

# Local Global Approximations (working title)

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January 23, 2023

## 1 Introduction

We will continue to work on the Lasso because that is a good place to start.

## 2 The Lasso Distribution

If  $x \sim \text{Lasso}(a, b, c)$  with then it has density given by

$$p(x, a, b, c) = Z^{-1} \exp \left( -\frac{1}{2}ax^2 + bx - c|x| \right)$$

where  $x \in \mathbb{R}$ ,  $a > 0$ ,  $b \in \mathbb{R}$ ,  $c > 0$ , and  $Z$  is the normalizing constant. Then

$$\begin{aligned} Z(a, b, c) &= \int_{-\infty}^{\infty} \exp \left[ -\frac{1}{2}ax^2 + bx - c|x| \right] dx \\ &= \int_0^{\infty} \exp \left[ -\frac{1}{2}ax^2 + (b - c)x \right] dx + \int_{-\infty}^0 \exp \left[ -\frac{1}{2}ax^2 + (b + c)x \right] dx \\ &= \int_0^{\infty} \exp \left[ -\frac{1}{2}ax^2 + (b - c)x \right] dx + \int_0^{\infty} \exp \left[ -\frac{1}{2}ay^2 - (b + c)y \right] dy \\ &= \int_0^{\infty} \exp \left[ -\frac{(x - \mu_1)^2}{2\sigma^2} + \frac{\mu_1^2}{2\sigma^2} \right] dx + \int_0^{\infty} \exp \left[ -\frac{(x - \mu_2)^2}{2\sigma^2} + \frac{\mu_2^2}{2\sigma^2} \right] dy \\ &= \sqrt{2\pi\sigma^2} \left[ \exp \left\{ \frac{\mu_1^2}{2\sigma^2} \right\} \int_0^{\infty} \phi(x; \mu_1, \sigma^2) dx + \exp \left\{ \frac{\mu_2^2}{2\sigma^2} \right\} \int_0^{\infty} \phi(y; \mu_2, \sigma^2) dy \right] \\ &= \sqrt{2\pi\sigma^2} \left[ \exp \left\{ \frac{\mu_1^2}{2\sigma^2} \right\} \{1 - \Phi(-\mu_1/\sigma)\} + \exp \left\{ \frac{\mu_2^2}{2\sigma^2} \right\} \{1 - \Phi(-\mu_2/\sigma)\} \right] \\ &= \sqrt{2\pi\sigma^2} \left[ \exp \left( \frac{\mu_1^2}{2\sigma^2} \right) \Phi \left( \frac{\mu_1}{\sigma} \right) + \exp \left( \frac{\mu_2^2}{2\sigma^2} \right) \Phi \left( \frac{\mu_2}{\sigma} \right) \right] \\ &= \sigma \left[ \frac{\Phi(\mu_1/\sigma)}{\phi(\mu_1/\sigma)} + \frac{\Phi(\mu_2/\sigma)}{\phi(\mu_2/\sigma)} \right] \end{aligned}$$

where  $\mu_1 = (b - c)/a$ ,  $\mu_2 = -(c + b)/a$  and  $\sigma^2 = 1/a$ . Care should be taken when evaluating  $Z$  (which is prone to overflow and divide by zero problems) and is a function of the Mills ratio.

## 2.1 The Moment Generating function and Moments

The moment generating function requires almost identical calculations with  $b$  replaced with  $b + t$ .

$$M(t) = \frac{Z(a, b + t, c)}{Z(a, b, c)}$$

While this is true it doesn't look useful for calculating moments.

## 2.2 Moments

The moments of the Lasso distribution are:

