

# Deterministic Objective Bayesian Inference for Spatial Models

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## Abstract

Berger et al. (2001) and Ren et al. (2012) developed noninformative priors for Gaussian process regression based off of the reference prior approach (Berger, Bernardo, 1991). The priors have good statistical properties and provide a basis for objective Bayesian analysis (Berger, 2006). This paper and the project <https://github.com/rnburn/bbai> provide deterministic algorithms to do statistical inference using the priors.

## 1 Introduction

Suppose we observe a Gaussian process  $Z(\cdot)$  at sample points  $\mathbf{s}_1, \dots, \mathbf{s}_n$ , where

$$\begin{aligned}\mathbb{E}\{Z(\mathbf{s})\} &= \beta_1 x_1(\mathbf{s}) + \dots + \beta_p x_p(\mathbf{s}) \\ &= \boldsymbol{\beta}' \mathbf{x}(\mathbf{s}), \\ \text{cov}\{Z(\mathbf{s}), Z(\mathbf{u})\} &= \sigma^2 \{\psi_\ell(\|\mathbf{s} - \mathbf{u}\|) + \eta\};\end{aligned}\tag{1}$$

$\mathbf{x}(\cdot)$  and  $\psi_\ell(\cdot)$  represent the known regressor function and correlation function; and  $\boldsymbol{\beta}$ ,  $\sigma^2$ ,  $\ell$ , and  $\eta$  represent the unknown regression coefficients, signal variance, length, and noise-to-signal ratio.

Let  $\boldsymbol{\theta}$  denote the unknown parameters

$$\boldsymbol{\theta} = (\boldsymbol{\beta}, \sigma^2, \ell, \eta)'$$

In order to reason about possible values at unobserved points, we'd like to know the distribution

$$P(Z(\mathbf{u}) \mid \mathbf{y}, \boldsymbol{\theta}_{\text{true}}),$$

where  $\mathbf{u}$  is an unobserved point and  $\mathbf{y}$  denotes the observations

$$\mathbf{y} = (Z(\mathbf{s}_1), \dots, Z(\mathbf{s}_n))'$$

Of course, different values of  $\boldsymbol{\theta}$  could reasonably produce  $\mathbf{y}$ , so there's no way we can identify  $\boldsymbol{\theta}_{\text{true}}$  or construct prediction distributions exactly. We need ways to approximate.

## Approach 1: Maximize Likelihood

Suppose the likelihood function

$$L(\boldsymbol{\theta}; \mathbf{y}) \propto P(\mathbf{y} \mid \boldsymbol{\theta})$$

is strongly peaked about an optimum,  $\boldsymbol{\theta}_{\text{ml}}$ . Then  $\boldsymbol{\theta}_{\text{true}}$  should be close to  $\boldsymbol{\theta}_{\text{ml}}$ , and

$$P(Z(\mathbf{u}) \mid \mathbf{y}, \boldsymbol{\theta}_{\text{ml}})$$

should be a reasonable substitute for

$$P(Z(\mathbf{u}) \mid \mathbf{y}, \boldsymbol{\theta}_{\text{true}}).$$

But what happens if a broad range of parameters could reasonably produce  $\mathbf{y}$ ?

**Example 1.1.** *Consider this data set.*

	<i>s</i>	<i>y</i>		<i>s</i>	<i>y</i>
1	0.00	6.34	11	0.53	2.25
2	0.05	1.62	12	0.58	4.30
3	0.11	7.38	13	0.63	-4.40
4	0.16	12.22	14	0.68	-2.54
5	0.21	3.03	15	0.74	10.94
6	0.26	-4.58	16	0.79	-2.81
7	0.32	-3.45	17	0.84	-2.82
8	0.37	-4.48	18	0.89	2.53
9	0.42	-8.02	19	0.95	10.01
10	0.47	2.61	20	1.00	1.52

*I randomly sampled the Gaussian process*

$$\sigma^2 = 25, \quad \ell = 0.01, \quad \eta = 0.1, \quad \psi_\ell(t) = \exp\left\{-\frac{t^2}{2\ell}\right\}$$

*at 20 evenly spaced points on the interval  $[0, 1]$ . Likelihood has a maximum at*

$$\sigma_{\text{ml}}^2 = 34.42, \quad \ell_{\text{ml}} = 0.035, \quad \eta_{\text{ml}} = 6.47 \times 10^{-7}.$$

*Note how much smaller  $\ell_{\text{ml}}$  and  $\eta_{\text{ml}}$  are than their true values. If we try to use  $\boldsymbol{\theta}_{\text{ml}}$  as a substitute for  $\boldsymbol{\theta}_{\text{true}}$ , we get wildly inaccurate results as Figure 1 shows.*

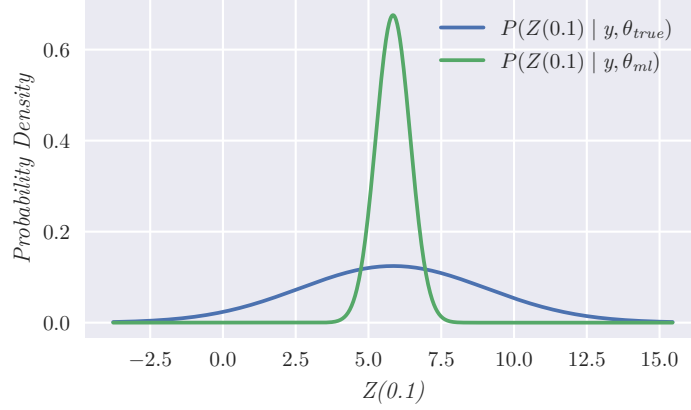


Figure 1: Compare prediction probability distributions when  $\theta_{ml}$  is used as a substitute for  $\theta_{true}$   
*Put*

$$g(t) = L(\theta_{ml}(1-t) + \theta_{true}t; \mathbf{y}) / L(\theta_{ml}; \mathbf{y}).$$

Figure 2 plots  $g(t)$  for  $0 \leq t \leq 1$ . We see that likelihood is definitely not strongly peaked about the optimum.

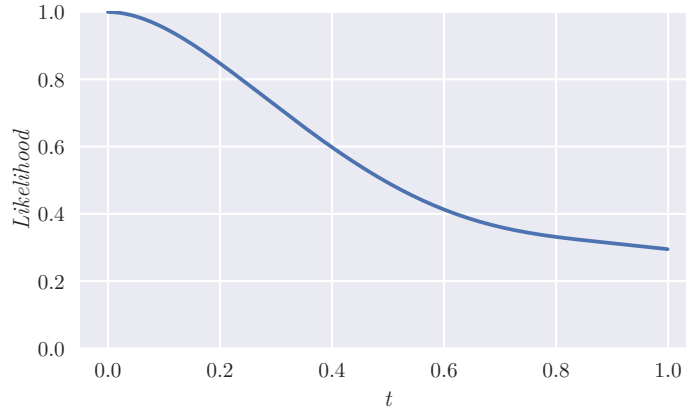


Figure 2: Likelihood for different values of  $\theta$  between  $\theta_{ml}$  and  $\theta_{true}$

## Approach 2: Integrate over Possible Parameters

Instead of approximating prediction distributions with only a single value of  $\theta$ , let's consider every  $\theta$  and weigh by a posterior distribution  $\pi(\theta | \mathbf{y})$ :

$$P^\pi(Z(\mathbf{u}) | \mathbf{y}) = \int P(Z(\mathbf{u}) | \mathbf{y}, \theta) \pi(\theta | \mathbf{y}) d\theta.$$

$\pi(\boldsymbol{\theta} \mid \mathbf{y})$  measures our belief that parameters  $\boldsymbol{\theta}$  generated the observations  $\mathbf{y}$ . To derive  $\pi(\boldsymbol{\theta} \mid \mathbf{y})$ , we apply Bayes' theorem

$$\pi(\boldsymbol{\theta} \mid \mathbf{y}) \propto L(\boldsymbol{\theta}; \mathbf{y}) \times \pi(\boldsymbol{\theta}),$$

where  $\pi(\boldsymbol{\theta})$  measures our prior belief that parameters  $\boldsymbol{\theta}$  generate the data before seeing observations.

Naturally, this leads to the question: How do we specify  $\pi(\boldsymbol{\theta})$  when we know nothing particular about  $\boldsymbol{\theta}$ ? Statisticians have grappled with the problem of specifying so-called noninformative priors ever since Bayes and Laplace first started applying the approach to the binomial model over 200 years ago.

While noninformative priors remain hotly debated, fortunately the modern approach of reference priors gives a general path forward, and particularly for the case of Gaussian processes works quite well.

Before getting into the details (see §3 and §4 for descriptions of the prior and inference algorithm), let's look at how the approach works on our example Gaussian process.

**Example 1.2.** (*Example 1.1 continued*) In Figure 3, I plot the prediction from Example 1.1 using the Bayesian approach with a reference prior. We see it's much more accurate than the maximum likelihood approach.

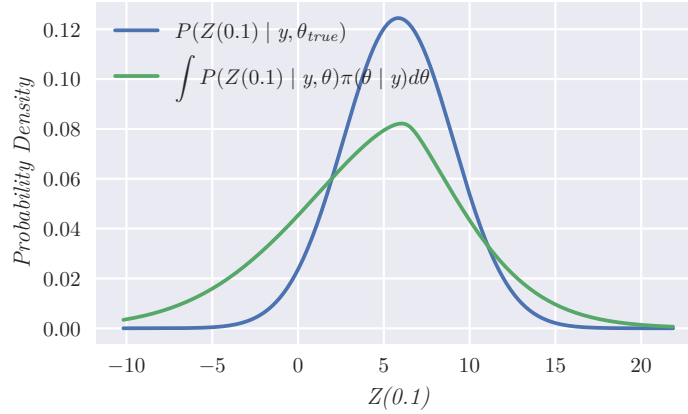


Figure 3: Compare prediction distribution of Bayesian approach with reference prior to the prediction distribution of  $\boldsymbol{\theta}_{\text{true}}$ .

## 2 How to Specify Noninformative Priors

A statistician hands you a prior. How do you determine if it's noninformative? or suitable for objective analysis?

Nailing down precise and universally acceptable definitions for “noninformative” and “objective” is mostly a fool's errand. But here's a simple experiment you can run to kick the tires of a prior. Let  $\Theta_1 \times \cdots \times \Theta_k$  denote the parameter

space for the model, pick  $\alpha$  to be something like 0.95, and run Algorithm 1 for different  $\tilde{\boldsymbol{\theta}}$  varied across the model's parameter space. If the prior is good, Algorithm 1 should produce results close to  $\alpha$ .

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**Algorithm 1** Test accuracy of credible sets produced with a prior

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1: function COVERAGE-TEST( $N, \tilde{\boldsymbol{\theta}}, j, \alpha$ )
2:    $cnt \leftarrow 0$ 
3:   for  $i \leftarrow 1$  to  $N$  do
4:      $\tilde{\mathbf{y}} \leftarrow \text{sample from } P(\mathbf{y} \mid \tilde{\boldsymbol{\theta}})$ 
5:      $\tilde{\boldsymbol{\Theta}} \leftarrow \Theta_1 \times \cdots \times \Theta_{j-1} \times \Theta_j \cap (-\infty, \tilde{\theta}_j] \times \Theta_{j+1} \times \cdots \times \Theta_k$ 
6:      $t \leftarrow \int_{\tilde{\boldsymbol{\Theta}}} \pi(\boldsymbol{\theta} \mid \tilde{\mathbf{y}}) d\boldsymbol{\theta}$ 
7:     if  $\frac{\alpha}{2} < t < 1 - \frac{\alpha}{2}$  then
8:        $cnt \leftarrow cnt + 1$ 
9:     end if
10:  end for
11:  return  $\frac{cnt}{N}$ 
12: end function

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With Algorithm 1 in our toolbox, let's look at a few approaches for specifying noninformative priors.

## Constant Prior

We begin with the simplest approach: Set

$$\pi(\boldsymbol{\theta}) \propto 1.$$

Immediately, we see one serious disadvantage of this approach: It's not invariant under reparameterization. If  $\varphi(\cdot)$  is some monotonically increasing surjective function, then

$$\frac{1}{Z} \int_a^b L(\boldsymbol{\theta}; \mathbf{y}) d\boldsymbol{\theta} = \frac{1}{Z} \int_{\varphi^{-1}(a)}^{\varphi^{-1}(b)} L(\varphi(u); \mathbf{y}) \dot{\varphi}(u) du.$$

Thus, different parameterizations with the constant prior lead to different posterior distributions.

Still, let's try the approach out on some examples.

