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# Problem 1

1)

$$T = \underbrace{X}_{n \times p} Q^T, \quad \gamma = \underbrace{Q}_{p \times p} \underbrace{\beta}_{p \times 1}$$

$$T\gamma = \underbrace{X}_{n \times p} \underbrace{Q^T}_{p \times p} \underbrace{Q}_{p \times p} \underbrace{\beta}_{p \times 1}$$

$$T\gamma = X\beta$$

where we used that  $Q^T Q = I_{p \times p}$

2)

y regressing on T is given by

$$y = Ty + \sigma e$$

Using that  $T\gamma = X\beta$  (found in 1)

$$y = X\beta + \sigma e$$

Using  $z = Py$ ,

$$z = Px\beta + P\sigma e$$

$$= \underbrace{PxQ'Q\beta}_{D\gamma} + P\sigma e$$

$$= D\gamma + P\sigma e$$

So, both regressions are equivalent,  
 we can obtain one in the other  
 by a linear transformation.

3) Using R and  $\gamma_j = \frac{z_j}{x_j}$

$$\hat{\gamma} = (-1.0936012, -0.3767857, -0.6785582, 2.1572303, -1.2684318)$$

Using R, using all components we obtain

$$\hat{\beta} = \begin{pmatrix} 0.6717704 \\ 1.3122409 \\ -0.2701956 \\ 1.9925564 \\ -1.3580854 \end{pmatrix}$$

4) with the highest 4 eigenvalues  
we have

$$\hat{\gamma} = (-1.0936012, -0.3767857, -0.6785582, 2.1572303)$$

5) We find flat for  $m = 2$

$$\frac{\sum_{j=1}^m \lambda_j^2}{\sum_{j=1}^p \lambda_j^2} = 0.9721144 > 0.9$$

So, we use the 2 components with the 2 smallest eigenvalues

Using R, we obtain

$$\hat{\beta}_{\text{PCA}} = \begin{pmatrix} 0.3812321 \\ 0.6976637 \\ 0.2992885 \\ 0.5230571 \\ 0.5854025 \end{pmatrix}$$

## Problem 2

$$1) p(y_1, \dots, y_n | z=0) = \frac{\int_{-\infty}^{\infty} \prod_{i=1}^N N(x_i \beta, \sigma^2) \pi(\beta | z=0) p(z=0) d\beta}{p(z=0)}$$

$$= \int_{-\infty}^{\infty} \prod_{i=1}^N N(x_i \beta, \sigma^2) \pi(\beta | z=0) d\beta$$

where

$$\prod_{i=1}^N N(x_i \beta, \sigma^2) = \prod_{i=1}^N \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{1}{2\sigma^2} (y_i - x_i \beta)^2\right)$$

$$= \frac{1}{(2\pi)^{n/2} \sigma^n} \exp\left(-\frac{1}{2\sigma^2} \sum_{i=1}^N (y_i - x_i \beta)^2\right)$$

and

$$\pi(\beta | z=0) = \delta_0(\beta)$$

So

$$p(y_1, \dots, y_n | z=0) = \int \frac{1}{(2\pi)^{n/2} \sigma^n} \exp\left(-\frac{1}{2\sigma^2} \sum_{i=1}^N (y_i - x_i \beta)^2\right) \delta_0(\beta) d\beta$$

The delta function sets the integral as 0 for any value  $\beta \neq 0$ . So, the integration makes to set  $\beta=0$ . Hence.

$$p(y_1, \dots, y_n | z=0) = \frac{1}{(2\pi)^{n/2} \sigma^n} \exp\left(-\frac{1}{2\sigma^2} \sum_{i=1}^N y_i^2\right)$$

2)

$$P(y_1, \dots, y_n | z=1) = \int \frac{\prod_{i=1}^N N(x_i|\beta, \sigma^2) \pi(\beta | z=1)}{\pi(z=1)} d\beta$$

$$= \prod_{i=1}^N N(x_i|\beta, \sigma^2) \pi(\beta | z=1)$$

where  $\prod_{i=1}^N N(x_i|\beta, \sigma^2) = \prod_{i=1}^N \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{1}{2\sigma^2}(y_i - x_i\beta)^2\right)$

$$= \frac{1}{(2\pi)^n \sigma^n} \exp\left(-\frac{1}{2\sigma^2} \sum_{i=1}^N (y_i - x_i\beta)^2\right)$$

and  $\pi(\beta | z=1) = \frac{1}{\sqrt{2\pi}\tau} \exp\left(-\frac{1}{2\tau^2}\beta^2\right)$

