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Geostatistical modelling with non-Euclidean distances

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Irregular locations

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Non stationarity

Barriers or other irregularities break the functional relationship between correlation and distance

Cost-based distances

Stationarity w.r.t. cost-based distance

- Build cost surface c from geographical characteristics
- Compute minimum-cost paths
- ► Set covariance model as a function of cost-based distance

Positive-definiteness

Choose the covariance model C such that

 $\forall \text{ locations } \boldsymbol{s}_1, \dots, \boldsymbol{s}_n \in \text{Region}, \\ \forall \text{ scalars } \alpha_1, \dots, \alpha_n \in \mathbb{C}, \\ end{tabular} \qquad \sum_{i=1}^n \sum_{j=1}^n \alpha_i \bar{\alpha}_j C(d_{\mathsf{cb}}(\boldsymbol{s}_i, \boldsymbol{s}_j)) \geq 0,$

where d_{cb} is the cost-based distance between its arguments.

Open lines of work

Riemannian Manifolds

Pseudo-Euclidean spaces

Bayesian Simulation

• Consider the region M as a Riemannian manifold $T_{X}M$



Define the Riemannian metric as

 $g_{\boldsymbol{s}}(u,v) = \boldsymbol{\mathfrak{c}}(\boldsymbol{s})^2 \langle u,v \rangle$ $\forall u, v \in T_x M$

Metric induced $\tau_q(\boldsymbol{s}, \boldsymbol{t}) = \inf \{ \text{lengths of the curves} \}$

connecting s and t

Definition

A pseudo-Euclidean space is a vector space of dimension d, say \mathbb{R}^d , with a non-degenerate symmetric bilinear form

 $(\cdot, \cdot) : \mathbb{R}^d \times \mathbb{R}^d \to \mathbb{R}$ $(\boldsymbol{x}, \boldsymbol{y}) = (x_1y_1 + \cdots + x_ky_k)$ $-(x_{k+1}y_{k+1}+\cdots+x_dy_d),$

where k is called the *index*, while the pair (k, d-k) is called the *signature* of the space. The space is denoted $E_{(k,d-k)}$.

Results

The original locations, together with their cost-based distances can be exactly represented in a pseudo-Euclidean space.

The Bochner's theorem is still valid in the pseudo-Euclidean space

► Too big

Model

$$s_{1}, \ldots, s_{n} \rightsquigarrow \mathbf{D}_{cb} = (r_{ij}); \begin{cases} r_{ii} = 0 \\ r_{ij} \ge 0 \\ r_{ij} = r_{ji} \end{cases}$$
$$y_{1}, \ldots, y_{n} \rightsquigarrow \mathbf{y} \sim \mathcal{N}(\mathbf{\mu}, \tau^{2}\mathbf{I}) \\ \mathbf{\mu} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\omega} \\ \boldsymbol{\omega} \sim \mathcal{N}(\mathbf{0}, \sigma^{2}\mathbf{P}) \\ \mathbf{P} = f(\mathbf{D}_{cb}) \\ f \sim \cdots$$

where f is a random function satisfying f(0) = 1, $|f(r)| \leq 1$ and most importantly, the (correlation) matrix resulting from the element-wise transformation of the (costbased) distance matrix must be positive definite.

Simulate f from a given family of functions Maybe a non-paramteric family, honour-

Characterise the family of positive-definite functions over MIn an analogous way to Bochner's and Shoenberg's theorems, this involves developing Fourier and spectral analysis in this (much) more general context, in order to compute transforms of positive measures and to integrate them out over the surfaces of constant radius.

- ► The constant-radius surface turns into a hyperboloid, causing integration to diverge.

The pseudo-Euclidean space is able to represent any set of *dissimilarities*. But this is unnecessary, since the cost-based distance is a (full) *metric*.

The family of positive definite functions (which includes the trivial constant function 1) is a subset of those in the space M,

 $1 \in \mathfrak{P}(E_{(k,d-k)}) \subset \mathfrak{P}(M).$

ing the restrictions, and hopefuly positivedefinite, most times.

Accept-reject Check the positivedefiniteness condition



Open questions

The procedure lacks theoretical foundation. The positive-definiteness of the covariance function is not guaranteed.

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