DTU Compute Department of Applied Mathematics and Computer Science

Regularized Sampling of Fractional Gaussian Processes on R^d

Lara Baalbaki^{1,*}, Mirza Karamehmedović ¹, Babak Maboudi Afkham¹, Faouzi Triki ²

¹ Technical University of Denmark, Kgs. Lyngby, Denmark

² Laboratoire Jean Kuntzmann, Université Grenoble Alpes
 * Corresponding author, Email: labaa@dtu.dk

1 Introduction

In many applications of inverse problems, we face the problem of estimating continuous quantities from indirect measurements. In addition, we must quantify uncertainties in such an estimate. The infinite-dimensional Bayesian approach is a promising method for estimating continuous quantities in inverse problems.

- The idea is to use pseudodifferential calculi and PDE theory to produce samplers in infinite dimensional function spaces with highly complex conditions built in.
- The pseudodifferential calculus is a method to model local irregularities and local inhomogeneity which would be challenging for current priors.
 This method helps reveal the singularities (e.g. discontinuities) in our estimate.

The Sampling Method:

Construct an operator **Q** of the elliptic operator $P = (k(x)I - \Delta)^{s(x)}$ where

$$QP = I + K$$

where K is a smoothing operator and apply it to (1) to get

 $u = Q\Psi + Ku$

with $Ku \in C^{\infty}$.

- 1. Find a symbol $p(x, \xi)$ of the pseudodifferential operator $(k(x)I \Delta)^{s(x)}$
- 2. Construct the excision function, $\psi(\xi)$
- 3. Construct $q_0(x, \xi) = \frac{\psi(\xi)}{p(x,\xi)}$

3 Some of the Numerical Results

Particular Case: s(x) = 1, $k(x) = x^2$ then:

UIU





2 Problem

Regularized sampling can be achieved, e.g., by solving pseudodifferential equations of the type

$$\left(k(x)I - \Delta\right)^{s(x)}U = \Psi \quad in \ R^n \tag{1}$$

where:

- $\bullet \ \Psi$ is a stochastic term, typically Gaussian white noise
- k(x) and s(x) carry information on the desired regularity of the sampled function u.
- Goal: Pose the sampling problem in terms

4. Find $r_0(x, \xi) \sim \sum_{\alpha > 0} D_{\xi}^{\alpha} q_0(x, \xi) D_x^{\alpha} p(x, \xi) - 1$ 5. Calculate $s(x, \xi) \sim \sum_{j \in N} (\sigma(-r_0(x, D))^j)$ 6. $q(x, \xi) \sim q_0(x, \xi) + \sum_{\alpha \in N_0^n} D_{\xi}^{\alpha} s(x, \xi) D_x^{\alpha} q_0(x, \xi)$

$$Q\Psi(x) = (2\pi)^{-n} \int_{\mathbb{R}^n} e^{ix\xi} q(x,\xi) \widehat{\Psi}(\xi) d\xi$$

The integral above can be evaluated numerically, yielding the sample u(x).

 $u = Q\Psi + Ku$

The term Ku does not carry singularities of u since $Ku \in C^{\infty}$.

Remarks:

so we get:

• The Whittle-Matern priors are a popular choice for such unknowns. However, incorporating spatial inhomogeneity, anisotropy, and local ir-





4 An Application



The boundary of the tumor is "u"

5 Conclusion

of a stochastic pseudodifferential equation, the numerical solution of each realization of the stochastic pseudodifferential equation amounts to a single sampling, where the solution function incorporates the desired properties.

regularities into such priors is challenging.

• This work has potential applications in many inverse problems with local inhomogeneity, e.g. in X-ray computed tomography, and fault detection in industrial applications.

In conclusion, successfully solving the elliptic pseudodifferential operator outlined above facilitates the sampling process from function spaces. The sampler produces and construct functions from the correct space.

Computational Uncertainty Quantification for Inverse Problems VILLUM FONDEN

