

1. DEFINITIONS

All definitions given are for 2-dimensional inputs.

1.1. Assume.

$$(1) \quad [y^*, y_1^\delta, y_2^\delta, y \mid \sigma^2, l] \sim N(0, K)$$

$$(2) \quad K = \begin{bmatrix} K^{00}(x^*, x^*) & K^{10}(x_1^\delta, x^*)^T & K^{10}(x_2^\delta, x^*)^T & K^{00}(x, x^*)^T \\ K^{10}(x_1^\delta, x^*) & K^{11}(x_1^\delta, x_1^\delta) & K^{11}(x_2^\delta, x_1^\delta)^T & K^{01}(x, x_1^\delta)^T \\ K^{10}(x_2^\delta, x^*) & K^{11}(x_2^\delta, x_1^\delta) & K^{11}(x_2^\delta, x_2^\delta) & K^{01}(x, x_2^\delta)^T \\ K^{00}(x, x^*) & K^{01}(x, x_1^\delta) & K^{01}(x, x_2^\delta) & K^{00}(x, x) \end{bmatrix}$$

where

- $y = y(x)$: observed target function values (training set)
- $y^* = y(x^*)$: unobserved function values
- $y_k^\delta = \frac{\partial}{\partial x_k} y(x^\delta)$: vectors of partial derivatives in the k th input dimension
- σ^2 : constant variance parameter
- l : length-scale parameter
- $K^{00}(\cdot, \cdot), K^{10}(\cdot, \cdot), K^{11}(\cdot, \cdot)$: covariance functions. The superscripts indicate the argument where the derivative is taken. Note that $K^{10}(x, x') = K^{01}(x', x)^T$.

1.2. Covariance functions.

$$(3) \quad Cov(y(x), y(x')) = K^{00}(x, x') = \sigma^2 \prod_{k=1}^d g(x_k, x'_k; l_k)$$

$$(4) \quad \frac{\partial}{\partial x_i} Cov(y(x), y(x')) = K^{10}(x, x') = \sigma^2 \frac{\partial}{\partial x_i} \prod_{k=1}^d g(x_k, x'_k; l_k)$$

$$(5) \quad \frac{\partial^2}{\partial x'_j \partial x_i} Cov(y(x), y(x')) = K^{11}(x, x') = \sigma^2 \frac{\partial^2}{\partial x'_j \partial x_i} \prod_{k=1}^d g(x_k, x'_k; l_k)$$

$$(6) \quad g(x, x') = \left[1 + \theta |x - x'| + \frac{1}{3} \theta^2 |x - x'|^2 \right] \exp \{ -\theta |x - x'| \}$$

$$(7) \quad \frac{\partial}{\partial x} g(x, x') = -\frac{1}{3} \theta^2 (x - x') [1 + \theta |x - x'|] \exp \{ -\theta |x - x'| \}$$

$$(8) \quad \frac{\partial^2}{\partial x' \partial x} g(x, x') = \frac{1}{3} \theta^2 \left[1 + \theta |x - x'| - \theta^2 (x - x')^2 \right] \exp \{ -\theta |x - x'| \}$$

where

- $d = 2$ for 2-dimensional inputs. i.e. x is $n \times 2$ matrix.
- $i, j \in \{1, 2, \dots, d\}$
- $g(\cdot, \cdot)$ is from the Matern class of covariance functions with parameter 5/2; the subscripts for the inputs in $g(\cdot, \cdot)$ are dropped for legibility

- $\theta = \sqrt{5}/l$

See derivatives of $g(\cdot, \cdot)$ in section 3.

2. SETUP

2.1. The posterior density.

$$(9) \quad [l, \sigma^2, y^*, y_1^\delta, y_2^\delta | y] \propto [y, y^*, y_1^\delta, y_2^\delta | \sigma^2, l] [\sigma^2, l]$$

$$(10) \quad \propto [y^*, y_1^\delta, y_2^\delta | y, \sigma^2, l] [[y | \sigma^2, l]] [\sigma^2, l]$$

The goal is to evaluate densities on the RHS. Specifically,

$$[y^*, y_1^\delta, y_2^\delta | y, \sigma^2, l] \sim N(m, S)$$

due to the properties of the multivariate normal distribution (https://en.wikipedia.org/wiki/Multivariate_normal_distribution#Conditional_distributions). That is, the formulas from Kriging follow immediately.

