

# Some Derivations Involving Matrix Calculus

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# Gaussian & Mean Prior

$$\boldsymbol{\mu} \sim \mathcal{N}(\boldsymbol{\mu}_0, \boldsymbol{\Sigma}_0)$$

$$\boldsymbol{x}_1, \dots, \boldsymbol{x}_n \stackrel{iid}{\sim} \mathcal{N}(\boldsymbol{\mu}, \boldsymbol{\Sigma})$$

Remember that:  $\boldsymbol{x} \sim \mathcal{N}(\boldsymbol{\mu}, \boldsymbol{\Sigma}) \Rightarrow p(\boldsymbol{x}) = \frac{1}{\sqrt{(2\pi)^d |\boldsymbol{\Sigma}|}} e^{-\frac{1}{2}(\boldsymbol{x}-\boldsymbol{\mu})^\top \boldsymbol{\Sigma}^{-1}(\boldsymbol{x}-\boldsymbol{\mu})}$

# Gaussian & Mean Prior

$$\begin{aligned}\boldsymbol{\mu} &\sim \mathcal{N}(\boldsymbol{\mu}_0, \boldsymbol{\Sigma}_0) \\ \mathbf{x}_1, \dots, \mathbf{x}_n &\stackrel{iid}{\sim} \mathcal{N}(\boldsymbol{\mu}, \boldsymbol{\Sigma})\end{aligned}$$

Write down the log-posterior  $\mathcal{L}(\boldsymbol{\mu}) = \log p(\boldsymbol{\mu} | \mathbf{x}_1, \dots, \mathbf{x}_n)$ :

$$p(\boldsymbol{\mu} | \mathbf{x}_1, \dots, \mathbf{x}_n) \propto p(\mathbf{x}_1, \dots, \mathbf{x}_n | \boldsymbol{\mu}) p(\boldsymbol{\mu}) = p(\boldsymbol{\mu}) \prod_{i=1}^n p(\mathbf{x}_i | \boldsymbol{\mu}) \Rightarrow$$

$$\mathcal{L}(\boldsymbol{\mu}) = \log p(\boldsymbol{\mu}) + \sum_{i=1}^n \log p(\mathbf{x}_i | \boldsymbol{\mu}) + \mathbf{C}$$

$$= -\frac{1}{2}(\boldsymbol{\mu} - \boldsymbol{\mu}_0)^\top \boldsymbol{\Sigma}_0^{-1}(\boldsymbol{\mu} - \boldsymbol{\mu}_0) - \frac{1}{2} \sum_{i=1}^n (\mathbf{x}_i - \boldsymbol{\mu})^\top \boldsymbol{\Sigma}^{-1}(\mathbf{x}_i - \boldsymbol{\mu}) + \mathbf{C}$$

Remember that:  $\mathbf{x} \sim \mathcal{N}(\boldsymbol{\mu}, \boldsymbol{\Sigma}) \Rightarrow p(\mathbf{x}) = \frac{1}{\sqrt{(2\pi)^d |\boldsymbol{\Sigma}|}} e^{-\frac{1}{2}(\mathbf{x} - \boldsymbol{\mu})^\top \boldsymbol{\Sigma}^{-1}(\mathbf{x} - \boldsymbol{\mu})}$

# Gaussian & Mean Prior

$$\begin{aligned}\boldsymbol{\mu} &\sim \mathcal{N}(\boldsymbol{\mu}_0, \boldsymbol{\Sigma}_0) \\ \mathbf{x}_1, \dots, \mathbf{x}_n &\stackrel{iid}{\sim} \mathcal{N}(\boldsymbol{\mu}, \boldsymbol{\Sigma})\end{aligned}$$

Derive the first derivative of the log-posterior.

