

STK3100 Exercises, Week 13

Jonas Moss

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Exercise 9.1

Let $\text{cor}(Y_{i1}^A, Y_{i2}^A) = \text{cor}(Y_{i1}^B, Y_{i2}^B) = \rho$, all other correlations equal to zero, and $\text{Var}Y_i^A = \text{Var}Y_i^B = \sigma^2$ for all i . Define

$$\begin{aligned} B &= \frac{1}{2} \left[(\bar{Y}_1^A + \bar{Y}_2^A) - (\bar{Y}_1^B + \bar{Y}_2^B) \right] \\ W &= \frac{1}{2} \left[(\bar{Y}_1^A - \bar{Y}_2^A) + (\bar{Y}_1^B - \bar{Y}_2^B) \right] \end{aligned}$$

Then

$$\begin{aligned} \text{Var}B &= \frac{1}{4} \text{Var}(\bar{Y}_1^A + \bar{Y}_2^A) + \frac{1}{4} \text{Var}(\bar{Y}_1^B + \bar{Y}_2^B) \\ \text{Var}W &= \frac{1}{4} \text{Var}(\bar{Y}_1^A - \bar{Y}_2^A) + \frac{1}{4} \text{Var}(\bar{Y}_1^B - \bar{Y}_2^B) \end{aligned}$$

Since $\text{Var}(\bar{Y}_1^A \pm \bar{Y}_2^A) = \text{Var}(\bar{Y}_1^B \pm \bar{Y}_2^B) = 2n^{-1}\sigma^2(1 \pm \rho)$, $\text{Var}B = n^{-1}\sigma^2(1 + \rho)$ and $\text{Var}W = n^{-1}\sigma^2(1 - \rho)$ as claimed.

Exercise 9.22

The mixed effect probit model can be written using two normal latent variables u and w :

$$\begin{aligned} p(u) &= \phi(u; 0, \Sigma) \\ p(w | u) &= \phi(w; \beta^T x + z^T u, 1) \\ p(y | w) &= 1_{[w \geq 0]} \end{aligned}$$

The marginal likelihood $p(y)$ is found by integrating out u and w . First we find $p(w) = \int p(w | u) p(u) du$.

To do this, we will only require $p(z^T u) = \phi(z^T u, 0, z^T \Sigma z)$. Then $p(w) = \int \phi(u; \beta^T x + v, 1) \phi(v, 0, z^T \Sigma z) dv$.

Now we show that this equals $\phi(w; \beta^T x, 1 + z^T \Sigma z)$. To this end, let $\mu = \beta^T x$ and $\sigma^2 = z^T \Sigma z$. Then

$$\begin{aligned} & \phi(w; \mu + v, 1) \phi(v, 0, \sigma^2) \propto \\ & \exp \left[\frac{-(\sigma^2 + 1)v^2 + 2\sigma^2(u - \mu)v + \sigma^2(\mu - w)^2}{2\sigma^2} \right] \\ & \exp \left[\frac{-v^2 + 2\sigma^2(w - \mu)/(\sigma^2 + 1)v - \sigma^2(\mu - w)^2/(\sigma^2 + 1)}{2\sigma^2/(\sigma^2 + 1)} \right] \end{aligned}$$

Notice that

$$A = \exp \left[\frac{-v^2 + 2\sigma^2(w - \mu)/(\sigma^2 + 1)v - \sigma^2(\mu - w)^2/(\sigma^2 + 1)}{2\sigma^2/(\sigma^2 + 1)} \right]$$

is proportional to a normal in v , so its integral is 1. (Notice the difference between A and the last line of the equation stack!)

We will take out the term $-\frac{(\mu - w)^2}{2}$ and add the term $-\frac{\sigma^2(\mu - w)^2}{2(\sigma^2 + 1)}$. The residual becomes

$$\begin{aligned} & \frac{-(\mu - w)^2(\sigma^2 + 1) + \sigma^2(\mu - w)^2}{2(\sigma^2 + 1)} = \\ & \frac{-(\mu - w)^2}{2(\sigma^2 + 1)} = \end{aligned}$$

Taking the exponential of this we recover the wished for normal in u .