**Example 2.1.** Suppose we observe  $n$  normally distributed values,  $\mathbf{y}$ , with variance 1 and unknown mean,  $\mu$ . Then

$$\begin{aligned}
L(\mu; \mathbf{y}) &\propto \exp \left\{ -\frac{1}{2} (\mathbf{y} - \mu \mathbf{1})' (\mathbf{y} - \mu \mathbf{1}) \right\} \\
&\propto \exp \left\{ -\frac{1}{2} (n\mu^2 - 2\mu n\bar{y}) \right\} \\
&\propto \exp \left\{ -\frac{n}{2} (\mu - \bar{y})^2 \right\}.
\end{aligned}$$

Thus,

$$\int_{-\infty}^t \pi(\mu | \mathbf{y}) d\mu = \frac{1}{2} \left[ 1 + \operatorname{erf} \left( \frac{t - \bar{y}}{\sqrt{2/n}} \right) \right].$$

I ran Algorithm 1 for  $N = 10,000$ ,  $\alpha = 0.95$ , and various values of  $\mu$  and  $n$ . These are the results

$n = 5$		$n = 10$		$n = 15$		$n = 20$	
$\sigma^2$	coverage	$\sigma^2$	coverage	$\sigma^2$	coverage	$\sigma^2$	coverage
0.1	0.9502	0.1	0.9486	0.1	0.9508	0.1	0.9493
0.5	0.9519	0.5	0.9478	0.5	0.9492	0.5	0.9488
1.0	0.9516	1.0	0.9495	1.0	0.9517	1.0	0.9494
2.0	0.9514	2.0	0.9521	2.0	0.9539	2.0	0.9489
5.0	0.9489	5.0	0.9455	5.0	0.9558	5.0	0.9488

**Example 2.2.** Suppose we observe  $n$  normally distributed values,  $\mathbf{y}$ , with zero-mean and unknown variance,  $\sigma^2$ . Then

$$L(\sigma^2; \mathbf{y}) \propto \left( \frac{1}{\sigma^2} \right)^{n/2} \exp \left\{ -\frac{ns^2}{2\sigma^2} \right\},$$

where

$$s^2 = \frac{\mathbf{y}'\mathbf{y}}{n}.$$

Put

$$\sigma^2 = \frac{ns^2}{2u}.$$

Then

$$\begin{aligned} \int_0^t \left( \frac{1}{\sigma^2} \right)^{n/2} \exp \left\{ -\frac{ns^2}{2\sigma^2} \right\} d\sigma^2 &\propto \int_{\frac{ns^2}{2t}}^{\infty} u^{n/2-2} \exp \{-u\} du \\ &= \Gamma \left( \frac{n-2}{2}, \frac{ns^2}{2t} \right). \end{aligned}$$

Thus,

$$\int_0^t \pi(\sigma^2 | \mathbf{y}) d\sigma^2 = \frac{1}{\Gamma(\frac{n-2}{2})} \Gamma \left( \frac{n-2}{2}, \frac{ns^2}{2t} \right).$$

I ran Algorithm 1 for  $N = 10,000$ ,  $\alpha = 0.95$ , and various values of  $\sigma^2$  and  $n$ . The results are below

$n = 5$		$n = 10$		$n = 15$		$n = 20$	
$\sigma^2$	coverage	$\sigma^2$	coverage	$\sigma^2$	coverage	$\sigma^2$	coverage
0.1	0.9014	0.1	0.9288	0.1	0.9418	0.1	0.9439
0.5	0.9035	0.5	0.9309	0.5	0.9415	0.5	0.9398
1.0	0.9048	1.0	0.9303	1.0	0.9404	1.0	0.9412
2.0	0.9079	2.0	0.9331	2.0	0.9402	2.0	0.9393
5.0	0.9023	5.0	0.9295	5.0	0.9339	5.0	0.9426

In Example 2.1, the constant prior produces nearly perfect results. In Example 2.2, the prior is notably off for smaller values of  $n$  but improves as  $n$  increases.

### Jeffreys Prior

Dissatisfied with the inconsistency of the constant prior under reparameterization, Harold Jeffreys searched for a better approach and proposed the prior

$$\pi(\boldsymbol{\theta}) \propto |\mathcal{I}(\boldsymbol{\theta})|^{1/2},$$

where  $\mathcal{I}(\boldsymbol{\theta})$  is the Fisher information matrix

$$\mathcal{I}(\boldsymbol{\theta})_{st} = \mathbb{E}_{\mathbf{y}} \left\{ \left( \frac{\partial}{\partial \theta_s} \log P(\mathbf{y} | \boldsymbol{\theta}) \right) \left( \frac{\partial}{\partial \theta_t} \log P(\mathbf{y} | \boldsymbol{\theta}) \right) \right\}.$$

We can check that unlike the constant prior, Jeffreys prior is invariant to reparameterization: If  $\boldsymbol{\varphi}(\mathbf{u})$  is an injective continuously differentiable function whose range includes  $U$ , then the change of variables formula gives us

$$\int_U L(\boldsymbol{\theta}; \mathbf{y}) |\mathcal{I}(\boldsymbol{\theta})|^{1/2} d\boldsymbol{\theta} = \int_{\boldsymbol{\varphi}^{-1}(U)} L(\boldsymbol{\varphi}(\mathbf{u}); \mathbf{y}) |\mathcal{I}(\boldsymbol{\varphi}(\mathbf{u}))|^{1/2} (|\mathbf{D}\boldsymbol{\varphi}(\mathbf{u})|) d\mathbf{u},$$

where  $\mathbf{D}\boldsymbol{\varphi}(\mathbf{u})$  denotes the Jacobian matrix

$$\mathbf{D}\boldsymbol{\varphi}(\mathbf{u})_{st} = \frac{\partial \varphi_s(\mathbf{u})}{\partial u_t}.$$

Let  $\mathcal{I}^{\boldsymbol{\varphi}}(\mathbf{u})$  denote the Fisher information matrix with respect to the reparameterization. Then

$$\begin{aligned} \mathcal{I}^{\boldsymbol{\varphi}}(\mathbf{u})_{st} &= \mathbb{E}_{\mathbf{y}} \left\{ \left( \frac{\partial}{\partial u_s} \log P(\mathbf{y} | \boldsymbol{\varphi}(\mathbf{u})) \right) \left( \frac{\partial}{\partial u_t} \log P(\mathbf{y} | \boldsymbol{\varphi}(\mathbf{u})) \right) \right\} \\ &= \mathbb{E}_{\mathbf{y}} \left\{ \left( \nabla_{\boldsymbol{\theta}} \log P(\mathbf{y} | \boldsymbol{\theta})' \frac{\partial \boldsymbol{\varphi}}{\partial u_s}(\mathbf{u}) \right) \left( \nabla_{\boldsymbol{\theta}} \log P(\mathbf{y} | \boldsymbol{\theta})' \frac{\partial \boldsymbol{\varphi}}{\partial u_t}(\mathbf{u}) \right) \right\} \\ &= \left( \frac{\partial \boldsymbol{\varphi}}{\partial u_s}(\mathbf{u}) \right)' \mathcal{I}(\boldsymbol{\varphi}(\mathbf{u})) \left( \frac{\partial \boldsymbol{\varphi}}{\partial u_t}(\mathbf{u}) \right). \end{aligned}$$

Thus,

$$\mathcal{I}^\varphi(\mathbf{u}) = \mathbf{D}\varphi(\mathbf{u})' \mathcal{I}(\varphi(\mathbf{u})) \mathbf{D}\varphi(\mathbf{u}),$$

and

$$\int_U L(\boldsymbol{\theta}; \mathbf{y}) |\mathcal{I}(\boldsymbol{\theta})|^{1/2} d\boldsymbol{\theta} = \int_{\varphi^{-1}(U)} L(\varphi(\mathbf{u}); \mathbf{y}) |\mathcal{I}^\varphi(\mathbf{u})|^{1/2} d\mathbf{u}.$$

**Example 2.3.** (Example 2.1 continued) To compute the Fisher information matrix, we first differentiate  $\log L(\mu; \mathbf{y})$

$$\begin{aligned} \frac{\partial}{\partial \mu} \log L(\mu; \mathbf{y}) &= \frac{\partial}{\partial \mu} \left( -\frac{n}{2} (\mu - \bar{y})^2 \right) \\ &= -n (\mu - \bar{y}). \end{aligned}$$

Then we compute

$$\mathbb{E}_{\mathbf{y}} \left\{ \left( \frac{\partial}{\partial \mu} L(\mu; \mathbf{y}) \right)^2 \mid \mu \right\} = \mathbb{E}_{\mathbf{y}} \left\{ n^2 (\mu - \bar{y})^2 \mid \mu \right\}.$$

$\bar{y} - \mu$  is normally distributed with zero mean and variance  $\frac{1}{n}$ , so

$$\mathbb{E}_{\mathbf{y}} \left\{ \left( \frac{\partial}{\partial \mu} L(\mu; \mathbf{y}) \right)^2 \mid \mu \right\} = n.$$

Jeffreys prior in this case is the same as the constant prior.

**Example 2.4.** (Example 2.2 continued) We differentiate  $\log L(\sigma^2; \mathbf{y})$  to get

$$\begin{aligned} \frac{\partial}{\partial \sigma^2} \log L(\sigma^2; \mathbf{y}) &= \frac{\partial}{\partial \sigma^2} \left( -\frac{n}{2} \log \sigma^2 - \frac{ns^2}{2\sigma^2} \right) \\ &= \frac{n}{2\sigma^2} \left( \frac{s^2}{\sigma^2} - 1 \right). \end{aligned}$$

Then

$$\mathbb{E}_{\mathbf{y}} \left\{ \left( \frac{\partial}{\partial \sigma^2} L(\sigma^2; \mathbf{y}) \right)^2 \mid \sigma^2 \right\} = \left( \frac{n}{2\sigma^2} \right)^2 \mathbb{E}_{\mathbf{y}} \left\{ \left( \frac{s^2}{\sigma^2} - 1 \right)^2 \mid \sigma^2 \right\}.$$

Now,  $y_1^2 + \dots + y_n^2$  follows a chi-squared distribution and with variance  $2n\sigma^4$  and mean  $n\sigma^2$ , so

$$\begin{aligned} \mathbb{E}_{\mathbf{y}} \{ s^4 \mid \sigma^2 \} &= \frac{\sigma^4 (2n + n^2)}{n^2} \\ &= \sigma^4 \left( 1 + \frac{2}{n} \right) \end{aligned}$$



and

$$\begin{aligned}\mathbb{E}_{\mathbf{y}} \left\{ \left( \frac{\partial}{\partial \sigma^2} L(\sigma^2; \mathbf{y}) \right)^2 \mid \sigma^2 \right\} &= \left( \frac{n}{2\sigma^2} \right)^2 \mathbb{E}_{\mathbf{y}} \left\{ \frac{s^4}{\sigma^4} - 2 \frac{s^2}{\sigma^2} + 1 \mid \sigma^2 \right\} \\ &= \left( \frac{n}{2\sigma^2} \right)^2 \left( \frac{2}{n} \right) \\ &= \frac{n}{2\sigma^4}.\end{aligned}$$

And we derive the prior

$$\pi(\sigma^2) \propto \frac{1}{\sigma^2}.$$

For the CDF, we apply the same derivations in Example 2.2 to get

$$\int_0^t \pi(\sigma^2 \mid \mathbf{y}) d\sigma^2 = \frac{1}{\Gamma(\frac{n}{2})} \Gamma\left(\frac{n}{2}, \frac{ns^2}{2t}\right).$$

Using the same setup in Example 2.2, I produced these coverage results:

$n = 5$		$n = 10$		$n = 15$		$n = 20$	
$\sigma^2$	coverage	$\sigma^2$	coverage	$\sigma^2$	coverage	$\sigma^2$	coverage
0.1	0.9516	0.1	0.9503	0.1	0.9509	0.1	0.9511
0.5	0.9501	0.5	0.949	0.5	0.952	0.5	0.948
1.0	0.9505	1.0	0.9511	1.0	0.9513	1.0	0.95
2.0	0.948	2.0	0.9514	2.0	0.9501	2.0	0.9482
5.0	0.9506	5.0	0.9497	5.0	0.9486	5.0	0.9485

So far, Jeffreys prior performs excellently. In fact, for a single parameter, Welch, Peers (1963) showed that in the limiting case coverage for  $(1 - \alpha)\%$  credible sets using Jeffreys prior approaches  $\alpha$  with an asymptotic error  $o(n^{-1})$ . Moreover, it's the only prior with this property; so, starting with the goal of matching coverage naturally leads us to Jeffreys prior.

Let's check how well Jeffreys prior performs in cases with more than a single variable.

