

# Kriging distribution under HSGP proof

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We claim that under HSGP, the kriging distribution  $\boldsymbol{\theta}^* \mid (\boldsymbol{\theta}, \Omega) \stackrel{d}{=} \Phi^* \mathbf{S}^{1/2} \mathbf{b}$  for  $\mathbf{b} \sim N_m(\mathbf{0}, \mathbf{I})$ .

*Proof.* We first highlight a few facts that we will use for this proof:

1. By property of multivariate normal, for any jointly normal, and possibly singular normal random vectors

$$\begin{pmatrix} \mathbf{X} \\ \mathbf{Y} \end{pmatrix} \sim N \left( \mathbf{0}, \begin{pmatrix} \Sigma_{xx} & \Sigma_{xy} \\ \Sigma_{yx} & \Sigma_{yy} \end{pmatrix} \right),$$

the conditional distribution  $\mathbf{Y} \mid \mathbf{X} = \mathbf{x} \sim N(\Sigma_{yx} \Sigma_{xx}^\dagger \mathbf{x}, \Sigma_{yy} - \Sigma_{yx} \Sigma_{xx}^{\dagger\top} \Sigma_{xy})^1$ , where  $\mathbf{A}^\dagger$  denotes a generalized inverse of matrix  $\mathbf{A}$  such that  $\mathbf{A} \mathbf{A}^\dagger \mathbf{A} = \mathbf{A}$ .

2. By the design of HSGP, if  $m \leq n$ ,  $\Phi$  always has full column rank.
3. By the design of HSGP,  $\mathbf{S}$  is always invertible.

By fact 1, under HSGP approximation,  $\boldsymbol{\theta}^* \mid (\boldsymbol{\theta}, \Omega) \sim N_q(\mathbb{E}_{\boldsymbol{\theta}^*}^{HS}, \mathbb{V}_{\boldsymbol{\theta}^*}^{HS})$ ,

$$\begin{aligned} \mathbb{E}_{\boldsymbol{\theta}^*}^{HS} &= (\Phi^* \mathbf{S} \Phi^\top) (\Phi \mathbf{S} \Phi^\top)^\dagger \boldsymbol{\theta} \\ \mathbb{V}_{\boldsymbol{\theta}^*}^{HS} &= (\Phi^* \mathbf{S} \Phi^{*\top}) - (\Phi^* \mathbf{S} \Phi^\top) (\Phi \mathbf{S} \Phi^\top)^\dagger (\Phi \mathbf{S} \Phi^{*\top}). \end{aligned}$$

Now we show that if  $m \leq n$ ,  $\mathbb{V}_{\boldsymbol{\theta}^*}^{HS} \equiv \mathbf{0}$ , and the kriging distribution is degenerate with  $\boldsymbol{\theta}^* \mid (\boldsymbol{\theta}, \Omega) = \mathbb{E}_{\boldsymbol{\theta}^*}^{HS}$ . This is equivalent to showing

$$(\Phi^* \mathbf{S} \Phi^{*\top}) = (\Phi^* \mathbf{S} \Phi^\top) (\Phi \mathbf{S} \Phi^\top)^\dagger (\Phi \mathbf{S} \Phi^{*\top}).$$

It's also equivalent to showing

$$\mathbf{S} = \mathbf{S} \Phi^\top (\Phi \mathbf{S} \Phi^\top)^\dagger \Phi \mathbf{S}.$$

By fact 2, for all  $\mathbf{x}, \mathbf{y} \in \mathbb{R}^m$ ,

$$\Phi \mathbf{x} = \Phi \mathbf{y} \implies \mathbf{x} = \mathbf{y}, \quad \mathbf{x}^\top \Phi^\top = \mathbf{y}^\top \Phi^\top \implies \mathbf{x} = \mathbf{y}.$$

Consequently for any matrices  $\mathbf{A}, \mathbf{B} \in \mathbb{R}^{m \times k}$ , for any  $k$ ,

$$\Phi \mathbf{A} = \Phi \mathbf{B} \implies \mathbf{A} = \mathbf{B} \quad \mathbf{A}^\top \Phi^\top = \mathbf{B}^\top \Phi^\top \implies \mathbf{A} = \mathbf{B}. \quad (1)$$

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<sup>1</sup>You can find this result on Wiki for multivariate normal distribution, under the section for conditional distribution. I'd like to highlight that if we don't insist on using a symmetric generalized inverse matrix, then there needs to be a "transpose" in the expression for the covariance matrix, i.e., it should be  $\Sigma_{xx}^{\dagger\top}$  instead of  $\Sigma_{xx}^\dagger$ . The result on Wiki page is actually using  $\Sigma_{xx}^\dagger$ . This is because, the source for the Wiki results is using a specific form of generalized inverse which is symmetric.