Finally,

$$\begin{aligned} p(y | x) &= \int p(y | w) p(w) du \\ &= \int_0^\infty \phi(w; \beta^T x, 1 + z^T \Sigma z) du \\ &= 1 - \Phi(0; \beta^T x, 1 + z^T \Sigma z) \\ &= 1 - \Phi\left(-\frac{\beta^T x}{\sqrt{1 + z^T \Sigma z}}\right) \\ &= \Phi\left(\frac{\beta^T x}{\sqrt{1 + z^T \Sigma z}}\right) \end{aligned}$$

Exercise 9.24

We want to show that

$$\text{Cov}(Y_{ij}, Y_{ik}) = \exp[(x_{ij} + x_{ik})\beta] [\exp(\sigma_u^2) (\exp(\sigma_u^2) - 1)]$$

for the Poisson GLM with a random intercept.

Recall the definition of the Poisson GLM with random intercept.

$$E(Y_{ij} | u_i) = \exp(x_{ij}\beta + u_i).$$

From this it follows that

$$\begin{aligned} E(Y_{ij}Y_{ik} | u_i) &= E[\exp(x_{ij}\beta + u_i) \exp(x_{ik}\beta + u_i)] \\ &= E\{\exp[(x_{ij} + x_{ik})\beta + 2u_i]\} \\ &= \exp((x_{ij} + x_{ik})\beta + 2\sigma_u^2) \end{aligned}$$

On the other hand

$$\begin{aligned} E(Y_{ij} | u_i) &= E[\exp(x_{ij}\beta + u_i)] \\ &= \exp\left(x_{ij}\beta + \frac{1}{2}\sigma_u^2\right) \end{aligned}$$

Hence

$$\begin{aligned} E(Y_{ij}Y_{ik} | u_i) - E(Y_{ij} | u_i)E(Y_{ik} | u_i) &= \\ \exp((x_{ij} + x_{ik})\beta + 2\sigma_u^2) - \exp((x_{ij} + x_{ik})\beta + \sigma_u^2) &= \\ \exp[(x_{ij} + x_{ik})\beta] \{ \exp(\sigma_u^2) [\exp(\sigma_u^2) - 1] \} \end{aligned}$$

Since none of the factors are ever zero, the correlation is positive.

Exercise 9.29

The book did not define V_i , at least not very clearly. This forces us to guess what it is. I guess it is $\frac{1}{\psi}R(\alpha)$ for the relevant section of $R(\alpha)$, which is I nonetheless.

Recall that $\frac{\partial \mu_{ij}}{\partial \beta_k} = \frac{\partial \mu_{ij}}{\partial \eta_{ij}} \frac{\partial \eta_{ij}}{\partial \beta_k} = \frac{\partial \mu_{ij}}{\partial \eta_{ij}} x_{ijk}$. Hence

$$\begin{aligned} D_{ijk} &= \partial \mu_{ij} / \partial \beta_k \\ &= x_{ijk} \frac{\partial \mu_{ij}}{\partial \eta_{ij}} \\ &= [\Delta_i X_i]_{jk} \end{aligned}$$

$$\begin{aligned} \sum_{i=1}^n D_i^T V_i^{-1} (y_i - \mu_i) &= 0 \\ &\Downarrow \\ \frac{1}{\psi} \sum_{i=1}^n X_i^T \Delta_i (y_i - \mu_i) &= 0 \end{aligned}$$

This is the same as equation (4.11) in chapter 4, with $V^{-1} = \frac{1}{\psi}I$.

Exam 2016, problem 3

a)

The i th observation vector is

$$Y_i = X_i\beta + Z_i b + \epsilon_i,$$

where $X_i = [X_{i1} \ X_{i2} \ \cdots \ X_{ik}]$ are the fixed effects covariate vectors belonging to the i th group and $Z_i = [Z_{i1} \ Z_{i2} \ \cdots \ Z_{ik}]$ the random effects covariate vector. The vector β are the fixed effects, while $b \sim N(0, \Sigma)$ are the random effects. The residual $\epsilon_i \sim N(0, \sigma^2 I)$ are uncorrelated residual variances that cannot be explained either by the fixed or random effects.

b)

The distribution of Y_i is normal with mean $\beta_0 + X_i\beta_1$ and variance $\psi X_i^2 + \sigma^2$. It's not possible to calculate these from the output, as we do not know X_i .

c)

Since $Y_{ij} - X_{ij}\beta_1 \mid X_{ij}b_i \sim N(X_{ij}b_i, \sigma^2 I)$ and $b \sim N(0, \psi^2)$, we can find the distribution of b by Bayes' rule. The posterior of $b_i \mid Y_i$ is normal with mean $\overline{Y_{ij} - X_{ij}\beta}$ and variance ψ^2/n . To estimate them we can use the signed residuals.