**Example 2.5.** Suppose we observe  $n$  normally distributed values,  $\mathbf{y}$ , with unknown mean,  $\mu$ , and variance,  $\sigma^2$ . Then

$$L(\mu, \sigma^2; \mathbf{y}) \propto \left( \frac{1}{\sigma^2} \right)^{n/2} \exp \left\{ -\frac{1}{2\sigma^2} (\mathbf{y} - \mu \mathbf{1})' (\mathbf{y} - \mu \mathbf{1}) \right\}.$$

We differentiate  $\log L(\cdot; \mathbf{y})$  to get

$$\begin{aligned}\frac{\partial}{\partial \mu} \log L(\mu, \sigma^2; \mathbf{y}) &= \frac{n}{\sigma^2} (\bar{y} - \mu) \\ \frac{\partial}{\partial \sigma^2} \log L(\mu, \sigma^2; \mathbf{y}) &= -\frac{n}{2\sigma^2} + \frac{1}{2} \left( \frac{1}{\sigma^2} \right)^2 (\mathbf{y} - \mu \mathbf{1})' (\mathbf{y} - \mu \mathbf{1}).\end{aligned}$$

We apply the derivations from Example 2.3 and Example 2.4 to get the Fisher information matrix

$$\mathcal{I}(\mu, \sigma^2) = \begin{pmatrix} \frac{n}{\sigma^2} & 0 \\ 0 & \frac{n}{2\sigma^4} \end{pmatrix}$$

and the Jeffreys prior

$$\pi(\mu, \sigma^2) \propto \left(\frac{1}{\sigma^2}\right)^{3/2}.$$

Let's check coverage for  $\sigma^2$ . First, we integrate out  $\mu$

$$\begin{aligned} & \int_{-\infty}^{\infty} L(\mu, \sigma^2; \mathbf{y}) \pi(\mu, \sigma^2) d\mu \\ & \propto \int_{-\infty}^{\infty} \left(\frac{1}{\sigma^2}\right)^{(n+3)/2} \exp\left\{-\frac{1}{2\sigma^2} \|\mathbf{y} - \mu \mathbf{1}\|^2\right\} d\mu \\ & = \left(\frac{1}{\sigma^2}\right)^{(n+3)/2} \exp\left\{-\frac{1}{2\sigma^2} (\mathbf{y}'\mathbf{y} - n\bar{y}^2)\right\} \\ & \quad \int_{-\infty}^{\infty} \exp\left\{-\frac{n}{2\sigma^2} (\mu - \bar{y})^2\right\} d\mu \\ & \propto \left(\frac{1}{\sigma^2}\right)^{(n+2)/2} \exp\left\{-\frac{1}{2\sigma^2} (\mathbf{y}'\mathbf{y} - n\bar{y}^2)\right\}. \end{aligned}$$

Then

$$\int_0^t \int_{-\infty}^{\infty} \pi(\mu, \sigma^2 | \mathbf{y}) d\mu d\sigma^2 = \frac{1}{\Gamma(\frac{n}{2})} \Gamma\left(\frac{n}{2}, \frac{1}{2t} (\mathbf{y}'\mathbf{y} - n\bar{y}^2)\right).$$

I ran Algorithm 1 for  $N = 10,000$ ,  $\alpha = 0.95$ ,  $\mu = 0$ , and various values of  $\sigma^2$ .

$n = 5$		$n = 10$		$n = 15$		$n = 20$	
$\sigma^2$	coverage	$\sigma^2$	coverage	$\sigma^2$	coverage	$\sigma^2$	coverage
0.1	0.9241	0.1	0.938	0.1	0.9419	0.1	0.9463
0.5	0.9219	0.5	0.9377	0.5	0.946	0.5	0.9441
1.0	0.9245	1.0	0.94	1.0	0.9431	1.0	0.944
2.0	0.9236	2.0	0.9391	2.0	0.9446	2.0	0.9432
5.0	0.9182	5.0	0.9395	5.0	0.9403	5.0	0.9458

Unfortunately, the multiparameter case is not so easy; and as we see in Example 2.5, Jeffreys prior doesn't perform nearly as well. Jeffreys considered modifications of his prior to handle the multiparameter case better but never developed a rigorous approach. For that, we turn to reference priors.

## Reference Priors

If Jeffreys prior works well in the single parameter case, why not apply it to parameters one-at-a-time? In the reference prior approach, we build up a multi-parameter prior by marginalizing the likelihood with a conditional prior of fewer parameters to form a new integrated likelihood function with only a single parameter, to which we can apply Jeffreys prior.

Suppose  $L(\theta_1, \theta_2; \mathbf{y})$  is a likelihood function of two variables. We fix  $\theta_1$  and use Jeffreys approach to derive a conditional prior  $\pi(\theta_2 | \theta_1)$ . Then we integrate out  $\theta_2$

$$L^I(\theta_1; \mathbf{y}) = \int_{\Theta_2} L(\theta_1, \theta_2; \mathbf{y}) \pi(\theta_2 | \theta_1) d\theta_2$$

to get the integrated likelihood function  $L^I(\cdot; \mathbf{y})$  of only a single variable. We apply Jeffreys approach again to the integrated likelihood function to get  $\pi(\theta_1)$  and form the complete prior

$$\pi(\theta_1, \theta_2) = \pi(\theta_1) \times \pi(\theta_2 | \theta_1).$$

If the prior  $\pi(\cdot | \theta_1)$  is improper, we can choose a sequence of compact subsets

$$A_1 \subset A_2 \subset \dots \subset \Theta_2$$

such that

$$\lim_{t \rightarrow \infty} A_t = \Theta_2,$$

apply the approach to  $A_t$ , and take the limit as  $t \rightarrow \infty$ .

Let's try this out on Example 2.5.

**Example 2.6.** (*Example 2.5 continued*). We first integrate out  $\mu$  using the constant conditional prior

$$\begin{aligned} L^I(\sigma^2; \mathbf{y}) &= \int_{-\infty}^{\infty} L(\mu, \sigma^2; \mathbf{y}) \pi(\mu | \sigma^2) d\mu \\ &\propto \left(\frac{1}{\sigma^2}\right)^{n/2} \exp\left\{-\frac{1}{2\sigma^2} (\mathbf{y}'\mathbf{y} - n\bar{y}^2)\right\} \int_{-\infty}^{\infty} \exp\left\{-\frac{n}{\sigma^2} (\mu - \bar{y})^2\right\} d\mu \\ &\propto \left(\frac{1}{\sigma^2}\right)^{(n-1)/2} \exp\left\{-\frac{1}{2\sigma^2} (\mathbf{y}'\mathbf{y} - n\bar{y}^2)\right\}. \end{aligned}$$

Now, we differentiate  $L^I(\cdot; \mathbf{y})$  to find the Fisher information matrix

$$\begin{aligned} \frac{\partial}{\partial \sigma^2} \log L^I(\sigma^2; \mathbf{y}) &= -\frac{n-1}{2\sigma^2} + \frac{1}{2} \left(\frac{1}{\sigma^2}\right)^2 (\mathbf{y}'\mathbf{y} - n\bar{y}^2) \\ &= \frac{1}{2\sigma^2} \left\{ \frac{1}{\sigma^2} (\mathbf{y}'\mathbf{y} - n\bar{y}^2) - (n-1) \right\}. \end{aligned}$$

Put

$$Z = \frac{1}{\sigma^2} (\mathbf{y}'\mathbf{y} - n\bar{y}^2).$$

Then  $Z$  follows a chi-squared distribution with  $n - 1$  degrees of freedom so that

$$\begin{aligned}\mathbb{E}[Z] &= n - 1 \\ \mathbb{E}[Z^2] &= 2(n - 1) + (n - 1)^2,\end{aligned}$$

and

$$\begin{aligned}\mathcal{I}(\sigma^2) &= \left(\frac{1}{2\sigma^2}\right)^2 \{\mathbb{E}[Z^2] - 2(n - 1)\mathbb{E}[Z] + (n - 1)^2\} \\ &= \frac{n - 1}{2\sigma^4}.\end{aligned}$$

Thus, we derive the reference prior

$$\pi(\mu, \sigma^2) = \frac{1}{\sigma^2}.$$

Following Example 2.5, we compute

$$\int_0^t \int_{-\infty}^{\infty} \pi(\mu, \sigma^2 | \mathbf{y}) d\mu d\sigma^2 = \frac{1}{\Gamma(\frac{n-1}{2})} \Gamma\left(\frac{n-1}{2}, \frac{1}{2t} (\mathbf{y}'\mathbf{y} - n\bar{y}^2)\right).$$

I reran the coverage simulation from Example 2.5 with this CDF and got these results:

$n = 5$		$n = 10$		$n = 15$		$n = 20$	
$\sigma^2$	coverage	$\sigma^2$	coverage	$\sigma^2$	coverage	$\sigma^2$	coverage
0.1	0.9533	0.1	0.948	0.1	0.9504	0.1	0.9519
0.5	0.9528	0.5	0.9499	0.5	0.9524	0.5	0.9486
1.0	0.948	1.0	0.9503	1.0	0.9507	1.0	0.9484
2.0	0.9529	2.0	0.9504	2.0	0.9515	2.0	0.9487
5.0	0.9525	5.0	0.9507	5.0	0.9484	5.0	0.9511

### 3 Noninformative Priors for Spatial Models

Let's consider noninformative priors for the Gaussian process (1).

- Using a constant prior isn't a viable option. In addition to the problem of incoherence, the resulting posterior would be improper (Berger, 2006). We might consider truncating the parameter space to make the constant prior proper; but that doesn't solve the problem as inference would be highly dependent on the truncation bounds.

- Certain modified forms of Jeffreys prior result in a proper posterior, but the credible sets produced from the priors perform poorly (Ren et al., 2012).

That brings us to the reference prior approach. Since the model has multiple parameters, we'll first integrate out  $\beta$  and  $\sigma^2$  using the conditional prior

$$\pi(\beta, \sigma^2 \mid \ell, \eta) \propto \frac{1}{\sigma^2}.$$

Likelihood for Gaussian process (1) is given by

$$L(\beta, \sigma^2, \ell, \eta; \mathbf{y}) \propto (\sigma^2)^{-n/2} |\mathbf{G}|^{-1/2} \exp \left\{ -\frac{1}{2\sigma^2} (\mathbf{y} - \mathbf{X}\beta)' \mathbf{G}^{-1} (\mathbf{y} - \mathbf{X}\beta) \right\},$$

where

$$\begin{aligned} \mathbf{X} &= (\mathbf{x}(\mathbf{s}_1), \dots, \mathbf{x}(\mathbf{s}_n))', \\ \mathbf{G} &= \eta \mathbf{I} + \mathbf{K}(\ell), \\ (\mathbf{K}(\ell))_{ij} &= \psi_\ell(\|\mathbf{s}_i - \mathbf{s}_j\|). \end{aligned}$$

Integrating likelihood with the conditional prior gives us

$$\begin{aligned} L^I(\ell, \eta; \mathbf{y}) &\propto \int_0^\infty \int_{\mathbb{R}^p} L(\beta, \sigma^2, \ell, \eta; \mathbf{y}) \pi(\beta, \sigma^2 \mid \ell, \eta) d\beta d\sigma^2 \\ &\propto \int_0^\infty (\sigma^2)^{-(n-p)/2} |\mathbf{G}|^{-1/2} |\mathbf{X}' \mathbf{G}^{-1} \mathbf{X}|^{-1/2} \exp \left\{ -\frac{S^2}{2\sigma^2} \right\} \left( \frac{1}{\sigma^2} \right) d\sigma^2 \\ &\propto |\mathbf{G}|^{-1/2} |\mathbf{X}' \mathbf{G}^{-1} \mathbf{X}|^{-1/2} (S^2)^{-(n-p)/2}, \end{aligned} \quad (2)$$

where

$$\begin{aligned} S^2 &= \mathbf{y}' \mathbf{R} \mathbf{y} \\ \mathbf{R} &= \mathbf{G}^{-1} - \mathbf{G}^{-1} \mathbf{X} (\mathbf{X}' \mathbf{G}^{-1} \mathbf{X})^{-1} \mathbf{X}' \mathbf{G}^{-1}. \end{aligned} \quad (3)$$

After computing the Fisher information matrix for  $L^I(\cdot; \mathbf{y})$  and forming its Jeffrey prior, we derive the complete prior

$$\pi(\beta, \sigma^2, \ell, \eta) \propto \left( \frac{1}{\sigma^2} \right) |\Sigma(\ell, \eta)|^{1/2}, \quad (4)$$

where

$$\Sigma(\ell, \eta) = \begin{pmatrix} \text{tr} \left\{ (\mathbf{R} \frac{\partial \mathbf{K}}{\partial \ell})^2 \right\} & \text{tr}(\mathbf{R}^2 \frac{\partial \mathbf{K}}{\partial \ell}) & \text{tr}(\mathbf{R} \frac{\partial \mathbf{K}}{\partial \ell}) \\ * & \text{tr}(\mathbf{R}^2) & \text{tr}(\mathbf{R}) \\ * & * & n - p \end{pmatrix}. \quad (5)$$

For a detailed derivation, see Ren et al. (2012).

