

Answers – Lecture 5

Undirected network reconstruction – part 1

Question 1

Graph omitted in answer, should be obvious.

Question 1b)

$A \perp\!\!\!\perp C; A \perp\!\!\!\perp D; B \perp\!\!\!\perp C; B \perp\!\!\!\perp D;$
 $A, B \perp\!\!\!\perp C, D; A, B \perp\!\!\!\perp C; A, B \perp\!\!\!\perp D; A \perp\!\!\!\perp C, D; B \perp\!\!\!\perp C, D;$
 $A \perp\!\!\!\perp C | B; A \perp\!\!\!\perp C | D; A \perp\!\!\!\perp D | B; A \perp\!\!\!\perp D | C; B \perp\!\!\!\perp C | A; B \perp\!\!\!\perp C | D; B \perp\!\!\!\perp D | A; B \perp\!\!\!\perp D | C;$
 $A \perp\!\!\!\perp C | B, D; A \perp\!\!\!\perp D | B, C; B \perp\!\!\!\perp C | A, D; B \perp\!\!\!\perp D | A, C.$

Question 1d)

$A \perp\!\!\!\perp C | B; A \perp\!\!\!\perp D | B; A \perp\!\!\!\perp C | B, D; A \perp\!\!\!\perp D | C; A \perp\!\!\!\perp D | B, C;$
 $B \perp\!\!\!\perp D | C; B \perp\!\!\!\perp D | A, C.$

Question 1f)

$A \perp\!\!\!\perp C | B, D; B \perp\!\!\!\perp D | A, C.$

Question 2

Question 2a)

The correlation matrix is:

$$\begin{aligned} \mathbf{R} &= \begin{pmatrix} \sqrt{2} & 0 \\ 0 & \sqrt{2} \end{pmatrix}^{-1} \begin{pmatrix} 2 & 1 \\ 1 & 2 \end{pmatrix} \begin{pmatrix} \sqrt{2} & 0 \\ 0 & \sqrt{2} \end{pmatrix}^{-1} \\ &= \begin{pmatrix} 1 & 1/2 \\ 1/2 & 1 \end{pmatrix}. \end{aligned}$$

Alternatively, use the fact that the diagonal of the correlation matrix contains only ones. And the off-diagonal elements are given by $\rho(Y_1, Y_2) = \text{Cov}(Y_1, Y_2) / \{[\text{Var}(Y_1)]^{1/2}[\text{Var}(Y_2)]^{1/2}\} = 1/(\sqrt{2}\sqrt{2}) = 1/2$.

Question 2b)

The mean and correlation have changed. Visually, this results in a shift of the location of the data and also a rotation of ‘sigar-shaped’ relation between the variates of \mathbf{Y} .

Question 3

The variance of Y : $\text{Var}(Y) = \text{Var}(X + \frac{1}{2}E) = \text{Var}(X) + \text{Var}(\frac{1}{2}E) = \text{Var}(X) + \frac{1}{4}\text{Var}(E) =$

$1 + \frac{1}{4}$, where we have used the independence between X and E . The covariance of X and Y : $\text{Cov}(X, Y) = \text{Cov}(X, X + \frac{1}{2}E) = \text{Cov}(X, X) + \text{Cov}(X, \frac{1}{2}E) = \text{Var}(X) + \frac{1}{2}\text{Cov}(X, E) = 1 + 0 = 1$, where again we have used the independence between X and Y . The correlation is now: $\text{Cov}(X, Y)/[\text{Var}(X)\text{Var}(Y)]^{1/2} = \sqrt{\frac{4}{5}}$.

Question 4

Question 4a)

For the conditional mean Y_A is temporarily fixed at some value, say $Y_A = y_a$. Hence, Y_A is temporarily non-random, equalling some constant. As a consequence, the only randomness in Y_B , which equals $3 - \frac{3}{4}Y_A + \varepsilon_B$ given Y_A , is in ε_B . Hence, the expectation of Y_B given Y_A is only with respect to ε_B . Thus: $E_{\varepsilon_B}(Y_B | Y_A = y_A) = E_{\varepsilon_B}(3 - \frac{3}{4}y_A + \varepsilon_B) = E_{\varepsilon_B}(3) - E_{\varepsilon_B}(\frac{3}{4}y_A) + E_{\varepsilon_B}(\varepsilon_B) = 3 - \frac{3}{4}y_A$.

