

Nonparametric Covariance Estimation for Longitudinal Data via Penalized Tensor Product Splines

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February 18, 2018

1 Appendix

Proof. Using the properties of reproducing kernels, we can rewrite ϕ^* as an inner product of itself with R :

$$\begin{aligned}
 \phi^*(l_j, m_j) &= \langle R((l_j, m_j), (\cdot, \cdot)), \phi^*(\cdot, \cdot) \rangle \\
 &= \langle R_0((l_j, m_j), (\cdot, \cdot)) + R_1((l_j, m_j), (\cdot, \cdot)), d_0 + d_1 k_1(\cdot) \\
 &\quad + \sum_{i=1}^{N_{\phi^*}} c_i R_1((l_i, m_i), (\cdot, \cdot)) + \rho((\cdot, \cdot)) \rangle \\
 &= \langle R_0((l_j, m_j), (\cdot, \cdot)), d_0 + d_1 k_1(\cdot) \rangle + \left\langle R_0((l_j, m_j), (\cdot, \cdot)), \sum_{i=1}^{N_{\phi^*}} c_i R_1((l_i, m_i), (\cdot, \cdot)) \right\rangle \\
 &\quad + \langle R_0((l_j, m_j), (\cdot, \cdot)), \rho((\cdot, \cdot)) \rangle + \langle R_1((l_j, m_j), (\cdot, \cdot)), d_0 + d_1 k_1(\cdot) \rangle \\
 &\quad + \left\langle R_1((l_j, m_j), (\cdot, \cdot)), \sum_{i=1}^{N_{\phi^*}} c_i R_1((l_i, m_i), (\cdot, \cdot)) \right\rangle + \langle R_1((l_j, m_j), (\cdot, \cdot)), \rho((\cdot, \cdot)) \rangle \\
 &= \langle R_0((l_j, m_j), (\cdot, \cdot)), d_0 + d_1 k_1(\cdot) \rangle + \left\langle R_1((l_j, m_j), (\cdot, \cdot)), \sum_{i=1}^{N_{\phi^*}} c_i R_1((l_i, m_i), (\cdot, \cdot)) \right\rangle \\
 &\quad + \underbrace{\langle R_0((l_j, m_j), (\cdot, \cdot)), \rho(\cdot, \cdot) \rangle}_0 + \underbrace{\langle R_1((l_j, m_j), (\cdot, \cdot)), \rho(\cdot, \cdot) \rangle}_0 \\
 &= d_0 + d_1 k_1(\cdot) + \sum_{i=1}^{N_{\phi^*}} c_i R_1((l_i, m_i), (l_j, m_j))
 \end{aligned}$$

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Rewriting the data fit functional, we have that

$$\begin{aligned}
& \sum_{i=1}^N \sum_{j=1}^{n_i} \sigma_{ij}^{-2} \left(y(t_{ij}) - \sum_{k=1}^{j-1} \phi^*(t_{ij}, t_{ik}) y(t_{ik}) \right)^2 \\
&= \sum_{i=1}^N \sum_{j=1}^{n_i} \sigma_{ij}^{-2} \left(y(t_{ij}) - \sum_{k=1}^{j-1} \langle R((l_{jk}^i, m_{jk}^i), (\cdot, \cdot)), \phi^*(\cdot, \cdot) \rangle y(t_{ik}) \right)^2
\end{aligned}$$

which is free of ρ . Consider the contribution of any nonzero ρ to $J(\phi^*)$:

$$\begin{aligned}
J(\phi^*) &= \|P_1 \phi^*\|^2 \\
&= \left\langle \sum_{i=1}^{N_{\phi^*}} c_i R_1((l_i, m_i), (\cdot, \cdot)) + \rho(\cdot, \cdot), \sum_{j=1}^{N_{\phi^*}} c_j R_1((l_j, m_j), (\cdot, \cdot)) + \rho(\cdot, \cdot) \right\rangle \\
&= \left\| \sum_{i=1}^{N_{\phi^*}} c_i R_1((l_i, m_i), (\cdot, \cdot)) \right\|^2 + \|\rho\|^2
\end{aligned}$$

Thus, including ρ in ϕ^* only increases the penalty without improving (decreasing) the data fit functional, so we indeed have that the minimizer of (??) has the form

$$\phi^*(l, m) = d_0 + d_1 k_1(l) + \sum_{i=1}^{N_{\phi^*}} c_i R_1((l, m), (l_i, m_i)) \tag{1}$$

□