To test the performance of the reference prior, we'll run the same simulations used in Ren et al. (2012). Details of how to compute the integrals will be given in §4.

**Example 3.1.** To generate observations, I sample Gaussian process (1) with

$$\sigma^2 = 1, \quad x_1(\mathbf{s}) = 1, \quad \beta_1 = 1, \quad \psi_\ell(d) = \exp\left\{-\frac{d}{\ell}\right\}$$

at  $10 \times 10$  evenly spaced points on the interval  $[0, 1] \times [0, 1]$ . I ran Algorithm 1 with  $N = 200$  and allowed  $\ell$  and  $\eta$  to vary. Here are the results:

	$\eta = 0.01$			$\eta = 0.05$		
	$\ell = 0.2$	$\ell = 0.5$	$\ell = 1.0$	$\ell = 0.2$	$\ell = 0.5$	$\ell = 1.0$
$\ell$ coverage	0.945	0.985	0.995	0.950	0.990	1.000
$\eta$ coverage	0.885	0.980	0.995	1.000	0.995	1.000
$\sigma^2$ coverage	0.990	0.995	0.980	0.975	0.985	0.985

	$\eta = 0.1$			$\eta = 0.2$		
	$\ell = 0.2$	$\ell = 0.5$	$\ell = 1.0$	$\ell = 0.2$	$\ell = 0.5$	$\ell = 1.0$
$\ell$ coverage	0.965	0.975	0.995	0.985	1.000	1.000
$\eta$ coverage	1.000	0.975	0.995	0.995	0.970	0.990
$\sigma^2$ coverage	1.000	0.985	0.985	0.970	0.985	0.980

See `gaussian_process_prior_coverage.ipynb` for source code.

**Example 3.2.** For the next simulation, I modify the Gaussian process in Example 3.1 to include additional regressors

$$\mathbf{x}((u, v)) = (1, u, v, u^2, uv, v^2)'$$

$$\beta = (0.15, -0.65, -0.1, 0.9, -1.0, 1.2)'.$$

Rerunning the simulation experiment with the same values of  $\ell$  and  $\eta$  gives this result

	$\eta = 0.01$			$\eta = 0.05$		
	$\ell = 0.2$	$\ell = 0.5$	$\ell = 1.0$	$\ell = 0.2$	$\ell = 0.5$	$\ell = 1.0$
$\ell$ coverage	0.995	1.000	0.960	1.000	1.000	0.910
$\eta$ coverage	0.865	0.950	0.915	1.000	1.000	0.990
$\sigma^2$ coverage	0.995	0.975	0.835	1.000	0.985	0.760

	$\eta = 0.1$			$\eta = 0.2$		
	$\ell = 0.2$	$\ell = 0.5$	$\ell = 1.0$	$\ell = 0.2$	$\ell = 0.5$	$\ell = 1.0$
$\ell$ coverage	1.000	1.000	0.890	1.000	1.000	0.815
$\eta$ coverage	0.990	1.000	1.000	0.990	1.000	1.000
$\sigma^2$ coverage	0.990	0.980	0.835	0.985	0.975	0.835

See `gaussian_process_prior_coverage.ipynb` for source code.

To test prediction performance, we use Algorithm 2 which modifies Algorithm 1.

---

**Algorithm 2** Test accuracy of prediction credible sets produced with a prior

---

```

1: function PREDICTION-COVERAGE-TEST( $N, \tilde{\boldsymbol{\theta}}, \alpha$ )
2:    $cnt \leftarrow 0$ 
3:   for  $i \leftarrow 1$  to  $N$  do
4:      $\tilde{\mathbf{y}} \leftarrow \text{sample from } P(\mathbf{y} \mid \tilde{\boldsymbol{\theta}})$ 
5:      $t \leftarrow \int P(\tilde{y}_1 \mid \boldsymbol{\theta}) \pi(\boldsymbol{\theta} \mid \tilde{y}_2, \dots, \tilde{y}_n) d\boldsymbol{\theta}$ 
6:     if  $\frac{\alpha}{2} < t < 1 - \frac{\alpha}{2}$  then
7:        $cnt \leftarrow cnt + 1$ 
8:     end if
9:   end for
10:  return  $\frac{cnt}{N}$ 
11: end function

```

---

**Example 3.3.** To generate observations, I sample from Gaussian process (1) with

$$\sigma^2 = 1 \quad \psi_\ell(d) = \exp\left\{-\frac{d^2}{2\ell}\right\}.$$

I sampled training observations at 20 evenly spaced points on the interval  $[0, 1]$  and test observations at random points on the interval  $[0, 1]$ . I ran Algorithm 2 with  $N = 100$  and varied  $\ell$  and  $\eta$ . Below I show the coverage results for Bayesian prediction distributions using the reference prior and maximum likelihood prediction distributions:

	$\eta = 0.001$			$\eta = 0.01$		
	$\ell = 0.1$	$\ell = 0.2$	$\ell = 0.5$	$\ell = 0.1$	$\ell = 0.2$	$\ell = 0.5$
Bay coverage	0.919	0.951	0.942	0.939	0.953	0.944
ML coverage	0.812	0.905	0.934	0.838	0.912	0.919
	$\eta = 0.1$			$\eta = 0.2$		
	$\ell = 0.1$	$\ell = 0.2$	$\ell = 0.5$	$\ell = 0.1$	$\ell = 0.2$	$\ell = 0.5$
Bay coverage	0.929	0.943	0.932	0.936	0.937	0.938
ML coverage	0.847	0.893	0.920	0.853	0.893	0.903

See `gaussian_process_prediction_coverage.ipynb` for source code.

## 4 Deterministic Bayesian Inference

The key component for deterministic inference is an accurate approximation to the posterior distribution that enables efficient computation of integrals

$$\tilde{\pi}(\ell, \eta \mid \mathbf{y}) \approx L^I(\ell, \eta; \mathbf{y}) \times \pi(\ell, \eta),$$

where

$$\pi(\ell, \eta) \propto |\Sigma(\ell, \eta)|^{1/2},$$

and  $\Sigma(\cdot)$  is defined in (5).

Given  $\tilde{\pi}(\cdot | \mathbf{y})$ , it's relatively straightforward to derive approximation for the marginal distributions

$$\begin{aligned}\pi(\ell | \mathbf{y}) &\approx \int_0^\infty \tilde{\pi}(\ell, \eta | \mathbf{y}) d\eta, \\ \pi(\eta | \mathbf{y}) &\approx \int_0^\infty \tilde{\pi}(\ell, \eta | \mathbf{y}) d\ell, \\ \pi(\sigma^2 | \mathbf{y}) &\approx \int_0^\infty \int_0^\infty P^\pi(\sigma^2 | \mathbf{y}, \ell, \eta) \tilde{\pi}(\ell, \eta | \mathbf{y}) d\ell d\eta\end{aligned}$$

and for prediction distributions

$$P^\pi(Z(\mathbf{s}) | \mathbf{y}) \approx \int_0^\infty \int_0^\infty P^\pi(Z(\mathbf{s}) | \mathbf{y}, \ell, \eta) \tilde{\pi}(\ell, \eta | \mathbf{y}) d\ell d\eta.$$

## Outline of Algorithm

Assume  $\varphi_\ell(\cdot)$  and  $\varphi_\eta(\cdot)$  are monotonically increasing surjective functions onto  $(0, \infty)$ . Put

$$\begin{aligned}f(\mathbf{u}) = & -\log L^I(\varphi_\ell(u_1), \varphi_\eta(u_2); \mathbf{y}) \\ & -\log \pi(\varphi_\ell(u_1), \varphi_\eta(u_2)) - \log \dot{\varphi}_\ell(u_1) - \log \dot{\varphi}_\eta(u_2).\end{aligned}\tag{6}$$

$f$  is the negative of the reparameterized log of the posterior  $\pi(\ell, \eta | \mathbf{y})$ . An approximation of  $f$  naturally leads to approximation and efficient integration of  $\pi(\ell, \eta | \mathbf{y})$ .

We build an approximation  $\tilde{f}$  in four steps

1. Using a trust-region optimizer and exact equations for  $\nabla f$  and  $\nabla^2 f$ , we minimize  $f$  to find  $\mathbf{u}_{\text{map}}$ .
2. Let  $\mathbf{v}_1$  and  $\mathbf{v}_2$  denote the two eigenvectors of the hessian at  $\mathbf{u}_{\text{map}}$

$$\nabla^2 f(\mathbf{u}_{\text{map}}).$$

We find values  $a_1 < 0 < b_1$ , and  $a_2 < 0 < b_2$  such that

$$\begin{aligned}-f(\mathbf{u}_{\text{map}} + a_i \mathbf{v}_i) + f(\boldsymbol{\phi}_{\text{map}}) &= \log \varepsilon_1(a_i) \\ -f(\mathbf{u}_{\text{map}} + b_i \mathbf{v}_i) + f(\boldsymbol{\phi}_{\text{map}}) &= \log \varepsilon_2(b_i)\end{aligned}$$

for  $i = 1, 2$  and  $\varepsilon_i(\cdot)$  small. These values bracket  $f$  around a rectangular region of high probability oriented along the eigenvectors  $\mathbf{v}_1$  and  $\mathbf{v}_2$ .



3. We find monotonic cubic splines  $s_1(\cdot)$  and  $s_2(\cdot)$  such that

$$s_i(0) = a_i, \quad s_i(0.5) = 0, \quad \text{and} \quad s_i(1) = b_i$$

for  $i = 1, 2$ .

4. Put

$$g(\mathbf{x}) = f((s_1(x_1), s_2(x_2))') - f(\mathbf{u}_{\text{map}}). \quad (7)$$

Using Chebyshev polynomials and the eigenvectors  $\mathbf{v}_1$  and  $\mathbf{v}_2$  for a basis, we adaptively build a sparse polynomial to approximate  $g$  (and hence  $f$ ) over the region  $[0, 1] \times [0, 1]$ .

Proposition 7 and Proposition 9 from Ren et al. (2012) show that  $\pi(\ell, \eta \mid \mathbf{y})$  is bounded as  $\ell \rightarrow 0$  or  $\eta \rightarrow 0$  and derive  $\mathcal{O}(\cdot)$  functions for when  $\ell \rightarrow \infty$  and  $\eta \rightarrow \infty$ . Using suitable choices of  $\varphi_\ell(\cdot)$ ,  $\varphi_\eta(\cdot)$ , and  $\varepsilon_i(\cdot)$ , we can achieve bounds for the probability mass outside of the bracketing region in Step 2. We'll consider only the simple case of

$$\phi_\ell(t) = \phi_\eta(t) = \exp(t)$$

and  $\varepsilon_i$  fixed to some small constant; but other choices could lead to tighter bounding.

We can use any decent line search algorithm (e.g. Newton's method) for Step 2; we use the monotonic cubic algorithm from Fritsch, Carlson (1980) for Step 3. The algorithms for Step 1 and Step 4 are more complicated, and I break down in greater detail in the next sections.

## Step 1: Trust-region Optimization

Let  $f: \mathbb{R}^p \rightarrow \mathbb{R}$  denote a twice-differentiable objective function. Trust-region methods are iterative, second-order optimization algorithms that produce a sequence  $\{\mathbf{x}_k\}$ , where the  $k^{\text{th}}$  iteration is generated by updating the previous iteration with a solution to the subproblem (Sorensen, 1982)

$$\begin{aligned} \mathbf{x}_k &= \mathbf{x}_{k-1} + \mathbf{s}_k \\ \mathbf{s}_k &= \underset{\mathbf{s}}{\operatorname{argmin}} \left\{ \nabla f(\mathbf{x}_{k-1})' \mathbf{s} + \frac{1}{2} \mathbf{s}' \nabla^2 f(\mathbf{x}_{k-1}) \mathbf{s} \right\} \\ \text{s.t.} \quad & \|\mathbf{s}\| \leq \delta_k. \end{aligned}$$

The subproblem minimizes the second-order approximation of  $f$  at  $\mathbf{x}_{k-1}$  within the neighborhood  $\|\mathbf{s}\| \leq \delta_k$ , called the trust region. Using the trust region, we can restrict the second-order approximation to areas where it models  $f$  well. Efficient algorithms exist to solve the subproblem regardless of whether  $\nabla^2 f(\mathbf{x}_{k-1})$  is positive-definite, making trust-region methods well-suited for non-convex optimization problems (Moré, Sorensen, 1983). With proper rules for updating  $\delta_k$  and standard assumptions, such as Lipschitz continuity of  $\nabla f$ , trust-region

methods are globally convergent. Moreover, if  $\nabla^2 f$  is Lipschitz continuous for all  $\mathbf{x}$  sufficiently close to a nondegenerate second-order stationary point  $\mathbf{x}_*$ , where  $\nabla^2 f(\mathbf{x}_*)$  is positive-definite, then trust-region methods have quadratic local convergence (Nocedal, Wright, 2006).