Hence,

$$P(y_1, \dots, y_n | z=1) = \int \frac{\exp\left(-\frac{1}{2\sigma^2} \sum_{i=1}^N (y_i - x_i\beta)^2\right) \exp\left(-\frac{\beta^2}{2\tau^2}\right)}{(2\pi)^n \sigma^n \sqrt{2\pi} \tau} d\beta$$

$$= \int \frac{\exp\left(-\frac{1}{2\sigma^2} \sum_{i=1}^N (y_i - x_i\beta)^2 - \beta^2/2\tau^2\right)}{(2\pi)^n \sigma^n \sqrt{2\pi} \tau} d\beta$$

Now, working the exponential terms

$$-\frac{1}{2\sigma^2} \sum_{i=1}^N (y_i - x_i\beta)^2 - \frac{\beta^2}{2\tau^2} =$$

$$= -\frac{1}{2\sigma^2} \left[ \sum_{i=1}^N y_i^2 - 2\beta \sum_{i=1}^N x_i y_i + (\sum_{i=1}^N x_i \beta)^2 \right] - \frac{\beta^2}{2\sigma^2}$$

$$= -\frac{1}{2\sigma^2} \left[ \sum_{i=1}^N y_i^2 - 2\beta \sum_{i=1}^N x_i y_i + \beta^2 \sum_{i=1}^N x_i^2 \right] - \frac{\beta^2}{2\sigma^2}$$

$$= -\frac{1}{2\sigma^2} \left[ \sum_{i=1}^N y_i^2 - 2\beta \gamma + \beta^2 n \right] - \frac{\beta^2}{2\sigma^2}$$

$$= -\frac{1}{2\sigma^2} \sum_{i=1}^N y_i^2 + \frac{\beta}{\sigma^2} \gamma - \frac{\beta^2 n}{2\sigma^2} = \frac{\beta^2 n}{2\sigma^2} = \frac{\beta^2}{2\sigma^2}$$

$$= -\frac{1}{2\sigma^2} \sum_{i=1}^N y_i^2 + \frac{\beta}{\sigma^2} \gamma - \frac{\beta^2}{2} \left( \frac{n}{\sigma^2} - \frac{1}{\tau^2} \right)$$

For the moment call  $c_1 = \frac{\gamma}{\sigma^2}$ ,  $c_2 = \frac{n}{\sigma^2} - \frac{1}{\tau^2}$

So,

$$-\frac{1}{2\sigma^2} \sum_{i=1}^N (y_i - x_i \beta)^2 - \frac{\beta^2}{2\sigma^2} = -\frac{1}{2\sigma^2} \sum_{i=1}^N y_i^2 + c_1 \beta - c_2 \frac{\beta^2}{2}$$

$$\leq -\frac{1}{2\sigma^2} \sum_{i=1}^N y_i^2 - \frac{c_2}{2} \left( \beta^2 - 2 \frac{c_1}{c_2} \beta \right)$$

$$= -\frac{1}{2\sigma^2} \sum_{i=1}^N y_i^2 - \frac{c_2}{2} \left( \beta^2 - 2 \frac{c_1}{c_2} \beta + \left( \frac{c_1}{c_2} \right)^2 - \left( \frac{c_1}{c_2} \right)^2 \right)$$

$$= -\frac{1}{2\sigma^2} \sum_{i=1}^n y_i^2 - \frac{c_2}{2} \left( (\beta - \frac{c_1}{c_2})^2 - \left( \frac{c_1}{c_2} \right)^2 \right)$$

Therefore

$$p(y_1, \dots, y_n | z=1) = \frac{\exp \left( -\frac{1}{2\sigma^2} \sum_{i=1}^n y_i^2 - \frac{c_2}{2} \left( (\beta - \frac{c_1}{c_2})^2 - \left( \frac{c_1}{c_2} \right)^2 \right) \right)}{(2\pi)^{n/2} \sigma^n \sqrt{2\pi}^n T} d\beta$$

