Bayesian Estimation in Linear Models

STA721 Linear Models Duke University

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Bayesian Estimation

Model $\mathbf{Y} = \mathbf{X}\beta + \boldsymbol{\epsilon}$ with $\boldsymbol{\epsilon} \sim \mathsf{N}(\mathbf{0}_n, \sigma^2 \mathbf{I}_n)$

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$$p(\boldsymbol{\beta}, \phi \mid \mathbf{Y}) \propto \mathcal{L}(\boldsymbol{\beta}, \phi) p(\boldsymbol{\beta}, \phi)$$

reweight prior beliefs by likelihood of parameters under observed data

Posterior

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$$p(\boldsymbol{\theta} \mid \mathbf{Y}) = \frac{p(\mathbf{Y} \mid \boldsymbol{\theta}) p(\boldsymbol{\theta})}{\int_{\boldsymbol{\Theta}} p(\mathbf{Y} \mid \boldsymbol{\theta}) p(\boldsymbol{\theta}) \, d\boldsymbol{\theta}}$$

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Easiest to work with Bayes Theorem in proportional form and then identify the normalizing constant.

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Factor joint prior distribution

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$$p(\phi) = \frac{1}{\Gamma(\nu_0/2)} \left(\frac{\mathsf{SS}_0}{2}\right)^{\nu_0/2} \phi^{\nu_0/2-1} e^{-\phi \mathsf{SS}_0/2}$$

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$$(\boldsymbol{\beta}, \phi)^T \mid \mathbf{Y} \sim \mathrm{NG}(\mathbf{b}_n, \Phi_n, \nu_n, \mathrm{SS}_n)$$

Finding the Posterior Distribution

Express Likelihood: $\mathcal{L}(\beta, \phi) \propto \phi^{n/2} e^{-\phi \frac{\mathsf{SSE}}{2}} e^{-\frac{\phi}{2}(\boldsymbol{\beta}-\hat{\boldsymbol{\beta}})^T(\mathbf{X}^T\mathbf{X})(\boldsymbol{\beta}-\hat{\boldsymbol{\beta}})}$

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p(\boldsymbol{\beta}, \phi \mid \mathbf{Y}) \quad \propto \quad & \phi^{\frac{n+p+\nu_0}{2}-1} e^{-\frac{\phi}{2}(\mathsf{SSE}+\mathsf{SS}_0)} \\
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\end{aligned}
$$

Quadratic in Normal

$$
\exp\left\{-\frac{\phi}{2}(\boldsymbol{\beta}-\mathbf{b})^T\Phi(\boldsymbol{\beta}-\mathbf{b})\right\} = \exp\left\{-\frac{\phi}{2}(\boldsymbol{\beta}^T\Phi\boldsymbol{\beta} - 2\boldsymbol{\beta}^T\Phi\mathbf{b} + \mathbf{b}^T\Phi\mathbf{b})\right\}
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- Expand quadratics and regroup terms

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- Expand quadratics and regroup terms
- Read off posterior precision from Quadratic in $\boldsymbol{\beta}$

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$$
\begin{aligned}
p(\boldsymbol{\beta}, \phi \mid \mathbf{Y}) \quad \propto \quad & \phi^{\frac{n+p+\nu_0}{2} - 1} e^{-\frac{\phi}{2}(\mathsf{SSE} + \mathsf{SS}_0)} \\
& e^{-\frac{\phi}{2}(\boldsymbol{\beta} - \hat{\boldsymbol{\beta}})^T (\mathbf{X}^T \mathbf{X})(\boldsymbol{\beta} - \hat{\boldsymbol{\beta}})} e^{-\frac{\phi}{2}(\boldsymbol{\beta} - \mathbf{b}_0)^T \Phi (\boldsymbol{\beta} - \mathbf{b}_0)}
\end{aligned}
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- Read off posterior mean from Linear term in $\boldsymbol{\beta}$

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- Expand quadratics and regroup terms
- Read off posterior precision from Quadratic in $\boldsymbol{\beta}$
- Read off posterior mean from Linear term in $\boldsymbol{\beta}$
- will need to complete the quadratic in the posterior mean

Expand and Regroup

Quadratic in Normal

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Expand and Regroup

Quadratic in Normal

$$\exp\left\{-\frac{\phi}{2}(\beta - \mathbf{b})^T\Phi(\beta - \mathbf{b})\right\} = \exp\left\{-\frac{\phi}{2}(\beta^T\Phi\beta - 2\beta^T\Phi\mathbf{b} + \mathbf{b}^T\Phi\mathbf{b})\right\}$$

$$\begin{aligned} p(\boldsymbol{\beta}, \phi \mid \mathbf{Y}) \quad \propto \quad & \phi^{\frac{n+p+\nu_0}{2}-1} e^{-\frac{\phi}{2}(\mathsf{SSE}+\mathsf{SS}_0)} \\ & e^{-\frac{\phi}{2}(\boldsymbol{\beta}-\hat{\boldsymbol{\beta}})^T(\mathbf{X}^T\mathbf{X})(\boldsymbol{\beta}-\hat{\boldsymbol{\beta}})} e^{-\frac{\phi}{2}(\boldsymbol{\beta}-\mathbf{b}_0)^T\Phi_0(\boldsymbol{\beta}-\mathbf{b}_0)} \end{aligned}$$