Algorithm 3 describes the trust-region algorithm we use for Step 1, and Appendix A derives equations for evaluating the value, gradient, and hessian of the objective (6).

---

**Algorithm 3** Minimize Objective Function  $f$

---

```

1: function MINIMIZE( $f, \mathbf{x}_0$ )
2:    $tol \leftarrow$  tolerance
3:    $\delta_0 \leftarrow$  an initial trust-region radius
4:    $v_0 \leftarrow f(\mathbf{x}_0)$ 
5:    $\mathbf{g}_0 \leftarrow \nabla f(\mathbf{x}_0)$ 
6:    $\mathbf{H}_0 \leftarrow \nabla^2 f(\mathbf{x}_0)$ 
7:    $k \leftarrow 0$ 
8:   while  $\|\mathbf{g}_k\|_\infty > tol$  or not IS-POSITIVE-DEFINITE( $\mathbf{H}_k$ ) do
9:      $\mathbf{x}_{k+1}, v_{k+1}, \delta_{k+1} \leftarrow$  COMPUTE-NEXT-STEP( $\mathbf{x}_k, v_k, \mathbf{g}_k, \mathbf{H}_k, \delta_k$ )
10:     $\mathbf{g}_{k+1} \leftarrow \nabla f(\mathbf{x}_{k+1})$ 
11:     $\mathbf{H}_{k+1} \leftarrow \nabla^2 f(\mathbf{x}_{k+1})$ 
12:     $k \leftarrow k + 1$ 
13:   end while
14:   return  $\mathbf{x}_k, v_k, \mathbf{H}_k$ 
15: end function
16: function COMPUTE-NEXT-STEP( $\mathbf{x}_k, v_k, \mathbf{g}_k, \mathbf{H}_k, \delta_k$ )
17:    $\delta_{k+1} \leftarrow \delta_k$ 
18:   while 1 do
19:      $\mathbf{s}_k \leftarrow \operatorname{argmin}_{\mathbf{s}} \{ \mathbf{g}'_k \mathbf{s} + \frac{1}{2} \mathbf{s}' \mathbf{H}_k \mathbf{s} \}$  s.t.  $\|\mathbf{s}\| \leq \delta_{k+1}$ 
20:      $\mathbf{x}_{k+1} \leftarrow \mathbf{x}_k + \mathbf{s}_k$ 
21:      $v_{k+1} \leftarrow f(\mathbf{x}_{k+1})$ 
22:      $\rho \leftarrow \frac{v_{k+1} - v_k}{\mathbf{g}'_k \mathbf{s}_k + \frac{1}{2} \mathbf{s}'_k \mathbf{H}_k \mathbf{s}_k}$ 
23:     if  $\rho < \frac{1}{4}$  then
24:        $\delta_{k+1} \leftarrow \frac{1}{3} \delta_{k+1}$ 
25:     else if  $\rho > \frac{3}{4}$  and  $\|\mathbf{s}_k\| = \delta_{k+1}$  then
26:        $\delta_{k+1} \leftarrow 2\delta_{k+1}$ 
27:     end if
28:     if  $\rho > \frac{1}{4}$  then
29:       return  $\mathbf{x}_{k+1}, v_{k+1}, \delta_{k+1}$ 
30:     end if
31:   end while
32: end function

```

---

#### Step 4: Sparse Polynomial Approximation

We seek to approximate  $g(\cdot)$  (7) by a polynomial  $\tilde{g}(\cdot)$  that interpolates  $g(\cdot)$  at points in  $[0, 1] \times [0, 1]$ . If we choose the points well, we can achieve high accuracy with a minimal number of points, making  $\tilde{g}(\cdot)$  cheaper to build and evaluate.

The simplest approach would be to interpolate at equispaced points, but polynomials at equispaced points perform terribly (see Runge's phenomenon). Much better is to interpolate at Chebyshev nodes. Polynomials at Chebyshev nodes have excellent approximation performance; but still, interpolating on a dense grid would be expensive. We can get better efficiency if we interpolate on a sparse grid, and we can get better efficiency still if we adaptively construct the sparse grid to avoid unnecessary evaluations in areas that can be approximated well by lower order polynomials.

Put

$$\begin{aligned} X^i &= \{x_1^i, \dots, x_{m_i}^i\}, \\ m_i &= \begin{cases} 1 & \text{if } i = 0, \\ 2^{i-1} & \text{otherwise,} \end{cases} \\ x_j^i &= \begin{cases} 1 & \text{if } i = 0, \\ \frac{1}{2} \left(1 - \cos \frac{\pi(j-1)}{m_i-1}\right) & \text{otherwise.} \end{cases} \end{aligned}$$

The Chebyshev-Gauss-Lobatto nodes,  $\{X^i\}$ , form a nested sequence of points

$$X^i \subset X^{i+1}$$

that serve as a building block for constructing interpolations and quadrature rules on sparse grids (Barthelmann et al., 2000; Klimke, 2006). Let  $\psi_j^i(\cdot)$  denote the unique  $m_i - 1$  degree polynomial where

$$\psi_j^i(x_{j'}^i) = \begin{cases} 1 & \text{if } j = j', \\ 0 & \text{otherwise,} \end{cases}$$

let  $V^i$  denote the vector space spanned by the basis functions  $\{\psi_j^i\}$  for  $j = 1, \dots, m_i$ , and define

$$\begin{aligned} \Delta V^0 &= V^0, \\ \Delta V^i &= V^i - V^{i-1} \quad \text{for } i > 0. \end{aligned}$$

We will build an approximation using functions from vector spaces

$$W^{\mathcal{I}} = \bigoplus_{i \in \mathcal{I}} \Delta V^{i_1} \otimes \dots \otimes \Delta V^{i_d},$$

where index set  $\mathcal{I}$  is required to be *admissible*: if  $\mathbf{i} \in \mathcal{I}$  and  $i_k > 0$ , then  $\mathbf{i} - \mathbf{e}_k \in \mathcal{I}$ . The vector spaces  $W^{\mathcal{I}}$  are a generalization of Smolyak sparse

grids and allow for different dimensions to have different levels of refinement (Gerstner, Griebel, 2003).

To build  $\mathcal{I}$ , we follow Jakeman, Roberts (2011) and greedily add indexes and nodes with the largest approximation errors until a given accuracy is achieved. The algorithm adapts by both dimension and locality.

---

**Algorithm 4** Approximate Function  $f$  over  $[0, 1]^d$

---

```

1: function APPROXIMATE( $f$ )
2:    $tol \leftarrow$  tolerance
3:    $\mathcal{I} \leftarrow ()$ 
4:    $Z \leftarrow ()$ 
5:    $\mathbf{i} \leftarrow (0, \dots, 0)$ 
6:   EVALUATE-SUBGRID( $f, \mathcal{I}, Z, \mathbf{i}$ )
7:    $\mathcal{A} \leftarrow \{\mathbf{i}\}$ 
8:   while 1 do
9:      $\mathbf{i} \leftarrow \operatorname{argmax}_{\mathbf{i} \in \mathcal{A}} \maxerr^{\mathbf{i}}$ 
10:    if  $\maxerr^{\mathbf{i}} < tol$  then
11:      return  $\mathcal{I}, Z$ 
12:    end if
13:     $\mathcal{I} \leftarrow \text{APPEND}(\mathcal{I}, \mathbf{i})$ 
14:     $Z \leftarrow \text{APPEND}(Z, \mathbf{z}^{\mathbf{i}})$ 
15:     $\mathcal{A} \leftarrow \mathcal{A} \setminus \{\mathbf{i}\}$ 
16:    for  $\mathbf{i}_{\text{fwd}} \in \{\mathbf{i} + \mathbf{e}_k \mid 1 \leq k \leq d\}$  do
17:      if  $\forall_k, (\mathbf{i}_{\text{fwd}})_k = 0 \vee \mathbf{i}_{\text{fwd}} - \mathbf{e}_k \in \mathcal{I}$  then
18:        EVALUATE-SUBGRID( $f, \mathcal{I}, Z, \mathbf{i}_{\text{fwd}}$ )
19:         $\mathcal{A} \leftarrow \mathcal{A} \cup \{\mathbf{i}_{\text{fwd}}\}$ 
20:      end if
21:    end for
22:  end while
23: end function
24: function EVALUATE-SUBGRID( $f, \mathcal{I}, Z, \mathbf{i}$ )
25:    $\maxerr^{\mathbf{i}} \leftarrow 0$ 
26:    $\mathbf{z}^{\mathbf{i}} \leftarrow \mathbf{0}$ 
27:   for  $\mathbf{x}_j^{\mathbf{i}} \in \Delta V^{i_1} \otimes \dots \otimes \Delta V^{i_d}$  do
28:     if IS-ACTIVE( $\mathbf{i}, j$ ) then
29:        $y \leftarrow f(\mathbf{x}_j^{\mathbf{i}})$ 
30:        $\tilde{y} \leftarrow \text{EVALUATE}(\mathcal{I}, Z, \mathbf{x}_j^{\mathbf{i}})$ 
31:        $z_j^{\mathbf{i}} \leftarrow y - \tilde{y}$ 
32:        $err_j^{\mathbf{i}} \leftarrow |\exp(y) - \exp(\tilde{y})|$ 
33:        $\maxerr^{\mathbf{i}} \leftarrow \max(\maxerr^{\mathbf{i}}, err_j^{\mathbf{i}})$ 
34:     end if
35:   end for
36: end function

```

---

---

```

37: function EVALUATE( $\mathcal{I}, Z, \mathbf{x}$ )
38:    $res \leftarrow 0$ 
39:   for  $i, \mathbf{z}^i \in \mathcal{I}, Z$  do
40:      $res \leftarrow res + \sum_{\mathbf{z}_j^i \in \mathbf{z}^i} z_j^i \psi_{j_1}^{i_1}(x_1) \cdots \psi_{j_d}^{i_d}(x_d)$ 
41:   end for
42:   return  $res$ 
43: end function
44: function IS-ACTIVE( $i, j$ )
45:    $\tau \leftarrow$  cutoff threshold
46:   for  $k \in \{k \mid i_k > 0\}$  do
47:      $\mathbf{i}_{\text{bwd}} \leftarrow \mathbf{i} - \mathbf{e}_k$ 
48:     for  $\mathbf{z}_{j_{\text{bwd}}}^{\mathbf{i}_{\text{bwd}}} \in \mathbf{z}^{\mathbf{i}_{\text{bwd}}}$  do
49:       if IS-POINT-NEIGHBOR( $i, j, j_{\text{bwd}}, k$ ) then
50:         if  $z_{j_{\text{bwd}}}^{\mathbf{i}_{\text{bwd}}} > 0$  and  $err_{j_{\text{bwd}}}^{\mathbf{i}_{\text{bwd}}} > \tau$  then
51:           return 1
52:         end if
53:       end if
54:     end for
55:   end for
56:   return 0
57: end function
58: function IS-POINT-NEIGHBOR( $i, j, j', k$ )
59:   if  $\exists_{k' \neq k, j_{k'} \neq j'_{k'}}$  then
60:     return 0
61:   end if
62:   if  $i_k = 1$  then
63:     return 1
64:   end if
65:   if  $j'_k > 1$  and  $x_{j'_k-1}^{i_k-1} < x_{j_k}^{i_k} < x_{j'_k}^{i_k-1}$  then
66:     return 1
67:   end if
68:   if  $j'_k < m_{i_k-1}$  and  $x_{j'_k}^{i_k-1} < x_{j_k}^{i_k} < x_{j'_k+1}^{i_k-1}$  then
69:     return 1
70:   end if
71:   return 0
72: end function

```

---

**Example 4.1.** (Example 1.2 continued) I ran Algorithm 4 on the data set from Example 1.1. Figure 4 shows contours for the log of the transformed posterior function, and Figure 5 shows the sparse grid used to approximate the reparameterized posterior.