$$\begin{aligned}\nabla_{\boldsymbol{\mu}} \mathcal{L}(\boldsymbol{\mu}) &= \frac{\partial}{\partial \boldsymbol{\mu}} \left( -\frac{1}{2} (\boldsymbol{\mu} - \boldsymbol{\mu}_0)^\top \boldsymbol{\Sigma}_0^{-1} (\boldsymbol{\mu} - \boldsymbol{\mu}_0) - \frac{1}{2} \sum_{i=1}^n (\mathbf{x}_i - \boldsymbol{\mu})^\top \boldsymbol{\Sigma}^{-1} (\mathbf{x}_i - \boldsymbol{\mu}) \right) \\ &= -\boldsymbol{\Sigma}_0^{-1} (\boldsymbol{\mu} - \boldsymbol{\mu}_0) - \frac{1}{2} \sum_{i=1}^n \frac{\partial}{\partial \boldsymbol{\mu}} (\mathbf{x}_i - \boldsymbol{\mu})^\top \boldsymbol{\Sigma}^{-1} (\mathbf{x}_i - \boldsymbol{\mu}) \\ &= -\boldsymbol{\Sigma}_0^{-1} (\boldsymbol{\mu} - \boldsymbol{\mu}_0) - \boldsymbol{\Sigma}^{-1} \sum_{i=1}^n (\mathbf{x}_i - \boldsymbol{\mu}) \frac{\partial}{\partial \boldsymbol{\mu}} (\mathbf{x}_i - \boldsymbol{\mu}) \\ &= -\boldsymbol{\Sigma}_0^{-1} (\boldsymbol{\mu} - \boldsymbol{\mu}_0) + \boldsymbol{\Sigma}^{-1} \sum_{i=1}^n (\mathbf{x}_i - \boldsymbol{\mu})\end{aligned}$$

$$\frac{\partial \mathbf{x}^\top \mathbf{A} \mathbf{x}}{\partial \mathbf{x}} = (\mathbf{A} + \mathbf{A}^\top) \mathbf{x}$$

# Gaussian & Mean Prior

$$\begin{aligned}\boldsymbol{\mu} &\sim \mathcal{N}(\boldsymbol{\mu}_0, \boldsymbol{\Sigma}_0) \\ \mathbf{x}_1, \dots, \mathbf{x}_n &\stackrel{iid}{\sim} \mathcal{N}(\boldsymbol{\mu}, \boldsymbol{\Sigma})\end{aligned}$$

Derive the Hessian of the log-posterior.

$$\begin{aligned}\nabla_{\boldsymbol{\mu}}^2 \mathcal{L}(\boldsymbol{\mu}) &= \frac{\partial}{\partial \boldsymbol{\mu}} \left( -\boldsymbol{\Sigma}_0^{-1} (\boldsymbol{\mu} - \boldsymbol{\mu}_0) + \boldsymbol{\Sigma}^{-1} \sum_{i=1}^n (\mathbf{x}_i - \boldsymbol{\mu}) \right) \\ &= -\boldsymbol{\Sigma}_0^{-1} + \boldsymbol{\Sigma}^{-1} \sum_{i=1}^n \frac{\partial}{\partial \boldsymbol{\mu}} (\mathbf{x}_i - \boldsymbol{\mu}) \\ &= -\boldsymbol{\Sigma}_0^{-1} - n\boldsymbol{\Sigma}^{-1}\end{aligned}$$

# Gaussian & Mean Prior

$$\begin{aligned}\boldsymbol{\mu} &\sim \mathcal{N}(\boldsymbol{\mu}_0, \boldsymbol{\Sigma}_0) \\ \mathbf{x}_1, \dots, \mathbf{x}_n &\stackrel{iid}{\sim} \mathcal{N}(\boldsymbol{\mu}, \boldsymbol{\Sigma})\end{aligned}$$

Derive the MAP solution.