Expand and Regroup

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Expand and Regroup

Quadratic in Normal

$$\exp\left\{-\frac{\phi}{2}(\beta-\mathbf{b})^T\Phi(\beta-\mathbf{b})\right\}=\exp\left\{-\frac{\phi}{2}(\beta^T\Phi\beta-2\beta^T\Phi\mathbf{b}+\mathbf{b}^T\Phi\mathbf{b})\right\}$$

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p(\boldsymbol{\beta},\phi\mid\mathbf{Y}) &\propto \phi^{\frac{n+p+\nu_0}{2}-1}e^{-\frac{\phi}{2}(\mathrm{SSE}+\mathrm{SS}_0)} \\
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&= \phi^{\frac{n+p+\nu_0}{2}-1}e^{-\frac{\phi}{2}(\mathrm{SSE}+\mathrm{SS}_0)} \\
&\quad e^{-\frac{\phi}{2}\left(\boldsymbol{\beta}^T(\mathbf{X}^T\mathbf{X}+\Phi_0)\boldsymbol{\beta}\right)}
\end{aligned}$$

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&= \quad \phi^{\frac{n+p+\nu_0}{2}-1} e^{-\frac{\phi}{2}(\mathsf{SSE}+\mathsf{SS}_0)} \\
&\quad\quad e^{-\frac{\phi}{2}\left(\boldsymbol{\beta}^T(\mathbf{X}^T\mathbf{X}+\boldsymbol{\Phi}_0)\boldsymbol{\beta}\right)} \\
&\quad\quad e^{-\frac{\phi}{2}\left(-2\boldsymbol{\beta}^T(\mathbf{X}^T\mathbf{X}\hat{\boldsymbol{\beta}}+\boldsymbol{\Phi}_0\mathbf{b}_0)\right)}
\end{aligned}$$

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Identify Hyperparameters and Complete the Quadratic

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duke.eps

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$$\begin{aligned} p(\boldsymbol{\beta}, \phi \mid \mathbf{Y}) \quad \propto \quad & \phi^{\frac{n+p+\nu_0}{2}-1} e^{-\frac{\phi}{2}(\mathsf{SSE}+\mathsf{SS}_0)} \\ & e^{-\frac{\phi}{2}\left(\boldsymbol{\beta}^T(\mathbf{X}^T\mathbf{X}+\Phi_0)\boldsymbol{\beta}\right)} \\ & e^{-\frac{\phi}{2}\left(-2\boldsymbol{\beta}^T\Phi_n\Phi_n^{-1}(\mathbf{X}^T\mathbf{X}\hat{\boldsymbol{\beta}}+\Phi_0\mathbf{b}_0)\right)} \end{aligned}$$

Identify Hyperparameters and Complete the Quadratic

Quadratic in Normal

$$\exp\left\{-\frac{\phi}{2}(\boldsymbol{\beta}-\mathbf{b})^T\Phi(\boldsymbol{\beta}-\mathbf{b})\right\} = \exp\left\{-\frac{\phi}{2}(\boldsymbol{\beta}^T\Phi\boldsymbol{\beta} - 2\boldsymbol{\beta}^T\Phi\mathbf{b} + \mathbf{b}^T\Phi\mathbf{b})\right\}$$

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\end{aligned}$$

Posterior Distribution

$$
\begin{aligned}
p(\boldsymbol{\beta}, \phi \mid \mathbf{Y}) \quad \propto \quad & \phi^{\frac{n+\nu_0}{2}-1} e^{-\frac{\phi}{2}(\mathrm{SSE}+\mathrm{SS}_0+\hat{\boldsymbol{\beta}}^T \mathbf{X}^T \mathbf{X} \hat{\boldsymbol{\beta}}+\mathbf{b}_0^T \Phi_0 \mathbf{b}_0-\mathbf{b}_n^T \Phi_n \mathbf{b}_n)} \\
& \phi^{\frac{p}{2}} e^{-\frac{\phi}{2}(\boldsymbol{\beta}-\mathbf{b}_n)^T \Phi_n(\boldsymbol{\beta}-\mathbf{b}_n)}
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\phi \mid \mathbf{Y} & \sim & \mathbf{G}\left(\frac{n+\nu_0}{2}, \frac{\mathrm{SSE}+\mathrm{SS}_0+\hat{\boldsymbol{\beta}}^T\mathbf{X}^T\mathbf{X}\hat{\boldsymbol{\beta}}+\mathbf{b}_0^T\Phi_0\mathbf{b}_0-\mathbf{b}_n^T\Phi_n\mathbf{b}_n}{2}\right)
\end{aligned}
$$