For the unconditional mean of Y_B let Y_A be random again. The mean of Y_B is now to be calculated taking into account both the uncertainty of ε_B and Y_A . Then $E_{Y_A}[E_{\varepsilon_B}(Y_B | Y_A)] = E_{Y_A}[3 - \frac{3}{4}Y_A] = 3 - \frac{3}{4}E_{Y_A}[Y_A] = 3 - \frac{3}{4} \cdot 2 = 3/2$.

Alternatively:

$$\begin{aligned}
 E(Y_B) &= E_{Y_A}(E_{\varepsilon_B}(Y_B | Y_A = y_A)) \\
 &= \int_{-\infty}^{\infty} E_{\varepsilon_B}(Y_B | Y_A = y_A) f_{Y_A}(y_A) dy_A \\
 &= \int_{-\infty}^{\infty} (3 - \frac{3}{4}y_A) f_{Y_A}(y_A) dy_A \\
 &= 3 \int_{-\infty}^{\infty} f_{Y_A}(y_A) dy_A - \frac{3}{4} \int_{-\infty}^{\infty} y_A f_{Y_A}(y_A) dy_A \\
 &= 3 - \frac{3}{4}E(Y_A) \\
 &= \frac{3}{2}.
 \end{aligned}$$

Question 4b)

Conditional variance: $\text{Var}(Y_B | Y_A) = \text{Var}(3 - \frac{3}{4}Y_A + \varepsilon_B | Y_A = y_a) = \text{Var}(3 | Y_A = y_a) + \text{Var}(-\frac{3}{4}Y_A | Y_A = y_a) + \text{Var}(\varepsilon_B | Y_A = y_a) = \text{Var}(3) + \text{Var}(-\frac{3}{4}y_a) + \text{Var}(\varepsilon_B) = 0 + 0 + \frac{1}{4} = \frac{1}{4}$.

Alternatively, note that because of the independence of Y_A and ε_B we have $f_{\varepsilon_B | Y_A} = f_{\varepsilon_B, Y_A} / f_{Y_A} = f_{\varepsilon_B} f_{Y_A} / f_{Y_A} = f_{\varepsilon_B}$. Then:

$$\begin{aligned}
 \text{Var}(Y_B | Y_A = y_A) &= \int_{-\infty}^{\infty} [3 - \frac{3}{4}y_A + \varepsilon_B - E_{\varepsilon_B}(Y_B | Y_A = y_A)]^2 f_{\varepsilon_B | Y_A = y_A}(\varepsilon_B, y_A) d\varepsilon_B \\
 &= \int_{-\infty}^{\infty} \varepsilon_B^2 f_{\varepsilon_B}(\varepsilon_B) d\varepsilon_B \\
 &= \text{Var}(\varepsilon_B) \\
 &= \frac{1}{4}.
 \end{aligned}$$

Unconditional variance:

$$\begin{aligned}
 \text{Var}(Y_B) &= \text{Var}\left(3 - \frac{3}{4}Y_A + \varepsilon_B\right) \\
 &= \text{Var}(3) + \text{Var}\left(-\frac{3}{4}Y_A\right) + \text{Var}(\varepsilon_B) \\
 &= \frac{9}{16}\text{Var}(Y_A) + \frac{1}{4} \\
 &= \frac{9}{16} + \frac{1}{4} \\
 &= \frac{13}{16},
 \end{aligned}$$

in which we have used the independence between Y_A and ε_B .

Alternatively:

$$\begin{aligned}
 \text{Var}(Y_B) &= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \left[3 - \frac{3}{4}y_A + \varepsilon_B - E(Y_B)\right]^2 f_{\varepsilon_B, Y_A}(\varepsilon_B, y_A) d\varepsilon_B dY_A \\
 &= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \left[3 - \frac{3}{4}y_A + \varepsilon_B - 3 + \frac{3}{4}E(Y_A)\right]^2 f_{Y_A}(y_A) f_{\varepsilon_B}(\varepsilon_B) d\varepsilon_B dY_A \\
 &= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \left[-\left(\frac{3}{4}y_A - \frac{3}{4}E(Y_A)\right) + \varepsilon_B\right]^2 f_{Y_A}(y_A) f_{\varepsilon_B}(\varepsilon_B) d\varepsilon_B dY_A \\
 &= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \left[\frac{9}{16}(y_A - E(Y_A))^2 + \varepsilon_B^2 - \frac{6}{4}(y_A - E(Y_A))\varepsilon_B\right] f_{Y_A}(y_A) f_{\varepsilon_B}(\varepsilon_B) d\varepsilon_B dY_A \\
 &= \frac{9}{16} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} (y_A - E(Y_A))^2 + \varepsilon_B^2 f_{Y_A}(y_A) f_{\varepsilon_B}(\varepsilon_B) d\varepsilon_B dY_A \\
 &\quad + \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \varepsilon_B^2 f_{Y_A}(y_A) f_{\varepsilon_B}(\varepsilon_B) d\varepsilon_B dY_A \\
 &\quad - \frac{6}{4} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} (y_A - E(Y_A))\varepsilon_B f_{Y_A}(y_A) f_{\varepsilon_B}(\varepsilon_B) d\varepsilon_B dY_A \\
 &= \frac{9}{16}\text{Var}(Y_A) + \text{Var}(\varepsilon_B) \\
 &= \frac{9}{16} + \frac{1}{4} \\
 &= \frac{13}{16},
 \end{aligned}$$