$$\nabla_{\boldsymbol{\mu}} \mathcal{L}(\boldsymbol{\mu}) = 0 \Rightarrow$$

$$-\boldsymbol{\Sigma}_0^{-1}(\boldsymbol{\mu}^* - \boldsymbol{\mu}_0) + \boldsymbol{\Sigma}^{-1} \sum_{i=1}^n (\mathbf{x}_i - \boldsymbol{\mu}^*) = 0 \Rightarrow$$

$$(\boldsymbol{\Sigma}_0^{-1} + n\boldsymbol{\Sigma}^{-1}) \boldsymbol{\mu}^* = \boldsymbol{\Sigma}^{-1} \sum_{i=1}^n \mathbf{x}_i + \boldsymbol{\Sigma}_0^{-1} \boldsymbol{\mu}_0 \Rightarrow$$

$$\boldsymbol{\mu}^* = (\boldsymbol{\Sigma}_0^{-1} + n\boldsymbol{\Sigma}^{-1})^{-1} \left( \boldsymbol{\Sigma}^{-1} \sum_{i=1}^n \mathbf{x}_i + \boldsymbol{\Sigma}_0^{-1} \boldsymbol{\mu}_0 \right)$$

# Gaussian & Joint Prior

$$\begin{aligned}\boldsymbol{\mu}, \boldsymbol{\Sigma} &\sim \mathcal{N}(\boldsymbol{\mu}|\boldsymbol{\mu}_0, \beta^{-1}\boldsymbol{\Sigma})\mathcal{W}^{-1}(\boldsymbol{\Sigma}|\boldsymbol{\Psi}, \nu) \\ \boldsymbol{x}_1, \dots, \boldsymbol{x}_n &\stackrel{iid}{\sim} \mathcal{N}(\boldsymbol{\mu}, \boldsymbol{\Sigma})\end{aligned}$$

$$\begin{aligned}\boldsymbol{\mu}, \boldsymbol{\Sigma} &\sim \text{NIW}(\boldsymbol{\mu}_0, \beta, \boldsymbol{\Psi}, \nu) = \mathcal{N}(\boldsymbol{\mu}|\boldsymbol{\mu}_0, \beta^{-1}\boldsymbol{\Sigma})\mathcal{W}^{-1}(\boldsymbol{\Sigma}|\boldsymbol{\Psi}, \nu) \\ \boldsymbol{x}_1, \dots, \boldsymbol{x}_n &\stackrel{iid}{\sim} \mathcal{N}(\boldsymbol{\mu}, \boldsymbol{\Sigma})\end{aligned}$$

Note:  $\boldsymbol{x} \sim \mathcal{N}(\boldsymbol{\mu}, \boldsymbol{\Sigma}) \Rightarrow p(\boldsymbol{x}) = \frac{1}{\sqrt{(2\pi)^d |\boldsymbol{\Sigma}|}} e^{-\frac{1}{2}(\boldsymbol{x}-\boldsymbol{\mu})^\top \boldsymbol{\Sigma}^{-1}(\boldsymbol{x}-\boldsymbol{\mu})}$ , and:

$$\boldsymbol{\Sigma} \sim \mathcal{W}^{-1}(\boldsymbol{\Psi}, \nu) \Rightarrow p(\boldsymbol{\Sigma}) = \frac{|\boldsymbol{\Psi}|^{\nu/2}}{2^{\nu d/2} \Gamma_d\left(\frac{\nu}{2}\right)} |\boldsymbol{\Sigma}|^{-(\nu+d+1)/2} e^{-\frac{1}{2}\text{Trace}(\boldsymbol{\Psi}\boldsymbol{\Sigma}^{-1})},$$

where  $\Gamma_d$  is the multivariate Gamma function.

# Gaussian & Joint Prior

$$\begin{aligned} \boldsymbol{\mu}, \boldsymbol{\Sigma} &\sim \mathcal{N}(\boldsymbol{\mu}|\boldsymbol{\mu}_0, \beta^{-1}\boldsymbol{\Sigma})\mathcal{W}^{-1}(\boldsymbol{\Sigma}|\boldsymbol{\Psi}, \nu) \\ \boldsymbol{x}_1, \dots, \boldsymbol{x}_n &\stackrel{iid}{\sim} \mathcal{N}(\boldsymbol{\mu}, \boldsymbol{\Sigma}) \end{aligned}$$

Write down the log-posterior  $\mathcal{L}(\boldsymbol{\mu}, \boldsymbol{\Sigma}) = \log p(\boldsymbol{\mu}, \boldsymbol{\Sigma}|\boldsymbol{x}_1, \dots, \boldsymbol{x}_n)$ :

