Computationally efficient spatial statistics, or “SPDEs aren’t as scary as they seem”

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Most realistic models in applied spatial statistics lead to a large computational problem. Unfortunately, traditional spatial statistics methods were not built with practical computation in mind. In particular, the most basic building block of spatial statistics models is the Gaussian random field, the use of which inevitably leads to $O(N^3)$ computer time, where $N$ is the number of spatial points we are interested in. Unsurprisingly, there has been a lot of work devoted to overcoming this problem, with covariance tapering, process convolution methods and low-rank representations all being popular.

In this talk, I will talk about a very recent method for constructing Markovian approximations to a class of Gaussian random fields. The resulting Gaussian Markov random fields (GMRFs) lead to very computationally efficient inference—it performs better than any of the methods listed above! These GMRFs are constructed by considering the oft-neglected connection between Gaussian random fields and stochastic partial differential equations (don’t panic!). This connection is particularly advantageous as it allows us to construct new classes of physically interpretable random field models that permit efficient inference. When applied to spatial point process models, these GMRF models lead to a new method of inference that is more computationally efficient, more flexible and more satisfying than the standard approach.