as before.

Question 4c)

Covariance:

$$\begin{aligned}
 \text{Cov}(Y_A, Y_B) &= \text{Cov}\left(Y_A, 3 - \frac{3}{4}Y_A + \varepsilon_B\right) \\
 &= \text{Cov}(Y_A, 3) - \text{Cov}\left(Y_A, \frac{3}{4}Y_A\right) + \text{Cov}(Y_A, \varepsilon_B) \\
 &= -\frac{3}{4}\text{Var}(Y_A) \\
 &= -\frac{3}{4},
 \end{aligned}$$

in which we have used the independence between Y_A and ε_B .

Question 4d)

Correlation:

$$\begin{aligned}\text{Cor}(Y_A, Y_B) &= \text{Cov}(Y_A, Y_B) / [\text{Var}(Y_A)\text{Var}(Y_B)]^{1/2} \\ &= -\frac{3}{4} / \sqrt{\frac{13}{16}}\end{aligned}$$

Question 4e)

The bivariate distribution is given by:

$$\begin{pmatrix} Y_A \\ Y_B \end{pmatrix} \sim \mathcal{N}\left(\begin{pmatrix} 2 \\ \frac{3}{2} \end{pmatrix}, \begin{pmatrix} 1 & -\frac{3}{4} \\ -\frac{3}{4} & \frac{13}{16} \end{pmatrix}\right).$$

Question 5

Question 5a)

The covariance between Y_a and Y_b is:

$$\begin{aligned}\text{Cov}(Y_a, Y_b) &= \text{Cov}(-S + \gamma \varepsilon_a, S + \gamma \varepsilon_b) \\ &= \text{Cov}(-S + \gamma \varepsilon_a, S + \gamma \varepsilon_b) \\ &= \text{Cov}(-S, S) + \text{Cov}(-S, \gamma \varepsilon_b) + \text{Cov}(\gamma \varepsilon_a, S) + \text{Cov}(\gamma \varepsilon_a, \gamma \varepsilon_b) \\ &= -\text{Var}(S, S) = -1.\end{aligned}$$

Similarly,

$$\begin{aligned}\text{Var}(Y_a) &= \text{Cov}(-S, -S) + \dots + \text{Cov}(\gamma \varepsilon_a, \gamma \varepsilon_a) \\ &= 1 + \gamma^2 \\ &= \text{Var}(Y_b).\end{aligned}$$

Together this yields: $\text{Cov}(Y_a, Y_b) = -1/(1 + \gamma^2)$.

Question 5b)

The correlation tends to zero as $\gamma \rightarrow \infty$. As $\gamma \rightarrow \infty$ the larger the contribution of $\gamma \varepsilon$: the larger the noise. As a consequence, the signal drowns in the noise, and its influence on Y_a and Y_b fades. The signal is shared by Y_a and Y_b and as its influence vanishes so will the correlation.

Question 6

Question 6a)

Assume the object Y contains the data with rows and columns corresponding to individuals and genes, respectively. Then, the mean parameters are estimated as:

`> mean(Y[, 1])`

`> mean(Y[, 2])`

and the covariance matrix by:

```
> cov(Y)
```

Question 6b)

In this bivariate case the incorporation of the independence assumption amounts to setting ρ equal to zero. This can be verified by univariate estimation of the parameters. For the mean the R-code is given above, for the variance:

```
> var(Y[,1])
```

```
> var(Y[,2])
```

Question 6c)

To calculate the correlation matrix:

```
> cov(Y) .
```

This clearly deviates from zero. Regression analysis confirms a non-zero relation between Y_1 and Y_2 :

```
> summary(Y[,1] ~ Y[,2]) .
```