Note:  $\boldsymbol{x} \sim \mathcal{N}(\boldsymbol{\mu}, \boldsymbol{\Sigma}) \Rightarrow p(\boldsymbol{x}) = \frac{1}{\sqrt{(2\pi)^d |\boldsymbol{\Sigma}|}} e^{-\frac{1}{2}(\boldsymbol{x}-\boldsymbol{\mu})^\top \boldsymbol{\Sigma}^{-1}(\boldsymbol{x}-\boldsymbol{\mu})}$ , and:

$$\boldsymbol{\Sigma} \sim \mathcal{W}^{-1}(\boldsymbol{\Psi}, \nu) \Rightarrow p(\boldsymbol{\Sigma}) = \frac{|\boldsymbol{\Psi}|^{\nu/2}}{2^{\nu d/2} \Gamma_d\left(\frac{\nu}{2}\right)} |\boldsymbol{\Sigma}|^{-(\nu+d+1)/2} e^{-\frac{1}{2}\text{Trace}(\boldsymbol{\Psi}\boldsymbol{\Sigma}^{-1})},$$

where  $\Gamma_d$  is the multivariate Gamma function.



# Gaussian & Joint Prior

$$\begin{aligned} \boldsymbol{\mu}, \Sigma &\sim \mathcal{N}(\boldsymbol{\mu}|\boldsymbol{\mu}_0, \beta^{-1}\Sigma)\mathcal{W}^{-1}(\Sigma|\Psi, \nu) \\ \mathbf{x}_1, \dots, \mathbf{x}_n &\stackrel{iid}{\sim} \mathcal{N}(\boldsymbol{\mu}, \Sigma) \end{aligned}$$

$$\begin{aligned} p(\boldsymbol{\mu}, \Sigma|\mathbf{x}_1, \dots, \mathbf{x}_n) &\propto p(\mathbf{x}_1, \dots, \mathbf{x}_n|\boldsymbol{\mu}, \Sigma)p(\boldsymbol{\mu}|\Sigma)p(\Sigma) \\ &\propto p(\boldsymbol{\mu}|\Sigma)p(\Sigma) \prod_{i=1}^n p(\mathbf{x}_i|\boldsymbol{\mu}) \Rightarrow \end{aligned}$$

Note:  $\mathbf{x} \sim \mathcal{N}(\boldsymbol{\mu}, \Sigma) \Rightarrow p(\mathbf{x}) = \frac{1}{\sqrt{(2\pi)^d |\Sigma|}} e^{-\frac{1}{2}(\mathbf{x}-\boldsymbol{\mu})^\top \Sigma^{-1}(\mathbf{x}-\boldsymbol{\mu})}$ , and:

$$\Sigma \sim \mathcal{W}^{-1}(\Psi, \nu) \Rightarrow p(\Sigma) = \frac{|\Psi|^{\nu/2}}{2^{\nu d/2} \Gamma_d\left(\frac{\nu}{2}\right)} |\Sigma|^{-(\nu+d+1)/2} e^{-\frac{1}{2}\text{Trace}(\Psi \Sigma^{-1})},$$

where  $\Gamma_d$  is the multivariate Gamma function.

# Gaussian & Joint Prior

$$\begin{aligned}\boldsymbol{\mu}, \boldsymbol{\Sigma} &\sim \mathcal{N}(\boldsymbol{\mu}|\boldsymbol{\mu}_0, \beta^{-1}\boldsymbol{\Sigma})\mathcal{W}^{-1}(\boldsymbol{\Sigma}|\boldsymbol{\Psi}, \nu) \\ \mathbf{x}_1, \dots, \mathbf{x}_n &\stackrel{iid}{\sim} \mathcal{N}(\boldsymbol{\mu}, \boldsymbol{\Sigma})\end{aligned}$$