To calculate m, S , start by dividing the covariance matrix K into the appropriate blocks:

$$(11) \quad K = \begin{bmatrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & \Sigma_{22} \end{bmatrix}, \text{ where}$$

$$(12) \quad \Sigma_{11} = \begin{bmatrix} K^{00}(x^*, x^*) & K^{10}(x_1^\delta, x^*)^T & K^{10}(x_2^\delta, x^*)^T \\ K^{10}(x_1^\delta, x^*) & K^{11}(x_1^\delta, x_1^\delta) & K^{11}(x_2^\delta, x_1^\delta)^T \\ K^{10}(x_2^\delta, x^*) & K^{11}(x_2^\delta, x_1^\delta) & K^{11}(x_2^\delta, x_2^\delta) \end{bmatrix}$$

$$(13) \quad \Sigma_{12} = \Sigma_{21}^T = \begin{bmatrix} K^{00}(x, x^*)^T \\ K^{01}(x, x_1^\delta)^T \\ K^{01}(x, x_2^\delta)^T \end{bmatrix} = \begin{bmatrix} K^{00}(x^*, x) \\ K^{10}(x_1^\delta, x) \\ K^{10}(x_2^\delta, x) \end{bmatrix}$$

$$(14) \quad \Sigma_{22} = K^{00}(x, x).$$

Then,

$$(15) \quad m = 0 + \Sigma_{12}\Sigma_{22}^{-1}(y - 0) = \begin{bmatrix} K^{00}(x^*, x) \\ K^{10}(x_1^\delta, x) \\ K^{10}(x_2^\delta, x) \end{bmatrix} K^{00}(x, x)^{-1}y$$

$$(16) \quad S = \Sigma_{11} - \Sigma_{12}\Sigma_{22}^{-1}\Sigma_{21}$$

2.2. **Example.** Given

$$(17) \quad y(x) = 11x_1^{10} + 9x_1^8 + 7x_1^6 + 10x_2^9 + 8x_2^7$$

$$(18) \quad \frac{\partial}{\partial x_1} y(x) = 110x_1^9 + 72x_1^7 + 42x_1^5$$

$$(19) \quad \frac{\partial}{\partial x_2} y(x) = 90x_2^8 + 56x_2^6$$

where

- y : 10×1
- x^* : 2×2
- x_1^δ : 8×2
- x_2^δ : 8×2

Then including the GP parameters σ^2 and l , there are 20 unknowns. Fixing GP parameters, we can calculate the covariance matrix S required for $[y^*, y_1^\delta, y_2^\delta | y, \sigma^2, l]$.

2.3. **Problem.** Assuming reasonable values for σ^2 and l , following the formula for S given above, the resulting matrix is negative definite. Adding small nuggets does not fix this.

It seems that if I use rather small values of l (all entries less than approximately 0.3), then this problem disappears.

3. DERIVATIVES FOR THE MATERN

Recall: $g(x, x') = [1 + \theta |x - x'| + \frac{1}{3}\theta^2 |x - x'|^2] \exp\{-\theta |x - x'|\}$

3.1. First derivative.

$$(20) \quad \frac{\partial}{\partial x} g(x, x') = \left[\theta \text{sign}(x - x') + \frac{2}{3}\theta^2 (x - x') \right] \exp\{-\theta |x - x'|\}$$

$$(21) \quad + \left[1 + \theta |x - x'| + \frac{1}{3}\theta^2 (x - x')^2 \right] \exp\{-\theta |x - x'|\} (-\theta \text{sign}(x - x'))$$

$$(22) \quad = \exp\{-\theta |x - x'|\} \left[-\frac{1}{3}\theta^2 (x - x') - \frac{1}{3}\theta^3 (x - x')^2 \text{sign}(x - x') \right]$$

$$(23) \quad = \exp\{-\theta |x - x'|\} \left(-\frac{1}{3}\theta^2 (x - x') \right) [1 + \theta (x - x') \text{sign}(x - x')]$$

$$(24) \quad = -\frac{1}{3}\theta^2 (x - x') [1 + \theta |x - x'|] \exp\{-\theta |x - x'|\}$$

3.2. Second derivative.

(25)

$$\frac{\partial^2}{\partial x' \partial x} g(x, x') = \frac{\partial}{\partial x'} \left[-\frac{1}{3} \theta^2 (x - x') [1 + \theta |x - x'|] \exp \{-\theta |x - x'|\} \right]$$

(26)
$$= \frac{\partial}{\partial x'} \left[\left[-\frac{1}{3} \theta^2 (x - x') - \frac{1}{3} \theta^3 (x - x')^2 \text{sign}(x - x') \right] \exp \{-\theta |x - x'|\} \right]$$

(27)
$$= \left[\frac{1}{3} \theta^2 - \frac{2}{3} \theta^3 (x - x') (-1) \text{sign}(x - x') \right] \exp \{-\theta |x - x'|\}$$

(28)
$$+ \left[-\frac{1}{3} \theta^2 (x - x') - \frac{1}{3} \theta^3 (x - x')^2 \text{sign}(x - x') \right] \exp \{-\theta |x - x'|\} (\theta \text{sign}(x - x'))$$

(29)
$$= \exp \{-\theta |x - x'|\} \left[\frac{1}{3} \theta^2 + \frac{2}{3} \theta^3 |x - x'| - \frac{1}{3} \theta^3 |x - x'| - \frac{1}{3} \theta^4 (x - x')^2 \right]$$

(30)
$$= \exp \{-\theta |x - x'|\} \left[\frac{1}{3} \theta^2 + \frac{1}{3} \theta^3 |x - x'| - \frac{1}{3} \theta^4 (x - x')^2 \right]$$

(31)
$$= \frac{1}{3} \theta^2 \left[1 + \theta |x - x'| - \theta^2 (x - x')^2 \right] \exp \{-\theta |x - x'|\}$$