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Homework 1 Solutions

Question 1

See file: list data and regression.R

Comments:

1. Much applied work has to worry about singular or near singular $X'X$ matrices. This applies even outside of linear models. As Bayesians, we never have to worry if we use proper priors, i.e. $X'X + A$ is always well conditioned
2. I used the QR decomposition to do the least squares computation. Generally, a good idea, but slower than the “direct” method using Cholesky roots.

Cholesky root method

Compute

- i.) $\hat{B} = (X'X)^{-1} X'Y$
- ii.) root of $(X'X)^{-1}$ (simulation)
- iii.) $E = Y - X\hat{B}$ and $S = E'E$

Compute Cholesky root of $(X'X)$

$$(X'X) = U'U \quad \text{chol(crossprod(X))}$$

$$(X'X)^{-1} = U^{-1}(U^{-1})'$$

Find U^{-1} by backsolving triangular system.

$$IU = \text{backsolve}(U, \text{diag}(\text{ncol}(U)))$$

- i.) $\hat{B} = IUIU' X'Y$ `crossprod(t(IU))**%crossprod(X, Y)`
- ii.) IU can be used for simulation
- iii.) $E = Y - X\hat{B}$ `S = crossprod(E)`

QR method

$$X_{n \times k} = Q_{n \times k} R_{n \times k} \quad \text{X has full column rank}$$

Columns of Q are orthogonal

$$Q = [q_1 \dots q_k] \quad \begin{aligned} q_i' q_i &= 1 \\ q_i' q_j &= 0 \end{aligned}$$

R is the Cholesky root up to a sign transformation.

$$\begin{aligned}
(Y - XB)'(Y - XB) &= Y'Y - Y'XB - B'X'Y + B'X'XB \\
&= Y'Y - Y'QRB - B'R'Q'Y + B'R'Q'QRB \\
&= Y'Y - Y'QQ'Y + Y'QQY - Y'QRB - B'RQY + B'RQY \\
&= Y'(I - QQ')Y + (RB - QY)'(RB - QY)
\end{aligned}$$

$$\Rightarrow \hat{B} \text{ solves } \begin{aligned} RB &= QY \\ \hat{B} &= R^{-1}QY \end{aligned}$$

- i.) $\hat{B} = R^{-1}QY$ $\begin{bmatrix} q = \text{qr}(X) \\ \hat{B} = \text{qr.coef}(q, Y) \end{bmatrix}$
- ii.) $S = Y'(I - QQ')Y$ $[S = \text{crossprod}(\text{qr.resid}(q, Y))]$
- iii.) root of $(X'X)^{-1}$ - additional computations!

Question 2

$$\begin{vmatrix} l_{11} & 0 \\ l_{21} & l_{22} \end{vmatrix} = l_{11}l_{22}$$

so true for 2 x 2 case.

Assume also true for (n-1) x (n-1) case.

expanding first row by co-factors

$$\begin{vmatrix} l_{11} & 0 & 0 \\ \dots & 0 & 0 \\ l_{n1} & l_{n1} & \dots \end{vmatrix} = l_{11} \begin{vmatrix} l_{22} & 0 & 0 \\ \dots & 0 & 0 \\ l_{n2} & l_{n2} & \dots \end{vmatrix} + 0 \begin{vmatrix} \dots & \dots & \dots \\ \dots & \dots & \dots \\ \dots & \dots & \dots \end{vmatrix} + \dots + 0 \begin{vmatrix} \dots & \dots & \dots \\ \dots & \dots & \dots \\ \dots & \dots & \dots \end{vmatrix}$$

\Rightarrow true for n x n case

Question 3

a. $Z \sim N(0, I)$ $y = LZ$ $Var(y) = LIL' = LL'$

b.