Marginal Distribution from Normal–Gamma

Theorem

Let $\boldsymbol{\theta} \mid \phi \sim N(m, \frac{1}{\phi}\Sigma)$ and $\phi \sim \mathbf{G}(\nu/2, \nu\hat{\sigma}^2/2)$. Then $\boldsymbol{\theta}$ $(p \times 1)$ has a p dimensional multivariate t distribution

$$\boldsymbol{\theta} \sim t_\nu(m, \hat{\sigma}^2\Sigma)$$

with density

$$p(\boldsymbol{\theta}) \propto \left[1 + \frac{1}{\nu}\frac{(\boldsymbol{\theta} - m)^T\Sigma^{-1}(\boldsymbol{\theta} - m)}{\hat{\sigma}^2}\right]^{-\frac{p+\nu}{2}}$$

Derivation

Marginal density $p(\boldsymbol{\theta}) = \int p(\boldsymbol{\theta} \mid \phi) p(\phi) \, d\phi$

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&\propto \int \phi^{p/2} \phi^{\nu/2-1} e^{-\phi\frac{(\boldsymbol{\theta}-m)^T\Sigma^{-1}(\boldsymbol{\theta}-m)+\nu\hat{\sigma}^2}{2}}\, d\phi
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&\propto \int \phi^{\frac{p+\nu}{2}-1} e^{-\phi\frac{(\boldsymbol{\theta}-m)^T\Sigma^{-1}(\boldsymbol{\theta}-m)+\nu\hat{\sigma}^2}{2}}\, d\phi \\
&= \Gamma((p+\nu)/2) \left(\frac{(\boldsymbol{\theta}-m)^T\Sigma^{-1}(\boldsymbol{\theta}-m)+\nu\hat{\sigma}^2}{2}\right)^{-\frac{p+\nu}{2}}
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&\propto \left((\boldsymbol{\theta}-m)^T\Sigma^{-1}(\boldsymbol{\theta}-m)+\nu\hat{\sigma}^2\right)^{-\frac{p+\nu}{2}} \\
&\propto \left(1+\frac{1}{\nu}\frac{(\boldsymbol{\theta}-m)^T\Sigma^{-1}(\boldsymbol{\theta}-m)}{\hat{\sigma}^2}\right)^{-\frac{p+\nu}{2}}
\end{aligned}
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Marginal Posterior Distribution of $\boldsymbol{\beta}$

$$\boldsymbol{\beta} \mid \phi, \mathbf{Y} \quad \sim \quad \mathsf{N}(\mathbf{b}_n, \phi^{-1}\Phi_n^{-1})$$

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Let $\hat{\sigma}^2 = \mathsf{SS}_n/\nu_n$ (Bayesian MSE)

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$$
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$$

Any linear combination $\lambda^T\boldsymbol{\beta}$

$$
\lambda^T\boldsymbol{\beta} \mid \mathbf{Y} \sim t_{\nu_n}(\lambda^T\mathbf{b}_n, \hat{\sigma}^2\lambda^T\Phi_n^{-1}\lambda)
$$

has a univariate t distribution with $\mathbf{v}_n$ degrees of freedom

Predictive Distribution

Suppose $\mathbf{Y}^* \mid \boldsymbol{\beta}, \phi \sim \mathsf{N}(\mathbf{X}^*\boldsymbol{\beta}, \mathbf{I}/\phi)$ and is conditionally independent of $\mathbf{Y}$ given $\boldsymbol{\beta}$ and ϕ

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$$\mathbf{X}^*\boldsymbol{\beta} + \boldsymbol{\epsilon}^* \mid \phi, \mathbf{Y} \quad \sim \quad \mathrm{N}(\mathbf{X}^*\mathbf{b}_n, (\mathbf{X}^*\Phi_n^{-1}\mathbf{X}^{*T} + \mathbf{I})/\phi)$$

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Use result about Marginals of Normal-Gamma family to integrate out ϕ

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Choice of conjugate prior?

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Cannot represent real prior beliefs; double use of data

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- $\frac{g}{1+g}$ weight given to the data
- Fixed g effect does not vanish as $n \to \infty$
- Use $g = n$ or place a prior diistribution on g

Shrinkage

Posterior mean under g-prior with $\mathbf{b}_0 = 0$ $\frac{g}{1+g}\hat{\beta}$