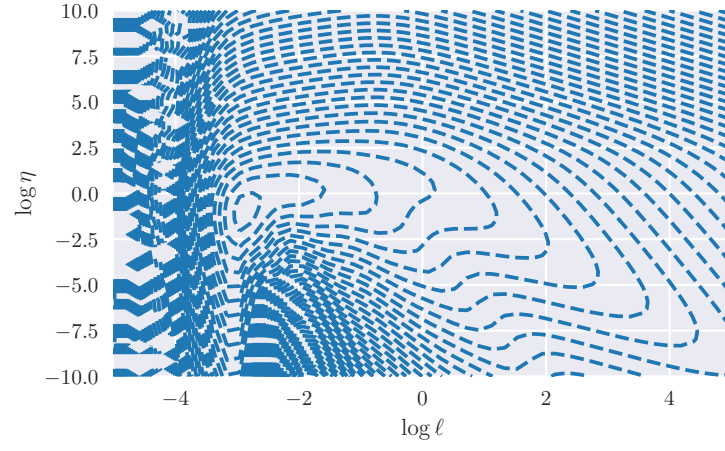


Figure 4: Reparameterized log posterior of the Example 1.1 data set

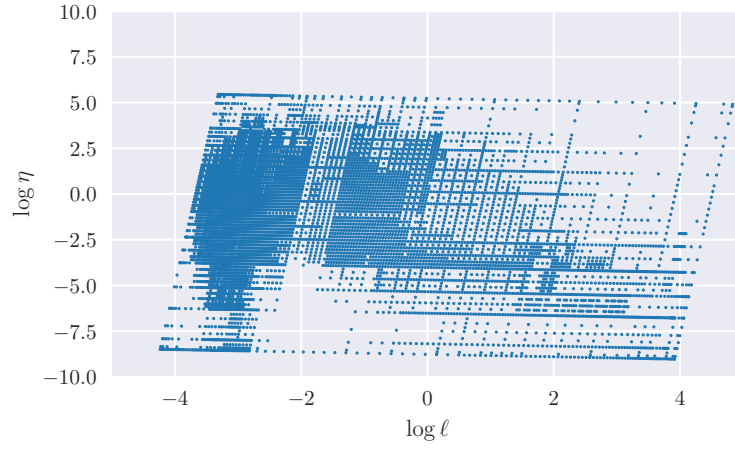


Figure 5: Sparse grid used to interpolate the log posterior

## Prediction Distributions

The sparse grid from Algorithm 4 naturally leads to a quadrature rule to approximate integration (Jakeman, Roberts, 2011)

$$\begin{aligned}
& \int_0^\infty \int_0^\infty h(\ell, \eta) \pi(\ell, \eta \mid \mathbf{y}) d\ell d\eta \\
& \approx \int_0^\infty \int_0^\infty h(\ell, \eta) \tilde{\pi}(\ell, \eta \mid \mathbf{y}) d\ell d\eta \\
& \approx \frac{1}{Z} \int_0^1 \int_0^1 h(\varphi_\ell(s_1(x_1)), \varphi_\eta(s_2(x_2))) g(x_1, x_2) \dot{s}_1(x_1) \dot{s}_2(x_2) d\ell d\eta \\
& \approx \sum_k w_k h(\ell_k, \eta_k), \tag{8}
\end{aligned}$$

where the points  $\{(\ell_k, \eta_k)'\}$  are chosen to be the transformed points of the sparse grid and weights are derived from integrals of the basis functions,

$$\int_0^1 \psi_j^i(x) dx.$$

Let  $\tilde{\mathbf{s}}$  denote unobserved locations. Then

$$\mathbf{P}^\pi(Z(\tilde{s}_1), \dots, Z(\tilde{s}_m) \mid \mathbf{y}) \approx \sum_k w_k \mathbf{P}^\pi(Z(\tilde{s}_1), \dots, Z(\tilde{s}_m) \mid \mathbf{y}, \ell_k, \eta_k)$$

gives us an approximation of the prediction distribution. Let's derive a more explicit formula for the conditional probability  $\mathbf{P}^\pi(\cdot \mid \mathbf{y}, \ell, \eta)$ . Use  $\mathbf{y}_1 = \mathbf{y}$  to denote the observations and suppose  $\mathbf{y}_2$  are possible values for the unobserved locations  $\tilde{s}_1, \dots, \tilde{s}_m$ . Applying (2), we have

$$\begin{aligned}
\mathbf{P}^\pi(\mathbf{y}_2 \mid \mathbf{y}_1, \ell, \eta) & \propto \int_0^\infty \int_{\mathbb{R}^p} \mathbf{P}(\mathbf{y}_1, \mathbf{y}_2 \mid \beta, \sigma^2, \ell, \eta) \left(\frac{1}{\sigma^2}\right) d\beta d\sigma^2 \\
& \propto [(\mathbf{y}_1, \mathbf{y}_2) \mathbf{R} (\mathbf{y}_1, \mathbf{y}_2)']^{-(n+m-p)/2},
\end{aligned}$$

where  $\mathbf{R}$  is given by (3). Put

$$\mathbf{R} = \begin{pmatrix} \mathbf{R}_{11} & \mathbf{R}_{12} \\ \mathbf{R}_{12}' & \mathbf{R}_{22} \end{pmatrix}.$$

Then

$$\begin{aligned}
(\mathbf{y}_1, \mathbf{y}_2) \mathbf{R} (\mathbf{y}_1, \mathbf{y}_2)' & = \mathbf{y}_1' \mathbf{R}_{11} \mathbf{y}_1 + 2\mathbf{y}_1' \mathbf{R}_{12} \mathbf{y}_2 + \mathbf{y}_2' \mathbf{R}_{22} \mathbf{y}_2 \\
& = (\mathbf{y}_2 - \bar{\mathbf{y}}_2)' \mathbf{R}_{22} (\mathbf{y}_2 - \bar{\mathbf{y}}_2) + b,
\end{aligned}$$

where

$$\begin{aligned}
\bar{\mathbf{y}}_2 & = -\mathbf{R}_{22}^{-1} \mathbf{R}_{12}' \mathbf{y}_1 \\
b & = \mathbf{y}_1' \mathbf{R}_{11} \mathbf{y}_1 - \bar{\mathbf{y}}_2' \mathbf{R}_{22} \bar{\mathbf{y}}_2.
\end{aligned}$$

## $\sigma^2$ Marginal

The marginal distribution of  $\sigma^2$  is given by

$$\begin{aligned} P^\pi(\sigma^2 | \mathbf{y}) &= \int_0^\infty \int_0^\infty P^\pi(\sigma^2 | \mathbf{y}, \ell, \eta) \pi(\ell, \eta | \mathbf{y}) d\ell d\eta \\ &\approx \sum_k w_k P^\pi(\sigma^2 | \mathbf{y}, \ell_k, \eta_k), \end{aligned}$$

where  $\{w_k\}$ ,  $\{\ell_k\}$ , and  $\{\eta_k\}$  are given by (8). From (2), we have

$$\begin{aligned} P^\pi(\sigma^2 | \mathbf{y}, \ell, \eta) &\propto \int_{\mathbb{R}^p} L(\boldsymbol{\beta}, \sigma^2, \ell, \eta; \mathbf{y}) \pi(\boldsymbol{\beta}, \sigma^2 | \ell, \eta) d\boldsymbol{\beta} \\ &\propto (\sigma^2)^{-(n-p)/2} |\mathbf{G}|^{-1/2} |\mathbf{X}'\mathbf{G}^{-1}\mathbf{X}|^{-1/2} \exp\left\{-\frac{S^2}{2\sigma^2}\right\} \left(\frac{1}{\sigma^2}\right) \\ &\propto \left(\frac{1}{\sigma^2}\right)^{(n-p)/2+1} \exp\left\{-\frac{S^2}{2\sigma^2}\right\}. \end{aligned} \quad (9)$$

(9) is the unnormalized PDF of an inverse-gamma distribution. Normalizing gives us

$$P^\pi(\sigma^2 | \mathbf{y}, \ell, \eta) = \frac{(S^2/2)^{(n-p)/2}}{\Gamma((n-p)/2)} \left(\frac{1}{\sigma^2}\right)^{(n-p)/2+1} \exp\left\{-\frac{S^2}{2\sigma^2}\right\}.$$

## $\boldsymbol{\beta}$ Marginals

Similarly, to compute the posterior distribution of a particular regressor  $\beta_j$ , we have

$$P^\pi(\beta_j | \mathbf{y}) = \int_0^\infty \int_0^\infty P^\pi(\beta_j | \mathbf{y}, \ell, \eta) \pi(\ell, \eta | \mathbf{y}) d\ell d\eta,$$



where

$$\begin{aligned}
P^\pi(\beta_j \mid \mathbf{y}, \ell, \eta) &\propto \int_0^\infty \int_{\mathbb{R}^{p-1}} \left(\frac{1}{\sigma^2}\right)^{n/2+1} \\
&\quad \exp\left\{-\frac{1}{2\sigma^2}(\mathbf{y} - \mathbf{X}\beta)' \mathbf{G}^{-1}(\mathbf{y} - \mathbf{X}\beta)\right\} d\beta_{/j} d\sigma^2 \\
&\propto \int_0^\infty \int_{\mathbb{R}^{p-1}} \left(\frac{1}{\sigma^2}\right)^{n/2+1} \\
&\quad \exp\left\{-\frac{1}{2\sigma^2}(\beta - \bar{\beta})' \mathbf{X}' \mathbf{G}^{-1} \mathbf{X}(\beta - \bar{\beta})\right\} \\
&\quad \exp\left\{-\frac{1}{2\sigma^2}(\mathbf{y}' \mathbf{G}^{-1} \mathbf{y} - \bar{\beta}' \mathbf{X}' \mathbf{G}^{-1} \mathbf{X} \bar{\beta})\right\} d\beta_{/j} d\sigma^2 \\
&\propto \int_0^\infty \left(\frac{1}{\sigma^2}\right)^{(n-p+1)/2+1} \exp\left\{-\frac{1}{2\sigma^2} \frac{1}{(\mathbf{A}^{-1})_{jj}} (\beta_j - \bar{\beta}_j)^2\right\} \\
&\quad \exp\left\{-\frac{1}{2\sigma^2}(\mathbf{y}' \mathbf{G}^{-1} \mathbf{y} - \bar{\beta}' \mathbf{X}' \mathbf{G}^{-1} \mathbf{X} \bar{\beta})\right\} d\sigma^2 \\
&\propto \int_0^\infty \left(\frac{1}{\sigma^2}\right)^{(n-p+1)/2+1} \exp\left\{-\frac{1}{2\sigma^2} \#1\right\} d\sigma^2 \\
&\propto (\#1)^{-(n-p+1)/2}
\end{aligned}$$

and

$$\begin{aligned}
\mathbf{A} &= \mathbf{X}' \mathbf{G}^{-1} \mathbf{X} \\
\bar{\beta} &= \mathbf{A}^{-1} \mathbf{X}' \mathbf{G}^{-1} \mathbf{y} \\
\#1 &= \frac{1}{(\mathbf{A}^{-1})_{jj}} (\beta_j - \bar{\beta}_j)^2 + \mathbf{y}' \mathbf{G}^{-1} \mathbf{y} - \bar{\beta}' \mathbf{A} \bar{\beta}.
\end{aligned}$$

### $\ell, \eta$ Marginals

Algorithm 4 gives us an interpolating function that is inexpensive to evaluate and accurately approximates the reparameterized posterior

$$\pi(u_1, u_2 \mid \mathbf{y}) = \pi(\varphi_\ell(u_1), \varphi_\eta(u_2) \mid \mathbf{y}) \dot{\varphi}_\ell(u_1) \dot{\varphi}_\eta(u_2).$$

Now,

$$\begin{aligned}
\pi(u_1 \mid \mathbf{y}) &= \int \pi(u_1, u_2 \mid \mathbf{y}) du_2 \\
&\approx \sum_k w_k \tilde{\pi}(u_1, t_k \mid \mathbf{y}),
\end{aligned}$$

where  $\{w_k\}$  and  $\{t_k\}$  are chosen by the Gauss-Legendre quadrature rule for the interval defined by the bracket in Step 2. If we evaluate  $\tilde{\pi}(u_1 \mid \mathbf{y})$  at Chebyshev

nodes across the range of  $u_1$  in the bracket, then we obtain a polynomial that approximates  $\pi(u_1 | \mathbf{y})$ .  $\pi(u_2 | \mathbf{y})$  can be similarly approximated by a Chebyshev polynomial.

If the error bounds from Step 2 are tight enough, the polynomial approximations for  $\pi(u_1 | \mathbf{y})$  and  $\pi(u_2 | \mathbf{y})$  will be suitable for estimating the CDFs. But since they are cutoff outside of the bracket, they don't accurately capture endpoint behavior and shouldn't be used for estimating moments. For example,  $\pi(\eta | \mathbf{y})$  has infinite mean, which won't be reflected by the polynomial approximation.