$$\begin{aligned} E(x^r) &= Z^{-1} \int_{-\infty}^{\infty} x^r \exp \left[ -\frac{1}{2}ax^2 + bx - c|x| \right] dx \\ &= Z^{-1} \int_0^{\infty} x^r \exp \left[ -\frac{1}{2}ax^2 + (b - c)x \right] dx + \int_{-\infty}^0 x^r \exp \left[ -\frac{1}{2}ax^2 + (b + c)x \right] dx \\ &= Z^{-1} \int_0^{\infty} x^r \exp \left[ -\frac{1}{2}ax^2 + (b - c)x \right] dx + (-1)^r \int_0^{\infty} y^r \exp \left[ -\frac{1}{2}ay^2 - (b + c)y \right] dy \\ &= Z^{-1} \sqrt{2\pi\sigma^2} \exp \left( \frac{\mu_1^2}{2\sigma^2} \right) \int_0^{\infty} x^r \phi(x; \mu_1, \sigma^2) dx \\ &\quad + (-1)^r \sqrt{2\pi\sigma^2} \exp \left( \frac{\mu_2^2}{2\sigma^2} \right) \int_0^{\infty} y^r \phi(y; \mu_2, \sigma^2) dy \\ &= \frac{\sigma}{Z} \left[ \frac{\Phi(\mu_1/\sigma)}{\phi(\mu_1/\sigma)} \frac{\int_0^{\infty} x^r \phi(x; \mu_1, \sigma^2) dx}{\Phi(\mu_1/\sigma)} + (-1)^r \frac{\Phi(\mu_2/\sigma)}{\phi(\mu_2/\sigma)} \frac{\int_0^{\infty} y^r \phi(y; \mu_2, \sigma^2) dy}{\Phi(\mu_2/\sigma)} \right] \\ &= \frac{\sigma}{Z} \left[ \frac{\Phi(\mu_1/\sigma)}{\phi(\mu_1/\sigma)} \mathbb{E}(A^r) + (-1)^r \frac{\Phi(\mu_2/\sigma)}{\phi(\mu_2/\sigma)} \mathbb{E}(B^r) \right] \end{aligned}$$

where  $A \sim TN_+(\mu_1, \sigma^2)$ ,  $B \sim TN_+(\mu_2, \sigma^2)$  and  $TN_+$  denotes the positively truncated normal distribution. Note that

$$\mathbb{E}(A) = \mu_1 + \frac{\sigma\phi(\mu_1/\sigma)}{\Phi(\mu_1/\sigma)} = \mu_1 + \sigma\zeta_1(\mu_1/\sigma)$$

and

$$\mathbb{V}(A) = \sigma^2 [1 + \zeta_2(\mu_1/\sigma)]$$

where  $\zeta_k(x) = d^k \log \Phi(x)/dx^k$ ,  $\zeta_1(t) = \phi(t)/\Phi(t)$ ,  $\zeta_2(t) = -t\zeta_1(t) - \zeta_1(t)^2$ . Here  $\zeta_1(x)$  is the inverse Mills ratio which too needs to be treated with care. Hence,

$$\mathbb{E}(A^2) = \mathbb{V}(A) + \mathbb{E}(A)^2 = \sigma^2 [1 + \zeta_2(\mu_1/\sigma)] + [\mu_1 + \sigma\zeta_1(\mu_1/\sigma)]^2$$

We now have sufficient information to calculate the moments of the Lasso distribution. We also have sufficient information to implement a VB approximation.

## 2.3 CDF

Similarly if  $z \leq 0$  the CDF is given by

$$\begin{aligned}
P(Z < z) &= Z^{-1} \int_{-\infty}^z \exp \left[ -\frac{1}{2}ax^2 + (b+c)x \right] dx \\
&= Z^{-1} \sqrt{2\pi\sigma^2} \exp \left( \frac{\mu_2^2}{2\sigma^2} \right) \int_{-\infty}^z \phi(x; -\mu_2, \sigma^2) \\
&= Z^{-1} \sqrt{2\pi\sigma^2} \exp \left( \frac{\mu_2^2}{2\sigma^2} \right) \Phi \left( \frac{z + \mu_2}{\sigma} \right) \\
&= \frac{\sigma}{Z} \frac{\Phi \left( \frac{z + \mu_2}{\sigma} \right)}{\phi(\mu_2/\sigma)}
\end{aligned}$$

and if  $z > 0$  we have

$$\begin{aligned}
P(Z < z) &= Z^{-1} \int_{-\infty}^z \exp \left( -\frac{1}{2}ax^2 + bx - c|x| \right) dx \\
&= Z^{-1} \sqrt{2\pi\sigma^2} \left[ \exp \left( \frac{\mu_1^2}{2\sigma^2} \right) \int_0^z \phi(x; \mu_1, \sigma^2) dx + \exp \left( \frac{\mu_2^2}{2\sigma^2} \right) \Phi \left( \frac{\mu_2}{\sigma} \right) \right] \\
&= \frac{\sigma}{Z} \left[ \frac{\Phi \left( \frac{z - \mu_1}{\sigma} \right) - \Phi \left( \frac{-\mu_1}{\sigma} \right)}{\phi(\mu_1/\sigma)} + \frac{\Phi(\mu_2/\sigma)}{\phi(\mu_2/\sigma)} \right]
\end{aligned}$$