$$\begin{aligned}\mathcal{L}(\boldsymbol{\mu}, \boldsymbol{\Sigma}) &= \log p(\boldsymbol{\mu}|\boldsymbol{\Sigma}) + \log p(\boldsymbol{\Sigma}) + \sum_{i=1}^n \log p(\mathbf{x}_i|\boldsymbol{\mu}, \boldsymbol{\Sigma}) + \mathbf{C} \\ &= -\frac{1}{2} \log |\boldsymbol{\Sigma}| - \frac{\beta}{2} (\boldsymbol{\mu} - \boldsymbol{\mu}_0)^\top \boldsymbol{\Sigma}^{-1} (\boldsymbol{\mu} - \boldsymbol{\mu}_0) \\ &\quad - \frac{\nu + d + 1}{2} \log |\boldsymbol{\Sigma}| - \frac{1}{2} \text{Trace}(\boldsymbol{\Psi} \boldsymbol{\Sigma}^{-1}) \\ &\quad - \frac{n}{2} \log |\boldsymbol{\Sigma}| - \frac{1}{2} \sum_{i=1}^n (\mathbf{x}_i - \boldsymbol{\mu})^\top \boldsymbol{\Sigma}^{-1} (\mathbf{x}_i - \boldsymbol{\mu}) + \mathbf{C}\end{aligned}$$

Note:  $\mathbf{x} \sim \mathcal{N}(\boldsymbol{\mu}, \boldsymbol{\Sigma}) \Rightarrow p(\mathbf{x}) = \frac{1}{\sqrt{(2\pi)^d |\boldsymbol{\Sigma}|}} e^{-\frac{1}{2}(\mathbf{x} - \boldsymbol{\mu})^\top \boldsymbol{\Sigma}^{-1} (\mathbf{x} - \boldsymbol{\mu})}$ , and:

$$\boldsymbol{\Sigma} \sim \mathcal{W}^{-1}(\boldsymbol{\Psi}, \nu) \Rightarrow p(\boldsymbol{\Sigma}) = \frac{|\boldsymbol{\Psi}|^{\nu/2}}{2^{\nu d/2} \Gamma_d\left(\frac{\nu}{2}\right)} |\boldsymbol{\Sigma}|^{-(\nu+d+1)/2} e^{-\frac{1}{2} \text{Trace}(\boldsymbol{\Psi} \boldsymbol{\Sigma}^{-1})},$$

where  $\Gamma_d$  is the multivariate Gamma function.

# Gaussian & Joint Prior

$$\mu, \Sigma \sim \mathcal{N}(\mu | \mu_0, \beta^{-1} \Sigma) \mathcal{W}^{-1}(\Sigma | \Psi, \nu)$$
$$\mathbf{x}_1, \dots, \mathbf{x}_n \stackrel{iid}{\sim} \mathcal{N}(\mu, \Sigma)$$

Derive  $\nabla_{\mu} \mathcal{L}(\mu, \Sigma)$ .

$$\begin{aligned} \nabla_{\mu} \mathcal{L}(\mu, \Sigma) &= \frac{\partial}{\partial \mu} \left( -\frac{\beta}{2} (\mu - \mu_0)^{\top} \Sigma^{-1} (\mu - \mu_0) - \frac{1}{2} \sum_{i=1}^n (\mathbf{x}_i - \mu)^{\top} \Sigma^{-1} (\mathbf{x}_i - \mu) \right) \\ &= -\beta \Sigma^{-1} (\mu - \mu_0) - \frac{1}{2} \sum_{i=1}^n \frac{\partial}{\partial \mu} (\mathbf{x}_i - \mu)^{\top} \Sigma^{-1} (\mathbf{x}_i - \mu) \\ &= -\beta \Sigma^{-1} (\mu - \mu_0) - \Sigma^{-1} \sum_{i=1}^n (\mathbf{x}_i - \mu) \frac{\partial}{\partial \mu} (\mathbf{x}_i - \mu) \\ &= -\beta \Sigma^{-1} (\mu - \mu_0) + \Sigma^{-1} \sum_{i=1}^n (\mathbf{x}_i - \mu) \end{aligned}$$

$$\frac{\partial \mathbf{x}^{\top} \mathbf{A} \mathbf{x}}{\partial \mathbf{x}} = (\mathbf{A} + \mathbf{A}^{\top}) \mathbf{x}$$

