22S:138
Bayesian Statistics

Bayesian Linear Regression

Lecture 15
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Kate Cowles
374 SH, 335-0727
kcowles@stat.uiowa.edu

Centering the covariate in (frequentist) simple linear regression

- particularly useful when all values of the covariate are far away from zero and of the same sign
- in this case, without centering, intercept is estimated very imprecisely
- example: heart rate and body temperature data
  - reponse variable: heart rate in beats/minute
  - covariate: body temperature in degrees F.
  - subjects: 130 healthy adults

Intro to Bayesian simple linear regression

- likelihood

$$y_i | x_i, \beta_0, \beta_1, \sigma^2 \ \sim \ N\left(\beta_0 + \beta_1(x_i - \bar{x}), \sigma^2\right)$$

- "reference prior": independently uniform on β_0, β_1, log σ^2

$$p(\beta_0, \beta_1, \sigma^2) \ \propto \ \frac{1}{\sigma^2}$$

  - IG(0, 0) on σ^2
  - We approximate this prior in WinBUGS with
    - vague normals (or "dflat()") priors on β_0 and β_1
    - vague gamma on precision

Analytically computing joint posterior

- notation

$$\begin{aligned}\hat{\beta}_0 &= \bar{y} \\ \hat{\beta}_1 &= \frac{\Sigma_i (x_i - \bar{x})(y_i - \bar{y})}{\Sigma_i (x_i - \bar{x})^2} \\ SSE &= \sum_i \left(y_i - \hat{\beta}_0 - \hat{\beta}_1(x_i - \bar{x})\right)^2\end{aligned}$$

  - these are all statistics – functions of the data alone
- *joint* posterior using reference prior

$$\begin{aligned}p(\beta_0, \beta_1, \sigma^2 | \mathbf{y}) &\propto \frac{1}{\sigma^2} \frac{1}{(\sigma^2)^{(\frac{n}{2})}} exp\left[\frac{-\sum_i (y_i - \beta_0 - \beta_1(x_i - \bar{x}))^2}{2\sigma^2}\right] \\ &= \frac{1}{(\sigma^2)^{(\frac{n+2}{2})}} exp\left[\frac{SSE + n(\beta_0 - \hat{\beta}_0)^2 + \sum(x_i - \bar{x})^2(\beta_1 - \hat{\beta}_1)^2}{2\sigma^2}\right]\end{aligned}$$

Steps to find marginal posterior distributions

- So conditional on σ^2

$$p(\beta_0|\mathbf{y},\sigma^2) = N(\hat{\beta}_0, \frac{\sigma^2}{n})$$
$$p(\beta_1|\mathbf{y},\sigma^2) = N(\hat{\beta}_1, \frac{\sigma^2}{\Sigma(x_i-\bar{x})^2})$$

- if we integrate β_1 out of the joint posterior we get

$$p(\beta_0,\sigma^2|\mathbf{y}) \propto \frac{1}{(\sigma^2)^{(\frac{n+1}{2})}} exp\left[\frac{SSE + n(\beta_0-\hat{\beta}_0)^2}{2\sigma^2}\right]$$

- now to get marginal of β_0, integrate σ^2 out of the preceding expression

$$p(\beta_0|\mathbf{y}) = t(\hat{\beta}_0, \frac{s^2}{n}, n-2)$$

  a t distribution with mean $\hat{\beta}_0$, scale $\frac{s^2}{n}$, and degrees of freedom $n-2$

  - recall that $s^2 = \frac{SSE}{n-2}$
- similarly

$$p(\beta_1|\mathbf{y}) = t(\hat{\beta}_1, \frac{s^2}{\Sigma((x_i-\bar{x})^2}, n-2)$$

- finally

$$p(\sigma^2)|\mathbf{y} = IG(\frac{n-2}{2}, \frac{SSE}{2})$$

  what GCSR calls a scaled Inverse $\chi^2(n-2, s^2)$

When will posterior be proper with the improper reference prior?

- $n > 2$
- x_is not all the same

Informative priors in simple linear regression

- If a previous dataset is available:
  - See handout from P.M. Lee book for exact method if you have only summary statistics from previous dataset
  - Or: just combine old and new datasets and use reference prior (if you have all the data from old dataset)
  - Or derive the following simplified, independent priors (formulas apply if covariate was centered in previous analysis and you will center it in your analysis):

$$p(\beta_0) = N\left(\hat{\beta}_{0,old}, \frac{s^2_{old}}{n_{old}}\right)$$
$$p(\beta_1) = N\left(\hat{\beta}_{1,old}, \frac{s^2_{old}}{\Sigma_i(x_{i,old}-\bar{x}_{old})^2}\right)$$
$$p(\sigma^2) = IG\left(\frac{n_{old}-2}{2}, \frac{SSE_{old}}{2}\right)$$

Example

- You wish to use an article in the literature regarding a previous study to construct a prior for a simple linear regression model.
- The investigators centered their covariate and report the following:

$$
\begin{aligned}
n &= 100\\
\hat{\beta}_0 &= 5 \ \ (s.e. 2)\\
\hat{\beta}_1 &= -2 \ \ (s.e. 1)
\end{aligned}
$$

or

$$
\begin{aligned}
\hat{\beta}_0 &= 5 \ \ 95\% \ c.i. \ (1.04, 8.96)\\
\hat{\beta}_1 &= -2 \ \ 95\% \ c.i. \ (-3.98, -0.02)
\end{aligned}
$$

- Recall that:

$$
\begin{aligned}
s.e.(\hat{\beta}_0) &= \sqrt{\frac{s^2}{n}}\\
s.e.(\hat{\beta}_1) &= \sqrt{\frac{s^2}{\Sigma_i (x_i - \bar{x})^2}}
\end{aligned}
$$

$$
s^2 = \frac{SSE}{n-2}
$$

- also:
  - width of 95% c.i. for $\beta_0 = 2 \ t_{n-2} s.e.(\hat{\beta}_0)$
  - width of 95% c.i. for $\beta_1 = 2 \ t_{n-2} s.e.(\hat{\beta}_1)$
  - get t coefficients from t table

Multiple regression

- likelihood

$$
\begin{aligned}
y_i | \mathbf{x}_i, \boldsymbol{\beta}, \sigma^2 \sim \ & N(\beta_0 + \beta_1(x_{1i} - \bar{x}_1)\\
& + \ \beta(x_{2i} - \bar{x})2) + \cdots \beta_{k-1}(x_{k-1,i} - \bar{x}_{k-}
\end{aligned}
$$

- Reference prior

$$
p(\boldsymbol{\beta}, \sigma^2) \ \propto \ \frac{1}{\sigma^2}
$$

- conditional on σ^2, joint posterior of βs

$$
p(\boldsymbol{\beta} | \sigma^2, \mathbf{x}, \mathbf{y}) \ = \ N\left(\hat{\boldsymbol{\beta}} \ , \sigma^2 (X^T X)^{-1}\right)
$$

- marginally
  - $p(\boldsymbol{\beta} \, | \mathbf{x}, \mathbf{y})$ is multivariate t with n-k degrees of freedom
  - $p(\sigma^2 | \mathbf{x}, \mathbf{y})$ is $IG\left(\frac{n-k}{2}, \frac{SSE}{2}\right)$

When is posterior proper with improper reference prior

- $n > k$
- columns of $\mathbf{X}$ matrix are linearly independent

What if observations y_i are not conditionally independent, given $\boldsymbol{\beta},\ \sigma^2,\ \mathbf{x}$?

- hierarchical linear models
- time series models