## 2.4 Inverse CDF

For the inverse CDF we again have two cases. Let  $u = P(Z < z)$ . When

$$u \leq \frac{\sigma}{Z} \frac{\Phi(\mu_2/\sigma)}{\phi(\mu_2/\sigma)}$$

we solve

$$u = \frac{\sigma \Phi \left( \frac{z + \mu_2}{\sigma} \right)}{Z \phi(\mu_2/\sigma)}$$

for  $z$  to obtain

$$z = \mu_2 + \sigma \Phi^{-1} \left[ (Z/\sigma) \phi_\sigma(\mu_2/\sigma) u \right]$$

When

$$u > \frac{\sigma}{Z} \frac{\Phi(\mu_2/\sigma)}{\phi(\mu_2/\sigma)}$$

we need to solve

$$u = \frac{\sigma}{Z} \left[ \frac{\Phi \left( \frac{z - \mu_1}{\sigma} \right) - \Phi \left( \frac{-\mu_1}{\sigma} \right)}{\phi(\mu_1/\sigma)} + \frac{\Phi(\mu_2/\sigma)}{\phi(\mu_2/\sigma)} \right]$$

for  $z$  to obtain

$$z = \mu_1 + \sigma \Phi^{-1} \left[ \phi(\mu_1/\sigma) \left\{ \frac{Zu}{\sigma} - \frac{\Phi(\mu_2/\sigma)}{\phi(\mu_2/\sigma)} \right\} + \Phi \left( \frac{-\mu_1}{\sigma} \right) \right]$$

which also involves the Mills ratio.

### 3 Tasks

Suppose that conformably we have

$$\boldsymbol{\mu} = \begin{bmatrix} \boldsymbol{\mu}_1 \\ \boldsymbol{\mu}_2 \end{bmatrix} \quad \text{and} \quad \boldsymbol{\Sigma} = \begin{bmatrix} \boldsymbol{\Sigma}_{11} & \boldsymbol{\Sigma}_{12} \\ \boldsymbol{\Sigma}_{21} & \boldsymbol{\Sigma}_{22} \end{bmatrix}$$

and  $\boldsymbol{\theta} = (\boldsymbol{\theta}_1, \boldsymbol{\theta}_2)$  and  $q(\boldsymbol{\theta}) \sim N(\boldsymbol{\mu}, \boldsymbol{\Sigma})$  approximates  $p(\boldsymbol{\theta} \mid \mathcal{D})$ .

1. Verify the algebra in Section 2 above for the Lasso distribution.
2. Show that

$$p(\boldsymbol{\theta}_1 \mid \mathcal{D}) = \int p(\boldsymbol{\theta}_1 \mid \mathcal{D}, \boldsymbol{\theta}_2) p(\boldsymbol{\theta}_2 \mid \mathcal{D}) d\boldsymbol{\theta}_2$$

3. Find  $q(\boldsymbol{\theta}_2 \mid \boldsymbol{\theta}_1)$ .

**Solution:** The conditional distribution of  $\boldsymbol{\theta}_1 \mid \boldsymbol{\theta}_2$  is

$$\phi(\boldsymbol{\theta}_2; \boldsymbol{\mu}_2 + \boldsymbol{\Sigma}_{21} \boldsymbol{\Sigma}_{11}^{-1} (\boldsymbol{\theta}_1 - \boldsymbol{\mu}_1), \boldsymbol{\Sigma}_{22} - \boldsymbol{\Sigma}_{21} \boldsymbol{\Sigma}_{11}^{-1} \boldsymbol{\Sigma}_{21})$$

4. Suppose that we approximate  $p(\boldsymbol{\theta}_2 \mid \mathcal{D})$  by  $q(\boldsymbol{\theta}_2) = N(\boldsymbol{\mu}_2, \boldsymbol{\Sigma}_{22})$ . Suppose we use this to approximate  $p(\boldsymbol{\theta}_1 \mid \mathcal{D})$  by

$$q^*(\boldsymbol{\theta}_1) = \int p(\boldsymbol{\theta}_1 \mid \mathcal{D}, \boldsymbol{\theta}_2) q(\boldsymbol{\theta}_2) d\boldsymbol{\theta}_2$$

Suppose that the mean of  $q^*(\boldsymbol{\theta}_1)$  is  $\boldsymbol{\mu}_1^*$ , covariance is  $\boldsymbol{\Sigma}_{11}^*$ , and  $q^*(\boldsymbol{\theta}_1) \approx N(\boldsymbol{\mu}_1^*, \boldsymbol{\Sigma}_{11}^*)$ . We update  $q(\boldsymbol{\theta})$  via

$$q^*(\boldsymbol{\theta}) = q(\boldsymbol{\theta}_2 \mid \boldsymbol{\theta}_1) \phi(\boldsymbol{\theta}_1; \boldsymbol{\mu}_1^*, \boldsymbol{\Sigma}_{11}^*)$$

Find  $q^*(\boldsymbol{\theta})$ .