# Gaussian & Joint Prior

$$\mu, \Sigma \sim \mathcal{N}(\mu | \mu_0, \beta^{-1} \Sigma) \mathcal{W}^{-1}(\Sigma | \Psi, \nu)$$
$$\mathbf{x}_1, \dots, \mathbf{x}_n \stackrel{iid}{\sim} \mathcal{N}(\mu, \Sigma)$$

Derive  $\nabla_{\Sigma} \mathcal{L}(\mu, \Sigma)$ .

$$\begin{aligned} \nabla_{\Sigma} \mathcal{L}(\mu, \Sigma) &= -\frac{\beta}{2} \frac{\partial}{\partial \Sigma} (\mu - \mu_0)^{\top} \Sigma^{-1} (\mu - \mu_0) - \frac{\nu + d + n + 2}{2} \frac{\partial}{\partial \Sigma} \log |\Sigma| - \frac{1}{2} \frac{\partial}{\partial \Sigma} \text{Trace}(\Psi \Sigma^{-1}) \\ &\quad - \frac{1}{2} \frac{\partial}{\partial \Sigma} \sum_{i=1}^n (\mathbf{x}_i - \mu)^{\top} \Sigma^{-1} (\mathbf{x}_i - \mu) \\ &= -\frac{\nu + d + n + 2}{2} \Sigma^{-1} + \frac{\beta}{2} \Sigma^{-1} (\mu - \mu_0) (\mu - \mu_0)^{\top} \Sigma^{-1} + \frac{1}{2} \Sigma^{-1} \Psi \Sigma^{-1} \\ &\quad + \frac{1}{2} \Sigma^{-1} \left[ \sum_{i=1}^n (\mathbf{x}_i - \mu) (\mathbf{x}_i - \mu)^{\top} \right] \Sigma^{-1} \end{aligned}$$

$$\frac{\partial \log |A|}{\partial A} = A^{-\top}$$
$$\frac{\partial \mathbf{x}^{\top} A^{-1} \mathbf{y}}{\partial A} = -A^{-\top} \mathbf{x} \mathbf{y}^{\top} A^{-\top}$$
$$\frac{\partial \text{Trace}(BA^{-1}C)}{\partial A} = -(A^{-1}CBA^{-1})^{\top}$$

# Gaussian & Joint Prior

$$\mu, \Sigma \sim \mathcal{N}(\mu|\mu_0, \beta^{-1}\Sigma)\mathcal{W}^{-1}(\Sigma|\Psi, \nu)$$
$$\mathbf{x}_1, \dots, \mathbf{x}_n \stackrel{iid}{\sim} \mathcal{N}(\mu, \Sigma)$$

Derive the MAP solution.

$$\nabla_{\mu}\mathcal{L}(\mu, \Sigma) = 0 \Rightarrow$$

$$-\beta\Sigma^{-1}(\mu^* - \mu_0) + \Sigma^{-1} \sum_{i=1}^n (\mathbf{x}_i - \mu^*) = 0 \Rightarrow$$

$$(\beta + n)\mu^* = \sum_{i=1}^n \mathbf{x}_i + \beta\mu_0 \Rightarrow$$

$$\mu^* = \frac{\sum_{i=1}^n \mathbf{x}_i + \beta\mu_0}{\beta + n}$$

$$\nabla_{\Sigma}\mathcal{L}(\mu, \Sigma) = 0 \Rightarrow$$

$$\beta\Sigma^{*-1}(\mu - \mu_0)(\mu - \mu_0)^{\top} + \Sigma^{*-1}\Psi + \Sigma^{*-1} \left[ \sum_{i=1}^n (\mathbf{x}_i - \mu)(\mathbf{x}_i - \mu)^{\top} \right] = \nu + d + n + 2 \Rightarrow$$

$$\Sigma^* = \frac{\beta(\mu - \mu_0)(\mu - \mu_0)^{\top} + \Psi + \sum_{i=1}^n (\mathbf{x}_i - \mu)(\mathbf{x}_i - \mu)^{\top}}{\nu + d + n + 2}$$

Done! :)