mathjax Famous statistician website

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Model: Challenges in Space-time Modelling Paper: <u>Sun et al.,(2012)</u> Matthew J. Heaton 50 Years of Data Science, (2015) Model: Gaussian Markov random field representation Paper: <u>Lindgren et al. (2011); Bakka et al. (2018); Rue, et al. (2017)</u> 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: Multiscale approximation Model: Nearest neighbor for Gaussian process Gaussian process Paper: Katzfuss, et al.(2017) Paper: <u>Datta et al. (2016a)</u>, Model: Multiresolution Gaussian process (2016b), (2016c); Paper: Nychka et al.(2018; 2015; 2002); Katzfuss, M.(2017). Konomi et al.(2020); Discription: Nychka et al.(2018) used a multi-resolution Model: lattice kriging representation of Gaussian processes to represent non-Paper: <u>Nychka et al.,(2015)</u> stationarity based on windowed estimates of the covariance function under the assumption of local stationarity, and Model: FRK successfully used this idea to emulate fields from climate models; Paper: <u>Cressie et al,(2014)</u>; Cressie and Johannesson(2008) Disadvantage: lack of flexibility Model: discrete process convolutions Disadvantage: loss of accuracy → Paper: <u>Higdon</u>, (2002); R Package: <u>Cressie et al, (2017)</u> <u>Lemos, et al.(2009)</u> Model: Covariance tapering Model: Predictive process Method: Gaussian process via local information Paper: Furrer et al. (2006); Paper: Banerjee et al. (2008); Paper: Karhunen-Loeve expansion (Chu et al. (2014)) <u>Furrer et al. (2016)</u> Sang and Huang (2012); Disadvantage: loss of accuracy Kaufman et al. (2008); Model: Adaptively partitioning the spatial domain <u>Katzfuss, et al. (2013)</u>. through a Bayesian treed Gaussian process <u>Stein (2013)</u>. Paper: Robert B(2012); Konomi et al.(2014). Note: basis functions need to be Model: Parallelizing Gaussian Process calculated iteratively Paper: Paciorek et al. (2015) Composite likelihood Model: Spatial Partitioning Model: Conditional distributions Model: Random spatial basis functions Heaton et al. (2017); Neelon et al. (2014); Konomi et al. (2014). Paper: Stein et al. (2004) Paper: Paciorek and Schervish (2006); Katzfuss (2013) Model: Pseudo-likelihoods Paper: <u>Varin et al. (2011)</u>; Model: Spectral methods Paper: <u>Duan et al. (2015);</u> <u>Guinness and Fuentes,(2017);</u> <u>Eidsvik et al. (2014)</u>. Method: Semiparametric modeling; Method: Kernel smoothing method Model: approximation by precision Target: a linear combination of multiresolutional basis functions Stroud et al. (2017). → Paper: <u>Higdon (1998)</u>, which uses a spatially varying kernel and a white noise Sun et al.(2016); Sun et al.(2018) and random coefficients; process to create the covariance structure; Advantage: tend to be more robust against misspecification of the spatial covariance function $oldsymbol{y} = oldsymbol{x}oldsymbol{eta} + oldsymbol{H}oldsymbol{w} + oldsymbol{\xi} + oldsymbol{arepsilon}$ Disadvantage: Relatively small number of basis functions (Cressie Model: Deformation method **Hierarchical framework** and Johannesson (2008), and by partitioning spatial domain into Paper: The deformation method in <u>Sampson and Guttorp (1992)</u> constructs a non-stationary identically shaped subdomains and assuming independence among covariance structure from a stationary structure by rescaling the spatial distance (Sampson Method: Stationary different subdomains in Chu et al. (2014), therefore, loss of and Guttorp, 1992), which was subsequently extended to the Bayesian context in **Damian et al.** 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 (2001) and Schmidt and O'Hagan (2003). Model: spatial subsemble Disadvantage: Misspecification of the spatial covariance function Rational SPDE Approach Ppaer: <u>Barbian and Assunção</u> Mixture model+Laplacian matrix (2017);Guhaniyogi and Paper: David Bolin et al. (2020); Method: Non-stationary; <u>Banerjee (2018)</u> Target: construct complex spatial processes; Advantage: can increase the flexibility of the David Bolin(2019). Parallel computing Target: grid cell Method: Additive model resulting spatial process;
Disadvantage: complicated algorithms and then computational cost Paper: Paciorek et al. (2013) Model: The process convolution Paper: <u>Douglas Nychka(2018)</u> →Book: <u>Benoîte de Saporta,(2014)</u> Target: basis-function approach **Massive spatial datasets** Modeling and emulation of Paper: <u>Katzfuss and</u> Model: Machine learning nonstationary Gaussian fields Hammerling (2017) and Paper: Wikle et al. (2019), (2020); <u>Katzfuss (2017)</u> Method: Spatially varying the coefficients Book: <u>Wikle et al.(2019)</u> Piecewise Gaussian Processes **Spatial** Comparison in the SPDEs . <u>Heaton, et al.(2018)</u>; <u>Appendix</u> statistics Interpolation . <u>Bradley J R, Cressie N, Shi T</u>(2016) or Prediction 3. <u>Liu et al.(2018)</u> Paper: Kim, Hyoung-Moon, (2005) Website: <u>A Common Task Framework</u> Model: spatial varying coef. <u>Fangzheng Lin, et al.</u> Paper: Hildeman et al. (2019) modelled non-(2020);Furong Li & Huiyan Model: Spatio-temporal Paper: <u>Bolin et al. (2011); Bakka et al. (201</u>9) stationarity in significant wave heights. Locally Paper: Another application of the SPDE <u>Sang.(2019);</u> response variate which defined a continuous solution to an non-stationary fields were considered in approach to model non-stationarity is to include <u>Liang et al. (2020)</u> SPDE with spatially varying coefficients for Fuglstad et al. (2015a) covariates directly into the model parameters; Model:Predictor Clusters solving problems that involve a physical ;Fuglstad(2015); Fuglstad et al.(2020) by see <u>Ingebrigtsen et al. (2014)</u> for an application see <u>Dunson, et al.(2008)</u>; barrier to spatial correlation. Spatio-temporal letting the coefficients in the SPDE vary with to annual precipitation in Norway. Model: Semiparametric join Cluster Join model position model, see <u>Bigelow et al.</u> (2010); Multipollutant Profiles, Model: FRK Massive spatial datasets Paper: <u>Matthias Katzfuss(2011)</u>; see Molitor et al.(2011) Matthias Katzfuss(2012); P.Ma, et al.(2020): fused GP. Model: Spatial Model: Dirichlet process multivariate cluster Reich et al. (2011); <u>Lagon et al. (2020)</u> <u>Hejblum, et al.(2019);</u> Gelfand, et al.(2019), Gelfand, et al.(2008); Model: Ensemble Kalman Model: State-space modeling <u>Liverani, et al.(2015)</u> Paper: <u>Lucia Paci(2018)</u> Paper: Katzfuss, et a. (2019) Mothod: Bayesian Paper: 1. <u>K. Shuvo Bakar(2016)</u>. 2. Model: Kalman filter + EM Alan E. Gelfand(2015); Paer: P Ma(2018) 3.<u>Finley(2019)</u>.