

Conditional Gaussian

- $\mathbf{X} = \begin{bmatrix} \mathbf{X}_a \\ \mathbf{X}_b \end{bmatrix}$ jointly Gaussian. We want to find $p(\mathbf{x}_a | \mathbf{x}_b)$. The joint pdf is

$$\mathcal{N}(\mathbf{x} | \boldsymbol{\mu}, \boldsymbol{\Sigma}) = \frac{1}{(2\pi)^{n/2}(\det \boldsymbol{\Sigma})^{1/2}} \exp\left(-\frac{1}{2}(\mathbf{x} - \boldsymbol{\mu})^\top \boldsymbol{\Sigma}^{-1}(\mathbf{x} - \boldsymbol{\mu})\right). \quad (1)$$

- We fix $\mathbf{X}_b = \mathbf{x}_b$ as a constant in $\mathcal{N}(\mathbf{x} | \boldsymbol{\mu}, \boldsymbol{\Sigma})$ and find its *functional form*, which tells us what $p(\mathbf{x}_a | \mathbf{x}_b)$ is.
- From (1), we know that $p(\mathbf{x}_a | \mathbf{x}_b)$ is a Gaussian pdf, so we only need to determine its mean $\boldsymbol{\mu}_{a|b}$ and covariance $\boldsymbol{\Sigma}_{a|b}$.

$$\boldsymbol{\mu} = \begin{bmatrix} \boldsymbol{\mu}_a \\ \boldsymbol{\mu}_b \end{bmatrix}, \quad \boldsymbol{\Sigma} = \begin{bmatrix} \boldsymbol{\Sigma}_{aa} & \boldsymbol{\Sigma}_{ab} \\ \boldsymbol{\Sigma}_{ba} & \boldsymbol{\Sigma}_{bb} \end{bmatrix}$$

$$\boldsymbol{\mu}_a = \mathbb{E}[\mathbf{X}_a]$$

$$\boldsymbol{\Sigma}_{aa} = \mathbb{E}[(\mathbf{X}_a - \boldsymbol{\mu}_a)(\mathbf{X}_a - \boldsymbol{\mu}_a)^\top], \quad \boldsymbol{\Sigma}_{ab} = \mathbb{E}[(\mathbf{X}_a - \boldsymbol{\mu}_a)(\mathbf{X}_b - \boldsymbol{\mu}_b)^\top] = \boldsymbol{\Sigma}_{ba}^\top$$

Conditional Gaussian

- Let $\Lambda = \Sigma^{-1} = \begin{bmatrix} \Lambda_{aa} & \Lambda_{ab} \\ \Lambda_{ba} & \Lambda_{bb} \end{bmatrix}$ and consider the exponent:

$$\begin{aligned} -\frac{1}{2}(\mathbf{x} - \boldsymbol{\mu})^\top \Lambda (\mathbf{x} - \boldsymbol{\mu}) &= -\frac{1}{2} \left[(\mathbf{x}_a - \boldsymbol{\mu}_a)^\top \Lambda_{aa} (\mathbf{x}_a - \boldsymbol{\mu}_a) \right. \\ &\quad + (\mathbf{x}_a - \boldsymbol{\mu}_a)^\top \Lambda_{ab} (\mathbf{x}_b - \boldsymbol{\mu}_b) \\ &\quad \left. + (\mathbf{x}_b - \boldsymbol{\mu}_b)^\top \Lambda_{ba} (\mathbf{x}_a - \boldsymbol{\mu}_a) \right] + \text{const.} \end{aligned}$$

Compare with

$$-\frac{1}{2}(\mathbf{x}_a - \boldsymbol{\mu}_{a|b})^\top \Sigma_{a|b}^{-1} (\mathbf{x}_a - \boldsymbol{\mu}_{a|b}) = -\frac{1}{2} \mathbf{x}_a^\top \Sigma_{a|b}^{-1} \mathbf{x}_a + \mathbf{x}_a^\top \Sigma_{a|b}^{-1} \boldsymbol{\mu}_{a|b} + \text{const.}$$

- Quadratic term in \mathbf{x}_a : $-\frac{1}{2} \mathbf{x}_a^\top \Lambda_{aa} \mathbf{x}_a \implies \Sigma_{a|b} = \Lambda_{aa}^{-1}$.
- Linear term in \mathbf{x}_a : $\mathbf{x}_a^\top (\Lambda_{aa} \boldsymbol{\mu}_a - \Lambda_{ab} (\mathbf{x}_b - \boldsymbol{\mu}_b)) \implies$

$$\begin{aligned} \boldsymbol{\mu}_{a|b} &= \Sigma_{a|b} (\Lambda_{aa} \boldsymbol{\mu}_a - \Lambda_{ab} (\mathbf{x}_b - \boldsymbol{\mu}_b)) \\ &= \boldsymbol{\mu}_a - \Lambda_{aa}^{-1} \Lambda_{ab} (\mathbf{x}_b - \boldsymbol{\mu}_b). \end{aligned}$$

Conditional Gaussian

- Inverse of partitioned matrix:

$$\begin{bmatrix} \mathbf{A} & \mathbf{B} \\ \mathbf{C} & \mathbf{D} \end{bmatrix}^{-1} = \begin{bmatrix} \mathbf{M} & -\mathbf{M}\mathbf{B}\mathbf{D}^{-1} \\ -\mathbf{D}^{-1}\mathbf{C}\mathbf{M} & \mathbf{D}^{-1} + \mathbf{D}^{-1}\mathbf{C}\mathbf{M}\mathbf{B}\mathbf{D}^{-1} \end{bmatrix},$$

where $\mathbf{M} = (\mathbf{A} - \mathbf{B}\mathbf{D}^{-1}\mathbf{C})^{-1}$ is called the Schur complement w.r.t. \mathbf{D} .

- Applying the above, we obtain

$$\Lambda_{aa} = (\Sigma_{aa} - \Sigma_{ab}\Sigma_{bb}^{-1}\Sigma_{ba})^{-1},$$

$$\Lambda_{ab} = -(\Sigma_{aa} - \Sigma_{ab}\Sigma_{bb}^{-1}\Sigma_{ba})^{-1}\Sigma_{ab}\Sigma_{bb}^{-1},$$

and finally

$$\mu_{a|b} = \mu_a + \Sigma_{ab}\Sigma_{bb}^{-1}(\mathbf{x}_b - \mu_b), \quad (2)$$

$$\Sigma_{a|b} = \Sigma_{aa} - \Sigma_{ab}\Sigma_{bb}^{-1}\Sigma_{ba}. \quad (3)$$