

## EXAM Graphical Models. TIME: 45 min.

### ALTERNATIVE WAY OF GETTING THE FINAL NOTE WITHOUT COMPUTER LAB REPORT: PRESENT EXERCISES FROM PARTS 3,4,5 + EXAM BY EMAIL

Let  $X$  be a centered Gaussian vector of dimension 3 given by  $X = (X_1, X_2, X_3)^T \sim N(0, \Sigma_X)$  with covariance matrix  $\Sigma_X = \begin{pmatrix} 2 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 2 \end{pmatrix}$  and precision matrix  $K_X = \begin{pmatrix} 1 & -1 & 0 \\ -1 & 3 & -1 \\ 0 & -1 & 1 \end{pmatrix}$ .

1. What is the relation between matrices  $\Sigma_X$  and  $K_X$ ?
2. Are there independent components  $X_i$ ? If yes, which ones?
3. Are there components  $X_i$  conditionally independent, knowing the others? If yes, which ones? What can we deduce on the prediction of  $X_1$ , if one knows  $X_2$  and  $X_3$ ?
4. Draw the dependance graph  $\mathcal{G}$  of  $X$ .
5. Determine the marginal law of  $(X_2, X_3)^T$ .
6. Determine the conditional law of  $(X_2, X_3)^T | X_1 = u$  and the conditional correlation  $\rho_{X_2, X_3 | X_1 = u}$ .
7. One knows that the random vector  $Y$  belongs to the graphical Gaussian model governed by the graph  $\mathcal{G}$ .
8. One does not know the covariance matrix  $\Sigma_Y$  of  $Y$ .

We have a sample of size  $n = 5$  of  $Y$  and one computes the sample (empirical) covariance matrix  $\tilde{\Sigma}_Y = \begin{pmatrix} 2 & 1 & 0.9 \\ 1 & 1 & 1 \\ 0.9 & 1 & 2 \end{pmatrix}$ .

Give the ML Estimator (MLE)  $\Sigma_Y$  and the MLE of the precision matrix  $K_Y$  of  $Y$ .

8. Is the graph  $\mathcal{G}$  complete? Decomposable? Give its decomposition into cliques.
9. Give an example of a non-decomposable graph.

**Some formulas from the lectures.** Let  $X$  be a Gaussian vector  $N(\xi, \Sigma)$  in  $\mathbf{R}^d$  with  $\Sigma$  invertible.

One partitions  $X = \begin{pmatrix} X_A \\ X_B \end{pmatrix}$  into sub-vectors  $X_A \in \mathbf{R}^r$  and  $X_B \in \mathbf{R}^s$ , where  $r + s = d$ .

One partitions  $\xi = \begin{pmatrix} \xi_A \\ \xi_B \end{pmatrix}$ ,  $\Sigma = \begin{pmatrix} \Sigma_{AA} & \Sigma_{AB} \\ \Sigma_{BA} & \Sigma_{BB} \end{pmatrix}$ ,  $K = \begin{pmatrix} K_{AA} & K_{AB} \\ K_{BA} & K_{BB} \end{pmatrix}$  into blocs  $\begin{pmatrix} r \times r & r \times s \\ s \times r & s \times s \end{pmatrix}$ .

The **conditional law**  $X_A | (X_B = x_B) \sim N(\xi_{A|B}, \Sigma_{A|B})$  where

$$\xi_{A|B} = \xi_A + \Sigma_{AB} \Sigma_{BB}^{-1} (x_B - \xi_B) \text{ and } \Sigma_{A|B} = K_{AA}^{-1}.$$

The **conditional correlation**  $\rho_{lm|V \setminus \{l,m\}} = -\tilde{\kappa}_{lm} = -\frac{\kappa_{lm}}{\sqrt{\kappa_{ll}} \sqrt{\kappa_{mm}}}$ .

**Maximum Likelihood Equation** :  $\pi_{\mathcal{G}}(\hat{K}^{-1}) = \pi_{\mathcal{G}}(\tilde{\Sigma})$ , where  $\tilde{\Sigma}$  is the sample covariance.