

# Gaussian likelihood with Gaussian prior on its mean

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## 1 Non-Conjugate Case

We have the following joint distribution of  $\mathbf{y}, \mathbf{w}$ ,

$$p(\mathbf{y}, \mathbf{w}) = \mathcal{N}(\mathbf{y}|X\mathbf{w}, \Sigma_y) \cdot \mathcal{N}(\mathbf{w}; \mathbf{0}, \Gamma) \quad (1)$$

$$= (2\pi)^{-(n+d)/2} |\Sigma_y^{-1/2}| |\Gamma^{-1/2}| \exp \left[ -\frac{1}{2} (\mathbf{y} - X\mathbf{w})^T \Sigma_y^{-1} (\mathbf{y} - X\mathbf{w}) \right] \exp \left[ -\frac{1}{2} \mathbf{w}^T \Gamma^{-1} \mathbf{w} \right] \quad (2)$$

Simplify the terms in exponential:

$$(\mathbf{y} - X\mathbf{w})^T \Sigma_y^{-1} (\mathbf{y} - X\mathbf{w}) + \mathbf{w}^T \Gamma^{-1} \mathbf{w} \quad (3)$$

$$= \mathbf{y}^T \Sigma_y^{-1} \mathbf{y} - 2\mathbf{y}^T \Sigma_y^{-1} X\mathbf{w} + \mathbf{w}^T X^T \Sigma_y^{-1} X\mathbf{w} + \mathbf{w}^T \Gamma^{-1} \mathbf{w} \quad (4)$$

$$= \mathbf{w}^T (X^T \Sigma_y^{-1} X + \Gamma^{-1}) \mathbf{w} - 2\mathbf{y}^T \Sigma_y^{-1} X\mathbf{w} + \mathbf{y}^T \Sigma_y^{-1} \mathbf{y} \quad (5)$$

Let  $K^{-1} = X^T \Sigma_y^{-1} X + \Gamma^{-1}$  and  $\boldsymbol{\mu} = K X^T \Sigma_y^{-1} \mathbf{y}$ , then the above expression is equal to

$$\mathbf{w}^T K^{-1} \mathbf{w} - 2\boldsymbol{\mu}^T K^{-1} \mathbf{w} + \mathbf{y}^T \Sigma_y^{-1} \mathbf{y} \quad (6)$$

$$= \mathbf{w}^T K^{-1} \mathbf{w} - 2\boldsymbol{\mu}^T K^{-1} \mathbf{w} + \boldsymbol{\mu}^T K^{-1} \boldsymbol{\mu} - \mathbf{y}^T \Sigma_y^{-1} X K X^T \Sigma_y^{-1} \mathbf{y} + \mathbf{y}^T \Sigma_y^{-1} \mathbf{y} \quad (7)$$

$$= (\mathbf{w} - \boldsymbol{\mu})^T K^{-1} (\mathbf{w} - \boldsymbol{\mu}) + \mathbf{y}^T (\Sigma_y^{-1} - \Sigma_y^{-1} X K X^T \Sigma_y^{-1}) \mathbf{y} \quad (8)$$

$$= (\mathbf{w} - \boldsymbol{\mu})^T K^{-1} (\mathbf{w} - \boldsymbol{\mu}) + \mathbf{y}^T (\Sigma_y + X \Gamma X^T)^{-1} \mathbf{y} \quad (9)$$

where the last step is obtained using the following matrix inversion lemma,

$$(A + UCV)^{-1} = A^{-1} - A^{-1}U(C^{-1} + VA^{-1}U)^{-1}VA^{-1} \quad (10)$$

Substituting back,

$$p(\mathbf{y}, \mathbf{w}) = (2\pi)^{-(n+d)/2} (|\Sigma_y| |\Gamma|)^{-1/2} \exp \left[ -\frac{1}{2} (\mathbf{w} - \boldsymbol{\mu})^T K^{-1} (\mathbf{w} - \boldsymbol{\mu}) \right] \exp \left[ -\frac{1}{2} \mathbf{y}^T (\Sigma_y + X \Gamma X^T)^{-1} \mathbf{y} \right] \quad (11)$$

$$= (2\pi)^{-(n)/2} (|\Sigma_y| |\Gamma| |K^{-1}|)^{-1/2} \mathcal{N}(\mathbf{w} | \boldsymbol{\mu}, K) \exp \left[ -\frac{1}{2} \mathbf{y}^T (\Sigma_y + X \Gamma X^T)^{-1} \mathbf{y} \right] \quad (12)$$

Using the following matrix-determinant lemma,

$$|A + U W V^T| = |W^{-1} + V^T A^{-1} U| |W| |A| \quad (13)$$

we get the following simplification for the determinant term,

$$|\Sigma_y| |\Gamma| |K^{-1}| = |\Sigma_y| |\Gamma| |X^T \Sigma_y^{-1} X + \Gamma^{-1}| \quad (14)$$

$$= |\Sigma_y| |\Gamma| |\Sigma_y^{-1}| |\Gamma^{-1}| |\Sigma_y + X \Gamma X^T| \quad (15)$$

$$= |\Sigma_y + X \Gamma X^T| \quad (16)$$

This gives us the final expression,

$$p(\mathbf{y}, \mathbf{w}) = (2\pi)^{-(n)/2} |\Sigma_y + X\Gamma X^T|^{-1/2} \mathcal{N}(\mathbf{w}|\boldsymbol{\mu}, K) \exp \left[ -\frac{1}{2} \mathbf{y}^T (\Sigma_y + X\Gamma X^T)^{-1} \mathbf{y} \right] \quad (17)$$

We have the following posterior for weights and marginal likelihood,

$$p(\mathbf{w}|\mathbf{y}) = \mathcal{N}(\mathbf{w}|\boldsymbol{\mu}, K) \quad (18)$$

$$p(\mathbf{y}) = (2\pi)^{-n/2} |\Sigma_y + X\Gamma X^T|^{-1/2} \exp \left[ -\frac{1}{2} \mathbf{y}^T (\Sigma_y + X\Gamma X^T)^{-1} \mathbf{y} \right] \quad (19)$$

where  $K^{-1} = X^T \Sigma_y^{-1} X + \Gamma^{-1}$  and  $\boldsymbol{\mu} = K X^T \Sigma_y^{-1} \mathbf{y}$ .

## 1.1 Fast computation

If  $n < d$ , then we can compute the marginal likelihood by computing the matrix  $\Sigma_y + X\Gamma X^T$  directly. In case  $\Gamma$  is diagonal,  $X\Gamma X^T = \sum_i \Gamma_{ii} x_i x_i^T$ . In any case, storing gram matrix should be sufficient for computing the inverse of the matrix.

If  $n > d$ , then we can resort to MIL and compute  $K$  instead which is  $d \times d$ . We can obtain the inverse of the desired matrix, using MIL as follows,

$$(\Sigma_y + X\Gamma X^T)^{-1} = \Sigma_y^{-1} - \Sigma_y^{-1} X K X^T \Sigma_y^{-1} \quad (20)$$