**Solution [The easy way]:** We know that  $q(\boldsymbol{\theta}_2|\boldsymbol{\theta}_1)$  and  $q(\boldsymbol{\theta}_1)$  are Gaussian. Hence, their joint distribution will also be Gaussian. The marginal mean and variance of the joint distribution for  $\boldsymbol{\theta}_1$  will be  $\boldsymbol{\mu}_1^*$  and  $\boldsymbol{\Sigma}_{11}^*$ . Suppose the mean and covariance of the joint distribution are  $\tilde{\boldsymbol{\mu}}$  and  $\tilde{\boldsymbol{\Sigma}}$  respectively. Then  $\tilde{\boldsymbol{\mu}}_1 = \boldsymbol{\mu}_1^*$ , and  $\tilde{\boldsymbol{\Sigma}}_{11} = \boldsymbol{\Sigma}_{11}^*$ . All we need to do is determine  $\tilde{\boldsymbol{\mu}}_2$ ,  $\tilde{\boldsymbol{\Sigma}}_{22}$  and  $\tilde{\boldsymbol{\Sigma}}_{12}$ .

We have

$$\begin{aligned}\mathbb{E}(\boldsymbol{\theta}_2) &= \mathbb{E}[\mathbb{E}(\boldsymbol{\theta}_2 | \boldsymbol{\theta}_1)] \\ &= \mathbb{E}[\boldsymbol{\mu}_2 + \boldsymbol{\Sigma}_{21}\boldsymbol{\Sigma}_{11}^{-1}(\boldsymbol{\theta}_1 - \boldsymbol{\mu}_1)] \\ &= \boldsymbol{\mu}_2 + \boldsymbol{\Sigma}_{21}\boldsymbol{\Sigma}_{11}^{-1}(\boldsymbol{\mu}_1^* - \boldsymbol{\mu}_1).\end{aligned}$$

Similarly,

$$\begin{aligned}\text{Cov}(\boldsymbol{\theta}_2) &= \mathbb{E}[\text{Cov}(\boldsymbol{\theta}_2 | \boldsymbol{\theta}_1)] + \text{Cov}[\mathbb{E}(\boldsymbol{\theta}_2 | \boldsymbol{\theta}_1)] \\ &= \mathbb{E}(\boldsymbol{\Sigma}_{22} - \boldsymbol{\Sigma}_{21}\boldsymbol{\Sigma}_{11}^{-1}\boldsymbol{\Sigma}_{22}) + \text{Cov}[\boldsymbol{\mu}_2 + \boldsymbol{\Sigma}_{21}\boldsymbol{\Sigma}_{11}^{-1}(\boldsymbol{\theta}_1 - \boldsymbol{\mu}_1)] \\ &= \boldsymbol{\Sigma}_{22} - \boldsymbol{\Sigma}_{21}\boldsymbol{\Sigma}_{11}^{-1}\boldsymbol{\Sigma}_{22} + \boldsymbol{\Sigma}_{21}\boldsymbol{\Sigma}_{11}^{-1}\text{Cov}(\boldsymbol{\theta}_1)\boldsymbol{\Sigma}_{11}^{-1}\boldsymbol{\Sigma}_{12} \\ &= \boldsymbol{\Sigma}_{22} + \boldsymbol{\Sigma}_{21}(\boldsymbol{\Sigma}_{11}^{-1}\boldsymbol{\Sigma}_{11}^*\boldsymbol{\Sigma}_{11}^{-1} - \boldsymbol{\Sigma}_{11}^{-1})\boldsymbol{\Sigma}_{12}.\end{aligned}$$

