

Exercise C Suppose the predictors z are orthogonal, that is

$$Z^T z = \text{diag}(\tilde{z}_1^T \tilde{z}_1, \dots, \tilde{z}_p^T \tilde{z}_p) = \begin{bmatrix} \tilde{z}_1^T \tilde{z}_1 & & & \emptyset \\ & \ddots & & \\ & & \tilde{z}_d^T \tilde{z}_d & \\ \emptyset & & & \ddots \\ & & & & \tilde{z}_p^T \tilde{z}_p \end{bmatrix}$$

$$\Rightarrow (Z^T z)^{-1} = \text{diag}(1 / \tilde{z}_1^T \tilde{z}_1, \dots, 1 / \tilde{z}_p^T \tilde{z}_p)$$

$$\Rightarrow \hat{\beta} = (Z^T z)^{-1} z^T y = \begin{bmatrix} (\tilde{z}_1^T \tilde{z}_1)^{-1} & & \emptyset \\ & \ddots & \\ \emptyset & & (\tilde{z}_p^T \tilde{z}_p)^{-1} \end{bmatrix} \begin{bmatrix} \sum_{i=1}^n \tilde{z}_{i1} y_i \\ \vdots \\ \sum_{i=1}^n \tilde{z}_{ip} y_i \end{bmatrix}$$

$$\text{Hence, } \hat{\beta}_d = \frac{\tilde{z}_d^T y}{\tilde{z}_d^T \tilde{z}_d}.$$

Now, suppose $y \sim \mathcal{N}(Z\beta, \sigma^2 I_m)$. Then, $\hat{\beta} \sim \mathcal{N}_p(\beta, \sigma^2(Z^T Z)^{-1})$, because $\hat{\beta} = (Z^T Z)^{-1} Z^T y$ is a linear transformation of a Gaussian random variable, then

$$E[\hat{\beta}] = (Z^T Z)^{-1} Z^T E[y] = \cancel{(Z^T Z)^{-1} Z^T Z} \beta = \beta$$

$$\begin{aligned} \text{var}(\hat{\beta}) &= (Z^T Z)^{-1} \underbrace{Z^T \text{var}(y) Z}_{\sigma^2 I_p} [(Z^T Z)^{-1} Z^T]^T = \\ &= \sigma^2 \cancel{(Z^T Z)^{-1} Z^T Z} (Z^T Z)^{-1} \\ &= \sigma^2 \underbrace{(Z^T Z)^{-1}} \end{aligned}$$

However, $(Z^T Z)^{-1}$ is **diagonal** and hence the covariances are zero. However, in the Gaussian case uncorrelation \Leftrightarrow independence.