Famous statistician website

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Model: Challenges in Space-time Modelling
Paper: Sun et al.,(2012)
50 Years of Data Science, (2015)

Model: **Gaussian Markov random field representation**

Paper: Lindgren et al. (2011);Bakka et al.(2018);Rue,et al.(2017)
Book:Blangiardo, et al.(2015), Krainski ET AL.(2019)
Discription: Avoiding modeling the covariance function altogether and modeled the data via a Stochastic Partial Differential Equation (SPDE); By considering a spatial field as a solution of an SPDE, and describing the covariance function only implicitly, inference is of the order O(n 3/2) (Rue et al ., 2017), thus allowing inference on considerably larger data sets than covariance-based methods.

Model: Nearest neighbor Gaussian process
Paper: Datta et al. (2016a), (2016b), (2016c);
Konomi et al.(2020);

Model: Multiscale approximation for Gaussian process
Paper: Katzfuss, et al.(2017)

Model: Multiresolution Gaussian process
Paper: Nychka et al.(2018; 2015; 2002); Katzfuss, M.(2017)
Discription: Nychka et al.(2018) used a multi-resolution representation of Gaussian processes to represent non-stationarity based on windowed estimates of the covariance function under the assumption of local stationarity, and successfully used this idea to emulate fields from climate models;
Disadvantage: lack of flexibility

Model: discrete process convolutions
Paper: Higdon , (2002);Lemos, et al. (2009)

Model: lattice kriging
Paper: Nychka et al.,(2015)

Model: Covariance tapering
Paper: Furrer et al. (2006);
Kaufman et al. (2008);Stein (2013).

Model: FRK
Paper: Cressie et al,(2014);
Cressie and Johannesson(2008)
Disadvantage: loss of accuracy
R Package:Cressie et al, (2017)

Method: Gaussian process via local information
Paper: Karhunen-Loeve expansion (Chu et al. (2014))
Disadvantage: loss of accuracy

Composite likelihood
Model: Conditional distributions
Paper: Stein et al. (2004)
Model: Pseudo-likelihoods
Paper: Varin et al. (2011), Eidsvik et al. (2014).
Model: approximation by precision
Sun et al.(2016); Sun et al.(2018)

Model: Predictive process
Paper: Banerjee et al. (2008);
Sang and Huang (2012);
Katzfuss, et al. (2013).

Model: Parallelizing Gaussian Process
Paper: Paciorek et al. (2015)

Model: Spectral methods
Paper: Duan et al. (2015);
Guinness and Fuentes,(2017);
Stroud et al. (2017).

Model: Adaptively partitioning the spatial domain through a Bayesian treed Gaussian process
Paper: Robert B(2012); Konomi et al.(2014).

Model: Random spatial basis functions
Paper: Paciorek and Schervish (2006); Katzfuss (2013)

Method: Kernel smoothing method
Paper: Higdon (1998), which uses a spatially varying kernel and a white noise process to create the covariance structure;

Method: Semiparametric modeling;
Target: a linear combination of multiresolutional basis functions and random coefficients;
Advantage: tend to be more robust against misspecification of the spatial covariance function
Disadvantage: Relatively small number of basis functions(Cressie and Johannesson (2008)), and by partitioning spatial domain into identically shaped subdomains and assuming independence among different subdomains in Chu et al. (2014), therefore, loss of accuracy

Method: Stationary
Process: Assume a specific form for the spatial covariance function, then use different approaches to represent or approximate this target function, the resulting covariance or precision matrix, or the likelihood function
Disadvantage: Misspecification of the spatial covariance function

Model: Deformation method
Paper: The deformation method in Sampson and Guttorp (1992) constructs a non-stationary covariance structure from a stationary structure by rescaling the spatial distance (Sampson and Guttorp, 1992), which was subsequently extended to the Bayesian context in Damian et al. (2001) and Schmidt and O'Hagan (2003).

Model: spatial subsemble
Ppaer: Barbian and Assunção (2017);Guhaniyogi and Banerjee (2018)
Target: grid cell
Paper: Paciorek et al. (2013)

Parallel computing

Method: Non-stationary;
Target: construct complex spatial processes;
Advantage: can increase the flexibility of the resulting spatial process;
Disadvantage: complicated algorithms and then computational cost

Method: Additive model

Model:
Rational SPDE Approach
Mixture model+Laplacian matrix
Paper: David Bolin et al. (2020);
David Bolin(2019).

Model: The process convolution
Paper: Douglas Nychka(2018).
Modeling and emulation of nonstationary Gaussian fields

Target: basis-function approach
Paper: Katzfuss and Hammerling (2017) and Katzfuss (2017)

Massive spatial datasets

Book: Benoîte de Saporta,(2014)

Model: Machine learning
Paper: Wikle et al. (2019), (2020);
Book: Wikle et al.(2019)

Spatial statistics

Comparison
1. Heaton M.J, et al.(2017)
2. Bradley J R, Cressie N, Shi T(2016)
3. Liu et al.(2018)
Website: A Common Task Framework

Method: Spatially varying the coefficients in the SPDEs

Piecewise Gaussian Processes

Paper: Kim, Hyoung-Moon, (2005)

Interpolation or Prediction

Model: spatial varying coef.
Fangzheng Lin, et al. (2020);Furong Li & Huiyan Sang.(2019);

Model: Spatio-temporal response variate
Liang et al. (2020)

Paper: Bolin et al. (2011); Bakka et al. (2019), which defined a continuous solution to an SPDE with spatially varying coefficients for solving problems that involve a physical barrier to spatial correlation.

Paper: Hildeman et al. (2019) modelled non-stationarity in significant wave heights. Locally non-stationary fields were considered in Fuglstad et al. (2015a) ;Fuglstad(2015); Fuglstad et al.(2020) by letting the coefficients in the SPDE vary with position

Paper: Another application of the SPDE approach to model non-stationarity is to include covariates directly into the model parameters; see Ingebrigtsen et al. (2014) for an application to annual precipitation in Norway.

Model:Predictor Clusters
see Dunson, et al.(2008);
Model: Semiparametric join model, see Bigelow et al. (2010);Multipollutant Profiles, see Molitor et al.(2011)

Join model

Cluster

Spatio-temporal

Model: FRK Massive spatial datasets
Paper: Matthias Katzfuss(2011);
Matthias Katzfuss(2012);P Ma, et al.(2020): fused GP.

Hierarchical Bayesian

Model: Dirichlet process
Reich et al. (2011);
Hejblum, et al.(2019);
Gelfand, et al.(2019),
Gelfand, et al.(2008);
Liverani, et al.(2015)

Model: Spatial multivariate cluster
Lagon et al. (2020)

Model: Ensemble Kalman filter
Paper:Katzfuss, et a.(2019)

Model: State-space modeling
Paper: Lucia Paci(2018)

Mothod: Bayesian
Paper: 1. K. Shuvo Bakar(2016). 2. Alan E. Gelfand(2015);
3.Finley(2019).

Model: Kalman filter + EM
Paer: P Ma(2018)