Lastly,

$$\begin{aligned}\text{Cov}(\boldsymbol{\theta}_1, \boldsymbol{\theta}_2) &= \mathbb{E}[(\boldsymbol{\theta} - \mathbb{E}(\boldsymbol{\theta}_1))(\boldsymbol{\theta}_2 - \mathbb{E}(\boldsymbol{\theta}_2))^T] \\ &= \mathbb{E}[\mathbb{E}\{(\boldsymbol{\theta}_1 - \mathbb{E}(\boldsymbol{\theta}_1))(\boldsymbol{\theta}_2 - \mathbb{E}(\boldsymbol{\theta}_2))^T | \boldsymbol{\theta}_1\}] \\ &= \mathbb{E}\left[(\boldsymbol{\theta}_1 - \boldsymbol{\mu}_1^*)(\boldsymbol{\Sigma}_{21}\boldsymbol{\Sigma}_{11}^{-1}(\boldsymbol{\theta}_1 - \boldsymbol{\mu}_1^*))^T\right] \\ &= \mathbb{E}\left[(\boldsymbol{\theta}_1 - \boldsymbol{\mu}_1^*)(\boldsymbol{\theta}_1 - \boldsymbol{\mu}_1^*)^T\right]\boldsymbol{\Sigma}_{11}^{-1}\boldsymbol{\Sigma}_{12} \\ &= \boldsymbol{\Sigma}_{11}^*\boldsymbol{\Sigma}_{11}^{-1}\boldsymbol{\Sigma}_{12}.\end{aligned}$$

Hence,  $q^*(\boldsymbol{\theta}) = N(\tilde{\boldsymbol{\mu}}, \tilde{\boldsymbol{\Sigma}})$  where

$$\tilde{\boldsymbol{\mu}} = \begin{bmatrix} \boldsymbol{\mu}_1^* \\ \boldsymbol{\mu}_2 + \boldsymbol{\Sigma}_{21}\boldsymbol{\Sigma}_{11}^{-1}(\boldsymbol{\mu}_1^* - \boldsymbol{\mu}_1) \end{bmatrix}$$

and

$$\tilde{\boldsymbol{\Sigma}} = \begin{bmatrix} \boldsymbol{\Sigma}_{11}^* & \boldsymbol{\Sigma}_{11}^*\boldsymbol{\Sigma}_{11}^{-1}\boldsymbol{\Sigma}_{12} \\ \boldsymbol{\Sigma}_{21}\boldsymbol{\Sigma}_{11}^{-1}\boldsymbol{\Sigma}_{11}^* & \boldsymbol{\Sigma}_{22} + \boldsymbol{\Sigma}_{21}\boldsymbol{\Sigma}_{11}^{-1}(\boldsymbol{\Sigma}_{11}^* - \boldsymbol{\Sigma}_{11})\boldsymbol{\Sigma}_{11}^{-1}\boldsymbol{\Sigma}_{12} \end{bmatrix}.$$

**Solution [The hard way]:** Consider,

$$\begin{aligned}
& q(\boldsymbol{\theta}_2 \mid \boldsymbol{\theta}_1) \phi(\boldsymbol{\theta}_1; \boldsymbol{\mu}_1^*, \boldsymbol{\Sigma}_{11}^*) \\
& \propto \exp \left[ -\frac{1}{2} (\boldsymbol{\theta}_2 - \boldsymbol{\mu}_2 - \boldsymbol{\Sigma}_{21} \boldsymbol{\Sigma}_{11}^{-1} (\boldsymbol{\theta}_1 - \boldsymbol{\mu}_1))^T \mathbf{Q} (\boldsymbol{\theta}_2 - \boldsymbol{\mu}_2 - \boldsymbol{\Sigma}_{21} \boldsymbol{\Sigma}_{11}^{-1} (\boldsymbol{\theta}_1 - \boldsymbol{\mu}_1)) \right] \\
& \quad \times \exp \left[ -\frac{1}{2} (\boldsymbol{\theta}_1 - \boldsymbol{\mu}_1^*)^T (\boldsymbol{\Sigma}_{11}^*)^{-1} (\boldsymbol{\theta}_1 - \boldsymbol{\mu}_1^*) \right] \\
& = \exp \left[ -\frac{1}{2} \boldsymbol{\theta}_2^T \mathbf{Q} \boldsymbol{\theta}_2 + (\boldsymbol{\mu}_2 - \boldsymbol{\Sigma}_{21} \boldsymbol{\Sigma}_{11}^{-1} \boldsymbol{\mu}_1)^T \mathbf{Q} \boldsymbol{\theta}_2 \right] \\
& \quad \times \exp \left[ -\frac{1}{2} \boldsymbol{\theta}_1^T ((\boldsymbol{\Sigma}_{11}^*)^{-1} + \boldsymbol{\Sigma}_{11}^{-1} \boldsymbol{\Sigma}_{12} \mathbf{Q} \boldsymbol{\Sigma}_{21} \boldsymbol{\Sigma}_{11}^{-1}) \boldsymbol{\theta}_1 \right] \\
& \quad \times \exp \left[ ((\boldsymbol{\Sigma}_{11}^*)^{-1} \boldsymbol{\mu}_1^* + \boldsymbol{\Sigma}_{11}^{-1} \boldsymbol{\Sigma}_{12} \mathbf{Q} (\boldsymbol{\mu}_2 - \boldsymbol{\Sigma}_{21} \boldsymbol{\Sigma}_{11}^{-1} \boldsymbol{\mu}_1))^T \boldsymbol{\theta}_1 \right] \\
& \quad \times \exp \left[ \boldsymbol{\theta}_2^T \mathbf{Q} \boldsymbol{\Sigma}_{21} \boldsymbol{\Sigma}_{11}^{-1} \boldsymbol{\theta}_1 \right]
\end{aligned}$$