## 5 Real Data Analysis

Let's try applying the algorithms from Section 4 to real data. We'll look at a data set from Schabenberger, Pierce (2001) of carbon-to-nitrogen ratios sampled across an agricultural field before and after tillage. The after tillage data was analyzed by Ren et al. (2012) and De Oliveira (2007) using random sampling algorithms and a Gaussian process of the form (1) with

$$\mathbb{E}\{Z(\mathbf{s})\} = \beta_1 \quad \text{and} \quad \psi_\ell(d) = \exp\left\{-\frac{d}{\ell}\right\}.$$

We'll use the same model and data set with our deterministic algorithm. When we fit a sparse polynomial to the posterior and marginalize, we get these values for the medians

$$\ell_{\text{med}} = 62.54, \quad \eta_{\text{med}} = 0.44, \quad \text{and} \quad \sigma_{\text{med}}^2 = 0.24.$$

Figure 6 plots the posterior marginalizations for  $\ell$ ,  $\eta$ , and  $\sigma^2$ . Figure 7 plots carbon-to-nitrogen predictions and credible sets across the agricultural field. See soil-cn.ipynb for source code for the example.

## A Appendix: Posterior Derivatives

We will derive equations to compute the value, gradient, and hessian of the negative log posterior  $\pi(\ell, \eta | \mathbf{y})$ . From (2) and (4), we have

$$\begin{aligned} \pi(\ell, \eta | \mathbf{y}) &\propto L^I(\ell, \eta; \mathbf{y}) \times \pi(\ell, \eta) \\ &\propto |\mathbf{G}|^{-1/2} |\mathbf{X}'\mathbf{G}^{-1}\mathbf{X}|^{-1/2} (S^2)^{-(n-p)/2} |\mathbf{\Sigma}|^{1/2}. \end{aligned}$$

Put  $\phi_1 = \ell$ ,  $\phi_2 = \eta$ ,  $\mathbf{A} = \mathbf{X}'\mathbf{G}^{-1}\mathbf{X}$ , and define

$$f(\phi) = \frac{1}{2} \log |\mathbf{G}| + \frac{1}{2} \log |\mathbf{A}| + \frac{n-p}{2} \log S^2 - \frac{1}{2} \log |\mathbf{\Sigma}|.$$

Let  $\mathbf{L}_G$  denote the Cholesky factorization of  $\mathbf{G}$

$$\mathbf{G} = \mathbf{L}_G' \mathbf{L}_G.$$

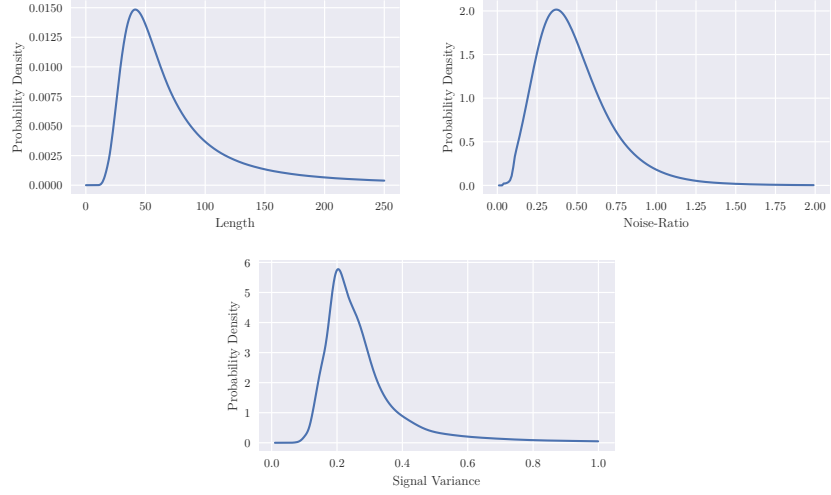


Figure 6: Marginalization of posterior distribution of soil carbon-to-nitrogen ratio data set

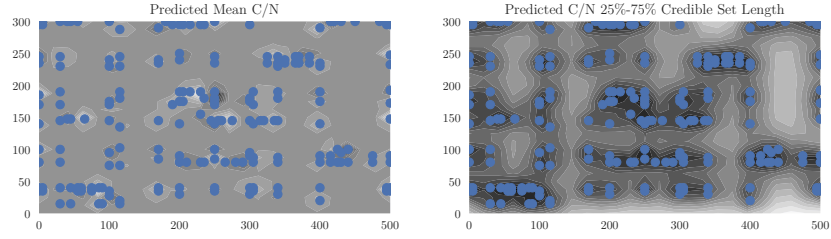


Figure 7: Prediction mean and credible sets of soil carbon-to-nitrogen ratios

Then

$$\begin{aligned}
 \mathbf{A} &= \mathbf{X}' (\mathbf{L}'_G \mathbf{L}_G)^{-1} \mathbf{X} \\
 &= \mathbf{X}' \mathbf{L}'_G^{-1} \mathbf{L}_G^{-1} \mathbf{X} \\
 &= (\mathbf{L}_G^{-1} \mathbf{X})' (\mathbf{L}_G^{-1} \mathbf{X}).
 \end{aligned}$$

Let  $\mathbf{Q}$  and  $\mathbf{R}_A$  denote the QR factorization of  $\mathbf{L}_G^{-1} \mathbf{X}$

$$\mathbf{A} = \mathbf{Q} \mathbf{R}_A.$$

Then

$$\begin{aligned}
\mathbf{A} &= (\mathbf{L}_G^{-1} \mathbf{X})' (\mathbf{L}_G^{-1} \mathbf{X}) \\
&= (\mathbf{Q} \mathbf{R}_A)' (\mathbf{Q} \mathbf{R}_A) \\
&= \mathbf{R}_A' \mathbf{Q}' \mathbf{Q} \mathbf{R}_A \\
&= \mathbf{R}_A' \mathbf{R}_A.
\end{aligned}$$

Put

$$\mathbf{H} = \mathbf{G}^{-1} \mathbf{X} \mathbf{A}^{-1} \mathbf{X}' \mathbf{G}^{-1} \quad \text{and} \quad \mathbf{F}_H = \mathbf{R}_A'^{-1} \mathbf{X}' \mathbf{G}^{-1}.$$

Applying to  $\mathbf{R}$  (3), we have

$$\mathbf{H} = \mathbf{F}_H' \mathbf{F}_H \quad \text{and} \quad \mathbf{R} = \mathbf{L}_G'^{-1} \mathbf{L}_G^{-1} + \mathbf{F}_H' \mathbf{F}_H.$$

## Gradient

Put

$$\#1 = \frac{1}{2} \log |\mathbf{G}|, \quad \#2 = \frac{1}{2} \log |\mathbf{A}|, \quad \#3 = \frac{n-p}{2} \log S^2, \quad \text{and} \quad \#4 = \frac{1}{2} \log |\mathbf{\Sigma}|.$$

Applying Jacobi's formula

$$\frac{d}{dt} |\mathbf{B}(t)| = |\mathbf{B}| \operatorname{tr} \left\{ \mathbf{B}^{-1} \frac{d\mathbf{B}}{dt} \right\},$$

we have

$$\begin{aligned}
\frac{\partial \#1}{\partial \phi_s} &= \frac{1}{2} \operatorname{tr} \left\{ \mathbf{G}^{-1} \frac{\partial \mathbf{G}}{\partial \phi_s} \right\} \\
\frac{\partial \#2}{\partial \phi_s} &= \frac{1}{2} \operatorname{tr} \left\{ \mathbf{A}^{-1} \frac{\partial \mathbf{A}}{\partial \phi_s} \right\} \\
\frac{\partial \#3}{\partial \phi_s} &= \frac{n-p}{2} \frac{1}{S^2} \frac{\partial S^2}{\partial \phi_s} = \frac{n-p}{2} \frac{1}{S^2} \mathbf{y}' \frac{\partial \mathbf{R}}{\partial \phi_s} \mathbf{y} \\
\frac{\partial \#4}{\partial \phi_s} &= \frac{1}{2} \operatorname{tr} \left\{ \mathbf{\Sigma}^{-1} \frac{\partial \mathbf{\Sigma}}{\partial \phi_s} \right\}.
\end{aligned}$$

Using this formula for differentiating an inverse matrix

$$\frac{d}{dt} \mathbf{B}(t)^{-1} = -\mathbf{B}^{-1} \frac{d\mathbf{B}}{dt} \mathbf{B}^{-1},$$

we derive the derivative of  $\mathbf{A}$

$$\frac{\partial \mathbf{A}}{\partial \phi_s} = \mathbf{X}' \frac{\partial \mathbf{G}^{-1}}{\partial \phi_s} \mathbf{X},$$

where

$$\frac{\partial \mathbf{G}^{-1}}{\partial \phi_s} = -\mathbf{G}^{-1} \frac{\partial \mathbf{G}}{\partial \phi_s} \mathbf{G}^{-1}.$$

Differentiating  $\mathbf{R}$  gives us

$$\frac{\partial \mathbf{R}}{\partial \phi_s} = \frac{\partial}{\partial \phi_s} (\mathbf{G}^{-1} - \mathbf{H}) = \frac{\partial \mathbf{G}^{-1}}{\partial \phi_s} - \frac{\partial \mathbf{H}}{\partial \phi_s}$$

and

$$\begin{aligned} \frac{\partial \mathbf{H}}{\partial \phi_s} &= \frac{\partial}{\partial \phi_s} (\mathbf{G}^{-1} \mathbf{X} \mathbf{A}^{-1} \mathbf{X}' \mathbf{G}^{-1}) \\ &= -\mathbf{G}^{-1} \frac{\partial \mathbf{G}}{\partial \phi_s} \mathbf{H} - \mathbf{H} \frac{\partial \mathbf{G}}{\partial \phi_s} \mathbf{G}^{-1} - \mathbf{G}^{-1} \mathbf{X} \mathbf{A}^{-1} \frac{\partial \mathbf{A}}{\partial \phi_s} \mathbf{A}^{-1} \mathbf{X} \mathbf{G}^{-1} \\ &= -\mathbf{G}^{-1} \frac{\partial \mathbf{G}}{\partial \phi_s} \mathbf{H} - \mathbf{H} \frac{\partial \mathbf{G}}{\partial \phi_s} \mathbf{G}^{-1} \\ &\quad + \mathbf{G}^{-1} \mathbf{X} \mathbf{A}^{-1} \left( \mathbf{X}' \mathbf{G}^{-1} \frac{\partial \mathbf{G}}{\partial \phi_s} \mathbf{G}^{-1} \mathbf{X} \right) \mathbf{A}^{-1} \mathbf{X} \mathbf{G}^{-1} \\ &= -\mathbf{G}^{-1} \frac{\partial \mathbf{G}}{\partial \phi_s} \mathbf{H} - \mathbf{H} \frac{\partial \mathbf{G}}{\partial \phi_s} \mathbf{G}^{-1} + \mathbf{H} \frac{\partial \mathbf{G}}{\partial \phi_s} \mathbf{H} \\ &= -\left( \mathbf{G}^{-1} - \frac{1}{2} \mathbf{H} \right) \frac{\partial \mathbf{G}}{\partial \phi_s} \mathbf{H} - \mathbf{H} \frac{\partial \mathbf{G}}{\partial \phi_s} \left( \mathbf{G}^{-1} - \frac{1}{2} \mathbf{H} \right). \end{aligned}$$

Put

$$\#5 = \text{tr} \left\{ \mathbf{R} \frac{\partial \mathbf{K}}{\partial \ell} \right\}.$$

Then

$$\begin{aligned} \left( \frac{\partial \boldsymbol{\Sigma}}{\partial \phi_s} \right)_{11} &= \frac{\partial}{\partial \phi_s} \text{tr} \{ \#5^2 \} = 2 \text{tr} \left\{ \#5 \frac{\partial \#5}{\partial \phi_s} \right\} \\ \left( \frac{\partial \boldsymbol{\Sigma}}{\partial \phi_s} \right)_{12} &= \frac{\partial}{\partial \phi_s} \text{tr} \left\{ \mathbf{R}^2 \frac{\partial \mathbf{K}}{\partial \ell} \right\} = \text{tr} \left\{ \frac{\partial \mathbf{R}^2}{\partial \phi_s} \frac{\partial \mathbf{K}}{\partial \ell} + \mathbf{R}^2 \frac{\partial^2 \mathbf{K}}{\partial \phi_s \partial \ell} \right\} \\ \left( \frac{\partial \boldsymbol{\Sigma}}{\partial \phi_s} \right)_{13} &= \text{tr} \left\{ \frac{\partial \#5}{\partial \phi_s} \right\} \\ \left( \frac{\partial \boldsymbol{\Sigma}}{\partial \phi_s} \right)_{22} &= \text{tr} \left\{ \frac{\partial \mathbf{R}^2}{\partial \phi_s} \right\} \\ \left( \frac{\partial \boldsymbol{\Sigma}}{\partial \phi_s} \right)_{23} &= \text{tr} \left\{ \frac{\partial \mathbf{R}}{\partial \phi_s} \right\} \\ \left( \frac{\partial \boldsymbol{\Sigma}}{\partial \phi_s} \right)_{33} &= 0 \end{aligned}$$

and

$$\begin{aligned}\frac{\partial \#5}{\partial \phi_s} &= \frac{\partial}{\partial \phi_s} \left( \mathbf{R} \frac{\partial \mathbf{K}}{\partial \ell} \right) = \frac{\partial \mathbf{R}}{\partial \phi_s} \frac{\partial \mathbf{K}}{\partial \ell} + \mathbf{R} \frac{\partial^2 \mathbf{K}}{\partial \phi_s \partial \ell} \\ \frac{\partial \mathbf{R}^2}{\partial \phi_s} &= \frac{\partial \mathbf{R}}{\partial \phi_s} \mathbf{R} + \mathbf{R} \frac{\partial \mathbf{R}}{\partial \phi_s}.\end{aligned}$$