$$\begin{bmatrix} l_{11} & & \\ l_{21} & l_{22} & \\ l_{31} & l_{32} & l_{33} \end{bmatrix} \begin{bmatrix} l_{11} & l_{21} & l_{31} \\ & l_{22} & l_{32} \\ & & l_{33} \end{bmatrix} = \begin{bmatrix} \sigma_{11} & & \\ \sigma_{21} & \sigma_{22} & \\ \sigma_{31} & \sigma_{32} & \sigma_{33} \end{bmatrix}$$

$$\sigma_{11} = l_{11}^2 \qquad l_{11} = \sqrt{\sigma_{11}}$$

$$l_{21}l_{11} = \sigma_{21} \quad l_{21} = \frac{\sigma_{21}}{l_{11}} = \frac{\sigma_{21}}{\sqrt{\sigma_{11}}}$$

$$l_{21}^2 + l_{22}^2 = \sigma_{22} \quad l_{22}^2 = \sigma_{22} - l_{21}^2$$

$$l_{22} = \sqrt{\sigma_{22} - \frac{\sigma_{21}^2}{\sigma_{11}}}$$

$$l_{31}l_{11} = \sigma_{31} \quad l_{31} = \frac{\sigma_{31}}{\sqrt{\sigma_{11}}}$$

$$l_{31}l_{21} + l_{32}l_{22} = \sigma_{32} \quad l_{32} = \frac{\sigma_{32} - l_{31}l_{21}}{l_{22}}$$

$$l_{32} = \frac{\sigma_{32} - \frac{\sigma_{31}}{\sqrt{\sigma_{11}}} \frac{\sigma_{21}}{l_{11}}}{\sqrt{\sigma_{22} - \frac{\sigma_{21}^2}{\sigma_{11}}}}$$

$$l_{31}^2 + l_{32}^2 + l_{33}^2 = \sigma_{33}$$

$$l_{33}^2 = \sigma_{33} - l_{31}^2 - l_{32}^2$$

$$l_{33} = \sqrt{\sigma_{33} - l_{31}^2 - l_{32}^2}$$

Note that l_{ij} are defined recursively, i.e. 2nd row depends on the first etc.

c.

We can orthogonalize y_1, \dots, y_p $Var(\underline{y}) = \Sigma$ via a series of regressions

$$y_1 = e_1$$

regress

$$y_2 \text{ on } y_1 \rightarrow e_{2,1}$$

$$y_3 \text{ on } y_1, y_2 \rightarrow e_{3,1,2}$$

...

$$y_p \text{ on } y_1, \dots, y_{p-1} \rightarrow e_{p,1,2,\dots,p-1}$$

$(e_1, e_{2,1}, e_{3,1,2}, \dots, e_{p,1,2,\dots,p-1})$ are uncorrelated (Gram-Schmidt)

But not with unit variance.

$$y_1 = \sigma_1 z_1$$

$$-\beta_{21}y_1 + y_2 = \sigma_2 z_2$$

...

$$\underbrace{-\beta_{p,1}y_1 - \beta_{p,2}y_2 - \dots - \beta_{p,p-1}y_{p-1} + y_p}_{e_{p,1,2,\dots,p-1}} = \sigma_p z_p$$

This can be written:

$$\underline{Ty} = D\underline{z}$$

$$T = \begin{pmatrix} 1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ -\beta_{p,1} & \cdots & -\beta_{p,p-1} & 1 \end{pmatrix}$$

$$D = \text{diag}(\sigma_1, \dots, \sigma_p)$$

$$\underline{Ty} = D\underline{z}$$

$$y = \underbrace{T^{-1}D}_{L \text{ by direct construction}} \underline{z}$$

How do we know T^{-1} is lower triangular?

Write out $TT^{-1} = I$

$$\begin{pmatrix} t_{11} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ t_{p1} & \cdots & t_{pp} \end{pmatrix} \begin{pmatrix} t^{11} & \cdots & t^{1p} \\ \vdots & \ddots & \vdots \\ t^{p1} & \cdots & t^{pp} \end{pmatrix} = \begin{pmatrix} 1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & 1 \end{pmatrix}$$

row1, col2:

$$t_{11}t^{12} = 0$$

$$\Rightarrow t^{12} = 0 \quad t_{11} \neq 0$$

row1, col3:

$$t_{11}t^{13} = 0$$

$$\Rightarrow t^{13} = 0$$

...

row2, col3:

$$t_{21}t^{23} = 0 \quad (t^{13} = 0)$$

$$\Rightarrow t^{23} = 0$$

...