where  $\mathbf{Q} = (\boldsymbol{\Sigma}_{22} - \boldsymbol{\Sigma}_{21} \boldsymbol{\Sigma}_{11}^{-1} \boldsymbol{\Sigma}_{22})^{-1}$

Now suppose that  $q^*(\boldsymbol{\theta}) = N(\tilde{\boldsymbol{\mu}}, \tilde{\boldsymbol{\Sigma}})$  then

$$\begin{aligned}
q(\boldsymbol{\theta}) & \propto \exp \left[ -\frac{1}{2} \left( \begin{pmatrix} \boldsymbol{\theta}_1 \\ \boldsymbol{\theta}_2 \end{pmatrix} - \begin{pmatrix} \tilde{\boldsymbol{\mu}}_1 \\ \tilde{\boldsymbol{\mu}}_2 \end{pmatrix} \right)^T \begin{pmatrix} \tilde{\mathbf{Q}}_{11} & \tilde{\mathbf{Q}}_{12} \\ \tilde{\mathbf{Q}}_{21} & \tilde{\mathbf{Q}}_{22} \end{pmatrix} \left( \begin{pmatrix} \boldsymbol{\theta}_1 \\ \boldsymbol{\theta}_2 \end{pmatrix} - \begin{pmatrix} \tilde{\boldsymbol{\mu}}_1 \\ \tilde{\boldsymbol{\mu}}_2 \end{pmatrix} \right) \right] \\
& \propto \exp \left[ -\frac{1}{2} (\boldsymbol{\theta}_1 - \tilde{\boldsymbol{\mu}}_1)^T \tilde{\mathbf{Q}}_{11} (\boldsymbol{\theta}_1 - \tilde{\boldsymbol{\mu}}_1) \right] \\
& \quad \times \exp \left[ -\frac{1}{2} (\boldsymbol{\theta}_2 - \tilde{\boldsymbol{\mu}}_2)^T \tilde{\mathbf{Q}}_{22} (\boldsymbol{\theta}_2 - \tilde{\boldsymbol{\mu}}_2) \right] \\
& \quad \times \exp \left[ -(\boldsymbol{\theta}_1 - \tilde{\boldsymbol{\mu}}_1)^T \tilde{\mathbf{Q}}_{12} (\boldsymbol{\theta}_2 - \tilde{\boldsymbol{\mu}}_2) \right] \\
& \propto \exp \left[ -\frac{1}{2} \boldsymbol{\theta}_1^T \tilde{\mathbf{Q}}_{11} \boldsymbol{\theta}_1 + \boldsymbol{\theta}_1^T (\tilde{\mathbf{Q}}_{11} \tilde{\boldsymbol{\mu}}_1 + \tilde{\mathbf{Q}}_{12} \tilde{\boldsymbol{\mu}}_2) \right] \\
& \quad \times \exp \left[ -\frac{1}{2} \boldsymbol{\theta}_2^T \tilde{\mathbf{Q}}_{22} \boldsymbol{\theta}_2 + \boldsymbol{\theta}_2^T (\tilde{\mathbf{Q}}_{22} \tilde{\boldsymbol{\mu}}_2 + \tilde{\mathbf{Q}}_{21} \tilde{\boldsymbol{\mu}}_1) - \boldsymbol{\theta}_2^T \tilde{\mathbf{Q}}_{21} \boldsymbol{\theta}_1 \right]
\end{aligned}$$