## Hessian

Computing second derivatives we have

$$\begin{aligned}\frac{\partial^2 \#1}{\partial \phi_s \partial \phi_t} &= \frac{\partial}{\partial \phi_s} \left( \frac{1}{2} \text{tr} \left\{ \mathbf{G}^{-1} \frac{\partial \mathbf{G}}{\partial \phi_t} \right\} \right) \\ &= \frac{1}{2} \text{tr} \left\{ -\mathbf{G}^{-1} \frac{\partial \mathbf{G}}{\partial \phi_s} \mathbf{G}^{-1} \frac{\partial \mathbf{G}}{\partial \phi_t} + \mathbf{G}^{-1} \frac{\partial^2 \mathbf{G}}{\partial \phi_s \partial \phi_t} \right\} \\ \frac{\partial^2 \#2}{\partial \phi_s \partial \phi_t} &= \frac{\partial}{\partial \phi_s} \left( \frac{1}{2} \text{tr} \left\{ \mathbf{A}^{-1} \frac{\partial \mathbf{A}}{\partial \phi_t} \right\} \right) \\ &= \frac{1}{2} \text{tr} \left\{ -\mathbf{A}^{-1} \frac{\partial \mathbf{A}}{\partial \phi_s} \mathbf{A}^{-1} \frac{\partial \mathbf{A}}{\partial \phi_t} + \mathbf{A}^{-1} \frac{\partial^2 \mathbf{A}}{\partial \phi_s \partial \phi_t} \right\} \\ \frac{\partial^2 \#3}{\partial \phi_s \partial \phi_t} &= \frac{\partial}{\partial \phi_s} \left( \frac{n-p}{2} \frac{1}{S^2} \frac{\partial S^2}{\partial \phi_t} \right) \\ &= \frac{n-p}{2} \left( -\frac{1}{S^4} \frac{\partial S^2}{\partial \phi_s} \frac{\partial S^2}{\partial \phi_t} + \frac{1}{S^2} \frac{\partial^2 S^2}{\partial \phi_s \partial \phi_t} \right) \\ \frac{\partial^2 \#4}{\partial \phi_s \partial \phi_t} &= \frac{\partial}{\partial \phi_s} \left( \frac{1}{2} \text{tr} \left\{ \mathbf{\Sigma}^{-1} \frac{\partial \mathbf{\Sigma}}{\partial \phi_t} \right\} \right) \\ &= \frac{1}{2} \text{tr} \left\{ -\mathbf{\Sigma}^{-1} \frac{\partial \mathbf{\Sigma}}{\partial \phi_s} \mathbf{\Sigma}^{-1} \frac{\partial \mathbf{\Sigma}}{\partial \phi_t} + \mathbf{\Sigma}^{-1} \frac{\partial^2 \mathbf{\Sigma}}{\partial \phi_s \partial \phi_t} \right\}.\end{aligned}$$

For the second derivative of  $\mathbf{A}$ , we have

$$\begin{aligned}\frac{\partial^2 \mathbf{A}}{\partial \phi_s \partial \phi_t} &= \frac{\partial}{\partial \phi_s} \left( -\mathbf{X}' \mathbf{G}^{-1} \frac{\partial \mathbf{G}}{\partial \phi_t} \mathbf{G}^{-1} \mathbf{X} \right) \\ &= \mathbf{X}' \mathbf{G}^{-1} \frac{\partial \mathbf{G}}{\partial \phi_s} \mathbf{G}^{-1} \frac{\partial \mathbf{G}}{\partial \phi_t} \mathbf{G}^{-1} \mathbf{X} + \mathbf{X}' \mathbf{G}^{-1} \frac{\partial \mathbf{G}}{\partial \phi_t} \mathbf{G}^{-1} \frac{\partial \mathbf{G}}{\partial \phi_s} \mathbf{G}^{-1} \mathbf{X} \\ &\quad - \mathbf{X}' \mathbf{G}^{-1} \frac{\partial^2 \mathbf{G}}{\partial \phi_s \partial \phi_t} \mathbf{G}^{-1} \mathbf{X}.\end{aligned}$$

Differentiating  $\mathbf{R}$  a second time gives us

$$\begin{aligned}\frac{\partial^2 \mathbf{R}}{\partial \phi_s \partial \phi_t} &= \frac{\partial}{\partial \phi_s} \left( \frac{\partial \mathbf{G}^{-1}}{\partial \phi_t} - \frac{\partial \mathbf{H}}{\partial \phi_t} \right) \\ &= \frac{\partial^2 \mathbf{G}^{-1}}{\partial \phi_s \partial \phi_t} - \frac{\partial^2 \mathbf{H}}{\partial \phi_s \partial \phi_t},\end{aligned}$$

where

$$\begin{aligned}
\frac{\partial^2 \mathbf{G}^{-1}}{\partial \phi_s \partial \phi_t} &= \frac{\partial}{\partial \phi_s} \left( -\mathbf{G}^{-1} \frac{\partial \mathbf{G}}{\partial \phi_t} \mathbf{G}^{-1} \right) \\
&= \mathbf{G}^{-1} \frac{\partial \mathbf{G}}{\partial \phi_s} \mathbf{G}^{-1} \frac{\partial \mathbf{G}}{\partial \phi_t} \mathbf{G}^{-1} + \mathbf{G}^{-1} \frac{\partial \mathbf{G}}{\partial \phi_t} \mathbf{G}^{-1} \frac{\partial \mathbf{G}}{\partial \phi_s} \mathbf{G}^{-1} \\
&\quad - \mathbf{G}^{-1} \frac{\partial^2 \mathbf{G}}{\partial \phi_s \partial \phi_t} \mathbf{G}^{-1} \\
\frac{\partial^2 \mathbf{H}}{\partial \phi_s \partial \phi_t} &= \frac{\partial}{\partial \phi_s} \left( - \left( \mathbf{G}^{-1} - \frac{1}{2} \mathbf{H} \right) \frac{\partial \mathbf{G}}{\partial \phi_t} \mathbf{H} - \mathbf{H} \frac{\partial \mathbf{G}}{\partial \phi_t} \left( \mathbf{G}^{-1} - \frac{1}{2} \mathbf{H} \right) \right) \\
&= \#D2H1 + \#D2H2 + \#D2H3,
\end{aligned}$$

and

$$\begin{aligned}
\#D2H1 &= - \left( \frac{\partial \mathbf{G}^{-1}}{\partial \phi_s} - \frac{1}{2} \frac{\partial \mathbf{H}}{\partial \phi_s} \right) \frac{\partial \mathbf{G}}{\partial \phi_t} \mathbf{H} - \mathbf{H} \frac{\partial \mathbf{G}}{\partial \phi_t} \left( \frac{\partial \mathbf{G}^{-1}}{\partial \phi_s} - \frac{1}{2} \frac{\partial \mathbf{H}}{\partial \phi_s} \right) \\
\#D2H2 &= - \left( \mathbf{G}^{-1} - \frac{1}{2} \mathbf{H} \right) \frac{\partial \mathbf{G}}{\partial \phi_t} \frac{\partial \mathbf{H}}{\partial \phi_s} - \frac{\partial \mathbf{H}}{\partial \phi_s} \frac{\partial \mathbf{G}}{\partial \phi_t} \left( \mathbf{G}^{-1} - \frac{1}{2} \mathbf{H} \right) \\
\#D2H3 &= - \left( \mathbf{G}^{-1} - \frac{1}{2} \mathbf{H} \right) \frac{\partial^2 \mathbf{G}}{\partial \phi_s \partial \phi_t} \mathbf{H} - \mathbf{H} \frac{\partial^2 \mathbf{G}}{\partial \phi_s \partial \phi_t} \left( \mathbf{G}^{-1} - \frac{1}{2} \mathbf{H} \right).
\end{aligned}$$

Computing the second derivative of  $\Sigma$ , we have

$$\begin{aligned}
\left( \frac{\partial^2 \Sigma}{\partial \phi_s \partial \phi_t} \right)_{11} &= \frac{\partial}{\partial \phi_s} \left( 2 \operatorname{tr} \left\{ \#5 \frac{\partial \#5}{\partial \phi_t} \right\} \right) \\
&= 2 \operatorname{tr} \left\{ \frac{\partial \#5}{\partial \phi_s} \frac{\partial \#5}{\partial \phi_t} + \#5 \frac{\partial^2 \#5}{\partial \phi_s \partial \phi_t} \right\} \\
\left( \frac{\partial^2 \Sigma}{\partial \phi_s \partial \phi_t} \right)_{12} &= \frac{\partial}{\partial \phi_s} \left( \operatorname{tr} \left\{ \frac{\partial \mathbf{R}^2}{\partial \phi_s} \frac{\partial \mathbf{K}}{\partial \ell} + \mathbf{R}^2 \frac{\partial^2 \mathbf{K}}{\partial \phi_t \partial \ell} \right\} \right) \\
&= \operatorname{tr} \left\{ \frac{\partial^2 \mathbf{R}^2}{\partial \phi_s \partial \phi_t} \frac{\partial \mathbf{K}}{\partial \ell} + \frac{\partial \mathbf{R}^2}{\partial \phi_s} \frac{\partial^2 \mathbf{K}}{\partial \phi_t \partial \ell} + \frac{\partial \mathbf{R}^2}{\partial \phi_s} \frac{\partial^2 \mathbf{K}}{\partial \phi_s \partial \ell} + \mathbf{R}^2 \frac{\partial^3 \mathbf{K}}{\partial \phi_s \partial \phi_t \partial \ell} \right\} \\
\left( \frac{\partial^2 \Sigma}{\partial \phi_s \partial \phi_t} \right)_{13} &= \operatorname{tr} \left\{ \frac{\partial \#5}{\partial \phi_s} \phi_t \right\} \\
\left( \frac{\partial^2 \Sigma}{\partial \phi_s \partial \phi_t} \right)_{22} &= \operatorname{tr} \left\{ \frac{\partial^2 \mathbf{R}^2}{\partial \phi_s \partial \phi_t} \right\} \\
\left( \frac{\partial^2 \Sigma}{\partial \phi_s \partial \phi_t} \right)_{23} &= \operatorname{tr} \left\{ \frac{\partial^2 \mathbf{R}}{\partial \phi_s \partial \phi_t} \right\},
\end{aligned}$$

and

$$\begin{aligned}
\frac{\partial^2 \#5}{\partial \phi_s \partial \phi_t} &= \frac{\partial}{\partial \phi_s} \left( \frac{\partial \mathbf{R}}{\partial \phi_t} \frac{\partial \mathbf{K}}{\partial \ell} + \mathbf{R} \frac{\partial^2 \mathbf{K}}{\partial \phi_t \partial \ell} \right) \\
&= \frac{\partial^2 \mathbf{R}}{\partial \phi_s \partial \phi_t} \frac{\partial \mathbf{K}}{\partial \ell} + \frac{\partial \mathbf{R}}{\partial \phi_s} \frac{\partial^2 \mathbf{K}}{\partial \phi_t \partial \ell} + \frac{\partial \mathbf{R}}{\partial \phi_t} \frac{\partial^2 \mathbf{K}}{\partial \phi_s \partial \ell} + \mathbf{R} \frac{\partial^3 \mathbf{K}}{\partial \phi_s \partial \phi_t \partial \ell} \\
\frac{\partial^2 \mathbf{R}^2}{\partial \phi_s \partial \phi_t} &= \frac{\partial}{\partial \phi_s} \left( \frac{\partial \mathbf{R}}{\partial \phi_t} \mathbf{R} + \mathbf{R} \frac{\partial \mathbf{R}}{\partial \phi_t} \right) \\
&= \left( \frac{\partial^2 \mathbf{R}}{\partial \phi_s \partial \phi_t} \mathbf{R} + \mathbf{R} \frac{\partial^2 \mathbf{R}}{\partial \phi_s \partial \phi_t} \right) + \left( \frac{\partial \mathbf{R}}{\partial \phi_s} \frac{\partial \mathbf{R}}{\partial \phi_t} + \frac{\partial \mathbf{R}}{\partial \phi_t} \frac{\partial \mathbf{R}}{\partial \phi_s} \right).
\end{aligned}$$

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