We integrate with respect to  $\beta$

$$\frac{\exp \left( -\frac{1}{2\sigma^2} \sum_{i=1}^n y_i^2 + \frac{c_1^2}{2c_2} \right)}{(2\pi)^{n/2} \sigma^n \sqrt{2\pi}^n T} \int_{-\infty}^{\infty} \exp \left( -\frac{c_2}{2} \left( \beta - \frac{c_1}{c_2} \right)^2 \right) d\beta$$

$$= \frac{\exp \left( -\frac{1}{2\sigma^2} \sum_{i=1}^n y_i^2 + \frac{c_1^2}{2c_2} \right)}{(2\pi)^{n/2} \sigma^n \sqrt{c_2} T}$$

$$= \frac{\exp \left( -\frac{1}{2\sigma^2} \sum_{i=1}^n y_i^2 + \frac{\sigma^2}{2n} \right)}{(2\pi)^{n/2} \sigma^n \sqrt{\frac{n}{\sigma^2} - \frac{1}{T^2}} T}$$

where we used  
that  $c_2 = \frac{n}{\sigma^2} - \frac{1}{T^2}$   
 $c_1 = \frac{\sigma}{\sigma^2}$

21)

$$P(z=1 | y_1, y_2, \dots, y_n) = \frac{P(y_1, \dots, y_n | z=1) p(z=1)}{P(y_1, \dots, y_n | z=0) p(z=0) + P(y_1, \dots, y_n | z=1) p(z=1)}$$

$$\frac{\exp\left(-\frac{1}{2\sigma^2} \sum_{i=1}^n y_i + \frac{\gamma^2}{2n}\right)}{(2\pi)^{n/2} \sigma^n \sqrt{\frac{n}{\sigma^2 - \frac{1}{T^2}}}} \stackrel{?}{=}$$

$$= \frac{1}{(2\pi)^{n/2} \sigma^n} \exp\left(-\frac{1}{2\sigma^2} \sum_{i=1}^n y_i^2\right) (1-q) + \frac{\exp\left(-\frac{1}{2\sigma^2} \sum_{i=1}^n y_i + \frac{\gamma^2}{2n}\right)}{(2\pi)^{n/2} \sigma^n \sqrt{\frac{n}{\sigma^2 - \frac{1}{T^2}}}} \stackrel{?}{=}$$

$$= \frac{\exp\left(-\frac{1}{2\sigma^2} \sum_{i=1}^n y_i + \frac{\gamma^2}{2n}\right) q}{\sqrt{\frac{n}{\sigma^2 - \frac{1}{T^2}}} T} \exp\left(-\frac{1}{2\sigma^2} \sum_{i=1}^n y_i^2\right) (1-q) + \exp\left(-\frac{1}{2\sigma^2} \sum_{i=1}^n y_i + \frac{\gamma^2}{2n}\right) q$$

If  $\gamma = 0$  and  $n$  is large

$$P(z=1 | y_1, \dots, y_n) \approx \frac{\exp\left(-\frac{1}{2\sigma^2} \sum_{i=1}^n y_i\right) q}{\sqrt{\frac{n}{\sigma^2}} T \exp\left(-\frac{1}{2\sigma^2} \sum_{i=1}^n y_i^2\right) (1-q)}$$

where we considered that in the denominator the first term dominates

when  $n \rightarrow \infty$  and  $\frac{n}{\sigma^2} - \frac{1}{\bar{z}^2} \approx \frac{n}{\sigma^2}$ .

$$P(z=1 | y_1, \dots, y_n) \approx \frac{T}{\sqrt{n}} \frac{q}{1-q}$$

5) From the assumption  $\sum x_i \geq b$ , we have

that  $\bar{x} = 0$ ,

And the least square estimator

$$\hat{\beta} = \frac{\sum x_i y_i}{\sum x_i^2} = \frac{\bar{y}}{n}$$

So, setting  $\gamma = 0$   
 is the same  
 estimator as

$\hat{\beta} = 0$ . So, in such case  
 the dummy variable must be 0,  
 not 1. Hence, we must expect  
 meet the probability

$$P(z=1 | y_1, \dots, y_n) \rightarrow 0$$

as actually happens if  $n \rightarrow \infty$   
 with what we observed in 4)

$$P(z=1 | y_1, \dots, y_n) \approx \lim_{n \rightarrow \infty} \frac{q}{\sqrt{n}} \frac{q}{1-q} = 0$$