where  $\tilde{\mathbf{Q}} = \tilde{\boldsymbol{\Sigma}}^{-1}$ . Matching term by term with the first expression above we find that

$$\begin{aligned}
\tilde{\mathbf{Q}}_{21} & = -\mathbf{Q} \boldsymbol{\Sigma}_{21} \boldsymbol{\Sigma}_{11}^{-1} \\
\tilde{\mathbf{Q}}_{11} & = (\boldsymbol{\Sigma}_{11}^*)^{-1} + \boldsymbol{\Sigma}_{11}^{-1} \boldsymbol{\Sigma}_{12} \mathbf{Q} \boldsymbol{\Sigma}_{21} \boldsymbol{\Sigma}_{11}^{-1} \\
\tilde{\mathbf{Q}}_{22} & = \mathbf{Q} \\
\tilde{\mathbf{Q}}_{11} \tilde{\boldsymbol{\mu}}_1 + \tilde{\mathbf{Q}}_{12} \tilde{\boldsymbol{\mu}}_2 & = (\boldsymbol{\Sigma}_{11}^*)^{-1} \boldsymbol{\mu}_1^* + \boldsymbol{\Sigma}_{11}^{-1} \boldsymbol{\Sigma}_{12} \mathbf{Q} (\boldsymbol{\mu}_2 - \boldsymbol{\Sigma}_{21} \boldsymbol{\Sigma}_{11}^{-1} \boldsymbol{\mu}_1) \\
\tilde{\mathbf{Q}}_{22} \tilde{\boldsymbol{\mu}}_2 + \tilde{\mathbf{Q}}_{21} \tilde{\boldsymbol{\mu}}_1 & = \mathbf{Q} (\boldsymbol{\mu}_2 - \boldsymbol{\Sigma}_{21} \boldsymbol{\Sigma}_{11}^{-1} \boldsymbol{\mu}_1)
\end{aligned}$$

We need to solve this system of equations to find  $\tilde{\mathbf{Q}}_{11}$ ,  $\tilde{\mathbf{Q}}_{12}$ ,  $\tilde{\mathbf{Q}}_{22}$ ,  $\tilde{\boldsymbol{\mu}}_1$  and  $\tilde{\boldsymbol{\mu}}_2$ . We then need to use  $\tilde{\mathbf{Q}}_{11}$ ,  $\tilde{\mathbf{Q}}_{12}$ , and  $\tilde{\mathbf{Q}}_{22}$  to find  $\tilde{\boldsymbol{\Sigma}}_{11}$ ,  $\tilde{\boldsymbol{\Sigma}}_{12}$ ,  $\tilde{\boldsymbol{\Sigma}}_{22}$ .

The block inverse formula states that the inverse of a real matrix can be written as

$$\begin{bmatrix} \mathbf{A} & \mathbf{B} \\ \mathbf{C} & \mathbf{D} \end{bmatrix}^{-1} = \begin{bmatrix} \mathbf{I} & \mathbf{0} \\ -\mathbf{D}^{-1}\mathbf{C} & \mathbf{I} \end{bmatrix} \begin{bmatrix} \tilde{\mathbf{A}} & \mathbf{0} \\ \mathbf{0} & \mathbf{D}^{-1} \end{bmatrix} \begin{bmatrix} \mathbf{I} & -\mathbf{B}\mathbf{D}^{-1} \\ \mathbf{0} & \mathbf{I} \end{bmatrix} \quad (1)$$

$$= \begin{bmatrix} \tilde{\mathbf{A}} & -\tilde{\mathbf{A}}\mathbf{B}\mathbf{D}^{-1} \\ -\mathbf{D}^{-1}\mathbf{C}\tilde{\mathbf{A}} & \mathbf{D}^{-1} + \mathbf{D}^{-1}\mathbf{C}\tilde{\mathbf{A}}\mathbf{B}\mathbf{D}^{-1} \end{bmatrix} \quad (2)$$

where  $\tilde{\mathbf{A}} = (\mathbf{A} - \mathbf{B}\mathbf{D}^{-1}\mathbf{C})^{-1}$ , provided all inverses in (1) and (2) exist.

