algorithm

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Algorithm

- 1. parameters:
- $M \succcurlyeq 0$

- K > 0• $\delta = \frac{\tau^2}{\sigma^2}$ $\theta = (\beta, \nu, \rho)'$ $\beta \in \mathcal{R}^L$ $\nu > 0$
- 2. objective function

$$n\log 2\pi + \frac{\boldsymbol{z}'\boldsymbol{R}^{-1}(\boldsymbol{\theta},\delta)\boldsymbol{z}}{\sigma^2} + \sum_{k=1}^{K} \left\{ \log(\eta_{K,k} + \sigma^2) - \frac{\eta_{K,k}}{\sigma^2(\eta_{K,k} + \sigma^2)} \right\} + (n-K)\log(\sigma^2) + \log|\boldsymbol{R}(\boldsymbol{\theta},\delta)|$$

3. Estimation

$$\hat{\sigma}^2 = \max \left\{ \frac{1}{n - K^*} \left(\boldsymbol{z}^{\top} \boldsymbol{R}^{-1} (\boldsymbol{\theta}, \delta) \mathbf{z} - \sum_{k=0}^{K^*} \eta_{K,k} \right), 0 \right\}$$

$$\hat{M}_{K} = \left[\mathbf{F}_{K}^{\top} \mathbf{R}^{-1}(\boldsymbol{\theta}, \delta) \mathbf{F}_{K} \right]^{-1/2} \boldsymbol{U} \operatorname{diag} \left(\hat{\eta}_{K,1}, \dots, \hat{\eta}_{K,K} \right) \boldsymbol{U}^{\top} \left[\mathbf{F}_{K}^{\top} \mathbf{R}^{-1}(\boldsymbol{\theta}, \delta) \mathbf{F}_{K} \right]^{-1/2}$$

$$- \mathbf{R}(\boldsymbol{\theta}, \delta) := \delta \operatorname{Cov}(\boldsymbol{\xi}) + \boldsymbol{I}_{n}$$

$$- \mathbf{R}(\boldsymbol{a}, \lambda) := \frac{1}{\lambda} \boldsymbol{\Phi} \mathbf{B}^{-1}(\boldsymbol{a}) \mathbf{B}^{-\top}(\boldsymbol{a}) \boldsymbol{\Phi}^{\top} + \mathbf{I}_{n}$$

$$- \mathbf{R}^{-1}(\boldsymbol{a}, \lambda) = \mathbf{I}_{n} - \boldsymbol{\Phi} \left(\boldsymbol{\Phi}^{\top} \boldsymbol{\Phi} + \lambda \mathbf{B}^{\top}(\boldsymbol{a}) \mathbf{B}(\boldsymbol{a}) \right)^{-1} \boldsymbol{\Phi}^{\top}$$

$$- \text{Wendland basis: } \boldsymbol{\Phi} = (\boldsymbol{\phi}(\mathbf{s}_{1}), \dots, \boldsymbol{\phi}(\mathbf{s}_{n}))^{\top}$$

$$* \boldsymbol{\phi}(\mathbf{s}) = (\boldsymbol{\phi}_{1}(\mathbf{s}), \dots, \boldsymbol{\phi}_{J}(\mathbf{s}))^{\top}$$

$$* \boldsymbol{\phi}_{j}(\mathbf{s}) = \frac{1}{3} \left(1 - \frac{\|\mathbf{s} - \mathbf{c}_{j}\|}{\Delta_{j}} \right)^{6} \left(35 \frac{\|\mathbf{s} - \mathbf{c}_{j}\|^{2}}{\Delta_{j}} + 18 \frac{\|\mathbf{s} - \mathbf{c}_{j}\|}{\Delta_{j}} + 3 \right) I(\|\mathbf{s} - \mathbf{c}_{j}\| \leq \Delta_{j})$$

3.

$$a^{(k+1)} = \arg\min_{a} \frac{\mathbf{z}^{\top} \mathbf{R}^{-1}(a, \lambda^{(k)}) \mathbf{z}}{(\sigma^2)^{(k)}} + \log |\Phi^{\top} \Phi + \lambda^{(k)} \mathbf{B}^{\top}(a) \mathbf{B}(a)| - \log |\mathbf{B}^{\top}(a) \mathbf{B}(a)|,$$

4.
$$\lambda^{(k+1)} = \arg\min_{\lambda} \frac{\mathbf{z}^{\top} \mathbf{R}^{-1}(a^{(k)}, \lambda^{(k)}) \mathbf{z}}{(\sigma^2)^{(k)}} - J \log \lambda + \log |\Phi^{\top} \Phi + \lambda \mathbf{B}^{\top}(a^{(k)}) \mathbf{B}(a^{(k)})|$$

 Ref: https://asreml.kb.vsni.co.uk/wp-content/uploads/sites/3/2018/02/ASReml-R-3-Reference-Manual.pdf