By the definition of generalized inverse, we have

$$(\Phi\mathbf{S}\Phi^\top)(\Phi\mathbf{S}\Phi^\top)^\dagger(\Phi\mathbf{S}\Phi^\top) = (\Phi\mathbf{S}\Phi^\top). \quad (2)$$

Taking transpose of both sides of the equation, we have

$$(\Phi\mathbf{S}\Phi^\top)^\top(\Phi\mathbf{S}\Phi^\top)^\dagger^\top(\Phi\mathbf{S}\Phi^\top)^\top = (\Phi\mathbf{S}\Phi^\top)^\top.$$

Now applying equation (1), we have  $\mathbf{S}\Phi^\top(\Phi\mathbf{S}\Phi^\top)^\dagger^\top\Phi\mathbf{S} = \mathbf{S}$ , which is exactly what's needed to show  $\mathbb{V}_{\theta^*}^{HS} \equiv \mathbf{0}$  as argued above. Applying the same arguments to equation (2) gives

$$\mathbf{S}\Phi^\top(\Phi\mathbf{S}\Phi^\top)^\dagger\Phi\mathbf{S} = \mathbf{S}. \quad (3)$$

Therefore under the reparameterized model, the kriging distribution is

$$\begin{aligned} \theta^* \mid (\theta, \Omega) &= (\Phi^*\mathbf{S}\Phi^\top)(\Phi\mathbf{S}\Phi^\top)^\dagger\theta \\ &= (\Phi^*\mathbf{S}\Phi^\top)(\Phi\mathbf{S}\Phi^\top)^\dagger(\Phi\mathbf{S}^{1/2}\mathbf{b}) \\ &= \Phi^*(\mathbf{S}\Phi^\top(\Phi\mathbf{S}\Phi^\top)^\dagger\Phi\mathbf{S})\mathbf{S}^{-1/2}\mathbf{b} \quad \text{by fact 3} \\ &= \Phi^*\mathbf{S}^{1/2}\mathbf{b}. \quad \text{by equation (3)} \end{aligned}$$

This completes the proof for  $m \leq n$  cases.

Next we prove for situation where  $m > n$ . Note in this case  $\mathbf{S}^{1/2}\Phi^\top \in \mathbb{R}^{m \times n}$  is a tall matrix. Let  $\mathbf{S}^{1/2}\Phi^\top = \mathbf{Q}\mathbf{R}$  be its QR decomposition where  $\mathbf{R} \in \mathbb{R}^{n \times n}$  is an invertible upper triangular matrix,  $\mathbf{Q} \in \mathbb{R}^{m \times n}$  has orthonormal columns such that  $\mathbf{Q}^\top\mathbf{Q} = \mathbf{I}$  and  $\mathbf{Q}\mathbf{Q}^\top$  is an orthogonal projection matrix. Now that  $m > n$ , we can replace the generalized inverse in the kriging distribution with proper inverse. Then plugging  $\mathbf{S}^{1/2}\Phi^\top = \mathbf{Q}\mathbf{R}$  in the kriging distribution under the reparameterized model gives:

$$\begin{aligned} \mathbb{E}_{\theta^*}^{HS} &= \Phi^*\mathbf{S}^{1/2}(\mathbf{Q}\mathbf{R})(\mathbf{R}^\top\mathbf{Q}^\top\mathbf{Q}\mathbf{R})^{-1}(\mathbf{Q}\mathbf{R})^\top\mathbf{b} \\ &= \Phi^*\mathbf{S}^{1/2}\mathbf{Q}\mathbf{Q}^\top\mathbf{b} \\ \mathbb{V}_{\theta^*}^{HS} &= (\Phi^*\mathbf{S}\Phi^{*\top}) - \Phi^*\mathbf{S}^{1/2}(\mathbf{Q}\mathbf{R})(\mathbf{R}^\top\mathbf{Q}^\top\mathbf{Q}\mathbf{R})^{-1}(\mathbf{Q}\mathbf{R})^\top\mathbf{S}^{1/2}\Phi^{*\top} \\ &= (\Phi^*\mathbf{S}\Phi^{*\top}) - \Phi^*\mathbf{S}^{1/2}\mathbf{Q}\mathbf{Q}^\top\mathbf{S}^{1/2}\Phi^{*\top} \\ &= \Phi^*\mathbf{S}^{1/2}(\mathbf{I} - \mathbf{Q}\mathbf{Q}^\top)\mathbf{S}^{1/2}\Phi^{*\top} \\ &= \Phi^*\mathbf{S}^{1/2}(\mathbf{I} - \mathbf{Q}\mathbf{Q}^\top)^2\mathbf{S}^{1/2}\Phi^{*\top}. \end{aligned}$$

Therefore, to sample from this distribution, we can generate  $\mathbf{b}^* \sim N_m(0, \mathbf{I}) \perp \mathbf{b}$ , and then use  $\Phi^*\mathbf{S}^{1/2}(\mathbf{I} - \mathbf{Q}\mathbf{Q}^\top)\mathbf{b}^* + \Phi^*\mathbf{S}^{1/2}\mathbf{Q}\mathbf{Q}^\top\mathbf{b}$ . However, it has the same distribution as  $\Phi^*\mathbf{S}^{1/2}\mathbf{b}$  because the covariance between  $(\mathbf{I} - \mathbf{Q}\mathbf{Q}^\top)\mathbf{b}$  and  $\mathbf{Q}\mathbf{Q}^\top\mathbf{b}$  is zero. This completes the proof.  $\square$