Timeseries;

Spectral representation 1 **Spectral representation 2**

Famous statistician website

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Model: Challenges in Space-time Modelling Paper: <u>Sun et al.,(2012)</u> Robert B. Gramacy; Furong Sun Matthew J. Heaton

50 Years of Data Science, (2015) Robert H. Shumway, Stoffer, (2017) Christopher M. Bishop, (2006) Sparse precision method 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 $O(n^{\frac{1}{2}})$ (Rue et al., 2017), thus allowing inference on considerably larger data sets than covariance-based methods. Model: Nearest neighbor Model: Multiscale Gaussian process approximation for Gaussian Paper: <u>Datta et al. (2016a)</u> (2016b), (2016c); Paper: <u>Katzfuss, et al.(2017)</u> Finley, et al. (2019); Model: Multiresolution Gaussian process Konomi et al.(2020); Paper: Nychka et al.(2018; 2015; 2002); Katzfuss, M.(2017). Model: lattice kriging Discription: Nychka et al.(2018) used a multi-resolution Model: Spectral methods Paper: <u>Duan et al. (2015);</u> <u>Guinness and Fuentes, (2017);</u> Paper: <u>Nychka et al.,(2015)</u> representation of Gaussian processes to represent non-Composite likelihood stationarity based on windowed estimates of the covariance Model: Conditional distributions function under the assumption of local stationarity, and Stroud et al. (2017), Paper: <u>Stein et al. (2004)</u> Model: discrete process <u>Stroud et al. (2017);</u> successfully used this idea to emulate fields from climate models; Model: Pseudo-likelihoods convolutions Disadvantage: lack of flexibility <u>Sykulski et al. (2019)</u> Paper: Varin et al. (2011); Paper: <u>Higdon</u>, (2002); <u>Guinness (2020);</u> Eidsvik et al. (2014). Lee & Zhu (2009); Whittle (1954). <u>Lemos, et al.(2009)</u> Model: approximation by precision Sun et al.(2016); Sun et al.(2018) Low-Rank method Method: Gaussian process via local information Model: FRK Paper: Karhunen-Loeve expansion (Chu et al. (2014)) Model: Adaptively partitioning the spatial domain Paper: Cressie et al, (2014); Disadvantage: loss of accuracy Sparse covariance method Cressie and Johannesson(2008) through a Bayesian treed Gaussian process Disadvantage: loss of accuracy Paper: Robert B(2012); Konomi et al.(2014). Model: Parallelizing Gaussian Process R Package: Cressie et al, (2017) Model: Spatial partitioning Paper: Model: Spatial Partitioning Paper: Paciorek et al. (2015) Model: Spatial Partitioning Heaton et al. (2017); Neelon et al. Model: Random spatial basis functions <u>Heaton et al. (2017); Neelon et al. (2014); Konomi et al. (2014).</u> (2014); Konomi et al.(2014). Model: Predictive process Paper: Paciorek and Schervish (2006); Katzfuss (2013) Paper: Banerjee et al. (2008); Sang and Huang (2012); Model: Covariance tapering Method: Semiparametric modeling; Katzfuss, et al. (2013). Paper: Furrer et al. (2006); Method: Kernel smoothing method Target: a linear combination of multiresolutional basis functions Furrer et al. (2016) Paper: <u>Higdon (1998)</u>, which uses a spatially varying kernel and a white noise and random coefficients; Note: basis functions need to be <u>Kaufman et al. (2008);</u> process to create the covariance structure: Advantage: tend to be more robust against misspecification of the calculated iteratively Stein (2013). spatial covariance function Disadvantage: Relatively small number of basis functions(<u>Cressie</u> Model: Deformation method $oldsymbol{y} = oldsymbol{x}oldsymbol{eta} + oldsymbol{H}oldsymbol{w} + oldsymbol{\xi} + oldsymbol{arepsilon}$ 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). accuracy Model: Model: spatial subsemble Rational SPDE Approach Disadvantage: Misspecification of the spatial covariance function Ppaer: <u>Barbian and Assunção</u> Mixture model+Laplacian matrix (2017);Guhaniyogi and Method: Non-stationary; Paper: David Bolin et al. (2020); <u>Banerjee (2018)</u> Target: construct complex spatial processes; David Bolin(2019). Parallel computing Target: grid cell Advantage: can increase the flexibility of the **Method: Additive model** resulting spatial process; Disadvantage: complicated algorithms and Paper: Paciorek et al. (2013) Model: The process convolution then computational cost Paper: Douglas Nychka(2018), →Book: <u>Benoîte de Saporta,(2014)</u> Target: basis-function approach Modeling and emulation of **Massive spatial datasets** Paper: <u>Katzfuss and</u> nonstationary Gaussian fields Model: Machine learning Hammerling (2017) and Paper: Wikle et al. (2019), (2020); <u>Katzfuss (2017)</u> Book: <u>Wikle et al.(2019)</u> Method: Spatially varying the coefficients **Piecewise Gaussian Processes Spatial** Comparison in the SPDEs . <u>Heaton, et al.(2018)</u>; <u>Appendix</u> statistics Interpolation 2. Bradley J R, Cressie N, Shi T(2016) or Prediction 3. <u>Liu et al.(2018)</u> Paper: Kim, Hyoung-Moon, (2005) Website: A Common Task Framework Model: spatial varying coef. Fangzheng Lin, et al. Paper: Hildeman et al. (2019) modelled non-(2020); Furong Li & Huiyan Model: Spatio-temporal Paper: Bolin et al. (2011); Bakka et al. (2019). stationarity in significant wave heights. Locally Paper: Another application of the SPDE Sang.(2019); 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, see Molitor et al.(2011) Model: FRK Massive spatial datasets Paper: Matthias Katzfuss(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> Hejblum, et al.(2019); 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. K. Shuvo Bakar(2016). 2. Model: Kalman filter + EM Alan E. Gelfand(2015); Paer: P Ma(2018)

3.<u>Finley(2019)</u>.