathbf{X})^-$ as a projection onto $C(\mathbf{X}^T)$

Example

```
> library("estimability" )

> outE = cbind(epredict(lm1234, test.set), epredict(lm3412,

> outE

  [,1] [,2]
1   14   14
2   NA   NA
3   23   23
4    5    5
5   NA   NA
6   NA   NA
```

Rows 2, 5, and 6 are not estimable! No linear unbiased estimator

Summary

- When BLUE exist under normality are MVUE (ditto for prediction)
- BLUE/BLUP do not always for estimation/prediction if $\mathbf{X}$ is not full rank
- may occur with redundancies for modest $p < n$ and of course $p > n$
- Eliminate redundancies by removing variables (variable selection)
- Consider alternative estimators

Other Estimators

What about some estimator $g(\mathbf{Y})$ that is not unbiased?

- Mean Squared Error for estimator $g(\mathbf{Y})$ of $\boldsymbol{\lambda}^T\beta$ is

$$\mathsf{E}[g(\mathbf{Y}) - \boldsymbol{\lambda}^T\beta]^2 = \mathsf{Var}(g(\mathbf{Y})) + \mathsf{Bias}^2(g(\mathbf{Y}))$$

  where $\mathsf{Bias} = \mathsf{E}[g(\mathbf{Y})] - \boldsymbol{\lambda}^T\boldsymbol{\beta}$
- Bias vs Variance tradeoff
- Can have smaller MSE if we allow some Bias!