Using the block inverse formula for the top left element of  $\Sigma$  we have

$$\begin{aligned} \tilde{\Sigma}_{11} &= \left( \tilde{\mathbf{Q}}_{11} - \tilde{\mathbf{Q}}_{12}\tilde{\mathbf{Q}}_{22}^{-1}\tilde{\mathbf{Q}}_{21} \right)^{-1} \\ &= \left( (\Sigma_{11}^*)^{-1} + \Sigma_{11}^{-1}\Sigma_{12}\mathbf{Q}\Sigma_{21}\Sigma_{11}^{-1} - \Sigma_{11}^{-1}\Sigma_{12}\mathbf{Q}\mathbf{Q}^{-1}\mathbf{Q}\Sigma_{21}\Sigma_{11}^{-1} \right)^{-1} \\ &= \Sigma_{11}^* \end{aligned}$$

as expected. Similarly, using the bottom right block inverse formula leads to

$$\tilde{\Sigma}_{22} = \Sigma_{22} + \Sigma_{21}(\Sigma_{11}^{-1}\Sigma_{11}^*\Sigma_{11}^{-1} - \Sigma_{11}^{-1})\Sigma_{12}$$

so that if  $\Sigma_{11}^* = \Sigma_{11}$  then there will be no changes to  $\Sigma_{22}$ . Finally, using the top left block inverse formula leads to

$$\tilde{\Sigma}_{12} = \Sigma_{11}^*\Sigma_{11}^{-1}\Sigma_{12}$$

Using the last equation in the system of equations to solve

$$\begin{aligned} \tilde{\mu}_2 &= \tilde{\mathbf{Q}}_{22}^{-1}\mathbf{Q}(\mu_2 - \Sigma_{21}\Sigma_{11}^{-1}\mu_1) - \tilde{\mathbf{Q}}_{22}^{-1}\tilde{\mathbf{Q}}_{21}\tilde{\mu}_1 \\ &= \mu_2 + \Sigma_{21}\Sigma_{11}^{-1}(\tilde{\mu}_1 - \mu_1) \end{aligned}$$

Using the 4th equation in the system of equations we have

$$\begin{aligned} \tilde{\mathbf{Q}}_{11}\tilde{\mu}_1 &= (\Sigma_{11}^*)^{-1}\mu_1^* + \Sigma_{11}^{-1}\Sigma_{12}\mathbf{Q}(\mu_2 - \Sigma_{21}\Sigma_{11}^{-1}\mu_1) - \tilde{\mathbf{Q}}_{12}\tilde{\mu}_2 \\ &= (\Sigma_{11}^*)^{-1}\mu_1^* + \Sigma_{11}^{-1}\Sigma_{12}\mathbf{Q}(\mu_2 - \Sigma_{21}\Sigma_{11}^{-1}\mu_1) - \Sigma_{11}^{-1}\Sigma_{12}\mathbf{Q}(\mu_2 + \Sigma_{21}\Sigma_{11}^{-1}(\tilde{\mu}_1 - \mu_1)) \\ &= (\Sigma_{11}^*)^{-1}\mu_1^* - \Sigma_{11}^{-1}\Sigma_{12}\mathbf{Q}\Sigma_{21}\Sigma_{11}^{-1}\tilde{\mu}_1 \end{aligned}$$

Using the 2nd of the system of equations leads to

$$\left[ (\Sigma_{11}^*)^{-1} + \Sigma_{11}^{-1}\Sigma_{12}\mathbf{Q}\Sigma_{21}\Sigma_{11}^{-1} \right] \tilde{\mu}_1 = (\Sigma_{11}^*)^{-1}\mu_1^* - \Sigma_{11}^{-1}\Sigma_{12}\mathbf{Q}\Sigma_{21}\Sigma_{11}^{-1}\tilde{\mu}_1$$

After some cancellation we have  $\tilde{\mu}_1 = \mu_1^*$ .

5. Consider the multivariate Lasso distribution

$$p(\mathbf{x}) \propto \exp\left(-\frac{1}{2}\mathbf{x}^T \mathbf{A} \mathbf{x} + \mathbf{b}^T \mathbf{x} - c\|\mathbf{x}\|_1\right)$$

where  $\mathbf{A} \in \mathcal{S}_d^+$  is a positive definite matrix of dimension  $d$ ,  $\mathbf{b} \in \mathbb{R}^d$  and  $c > 0$  with  $\|\mathbf{x}\|_1 = \sum_{j=1}^d |x_j|$ . For the case  $d = 2$

- Find the normalizing constant.
- Find an expression for the expectation and the covariance.