1 ADMM details

We first re-parameterize $\phi_j = y - \theta_j$ so the problem is

$$\text{minimize } \rho_\tau(\phi) + \lambda ||D^{(k)}(y - \phi)||_1 \tag{1}$$

We further divide ϕ order to solve smaller problems: Defining

$$\begin{aligned}
\phi_1 &= (\phi_{11}, \phi_{12}) && (2)\\
\phi_2 &= (\phi_{21}, \phi_{22}, \phi_{23}) && (3)\\
\phi_3 &= (\phi_{31}, \phi_{32}) && (4)\\
\phi &= (\phi_{11}, \phi_{12} = \phi_{21}, \phi_{22}, \phi_{23} = \phi_{31}, \phi_{32}) && (5)\\
& && (6)
\end{aligned}$$

Dividing y similarly, the problem then becomes

$$\begin{aligned}
&\text{minimize } \sum_{i=1}^{3} \rho_\tau(\phi_i) + \lambda ||D^{(k)}(y_i - \phi_i)||_1 && (7)\\
&\text{subject to: } \phi_{12} = \phi_{21}, \quad \phi_{23} = \phi_{31} && (8)\\
& && (9)
\end{aligned}$$

We can further simplify by defining

$$\begin{aligned}
\overline{\phi} &= (\phi_{11}, \frac{\phi_{12} + \phi_{21}}{2}, \phi_{22}, \frac{\phi_{23} + \phi_{31}}{2}, \phi_{32}) && (10)\\
\overline{\phi_1} &= (\phi_{11}, \frac{\phi_{12} + \phi_{21}}{2}) && (11)\\
\overline{\phi_2} &= (\frac{\phi_{12} + \phi_{21}}{2}, \phi_{22}, \frac{\phi_{23} + \phi_{31}}{2}) && (12)\\
\overline{\phi_3} &= (\frac{\phi_{23} + \phi_{31}}{2}, \phi_{32}) && (13)
\end{aligned}$$

so the problem becomes

$$\begin{aligned}
&\text{minimize } \sum_{i=1}^{3} \rho_\tau(\phi_i) + \lambda ||D^{(k)}(y_i - \phi_i)||_1 && (14)\\
&\text{subject to: } \phi_i = \overline{\phi_i} && (15)\\
& && (16)
\end{aligned}$$

The augmented Lagrangian for this problem is

$$\begin{aligned}
&L_\gamma(\phi_1, \phi_2, \phi_3, \overline{\phi_1}, \overline{\phi_2}, \overline{\phi_3}, \omega) = && (17)\\
&\sum_{i=1}^{3} \rho_\tau(\phi_i) + \lambda ||D^{(k)}(y_i - \phi_i)||_1 + \omega_i^T(\phi_i - \overline{\phi_i}) + \frac{\gamma}{2} ||\phi_i - \overline{\phi_i}||_2^2 && (18)
\end{aligned}$$

The ADMM updates are then given by

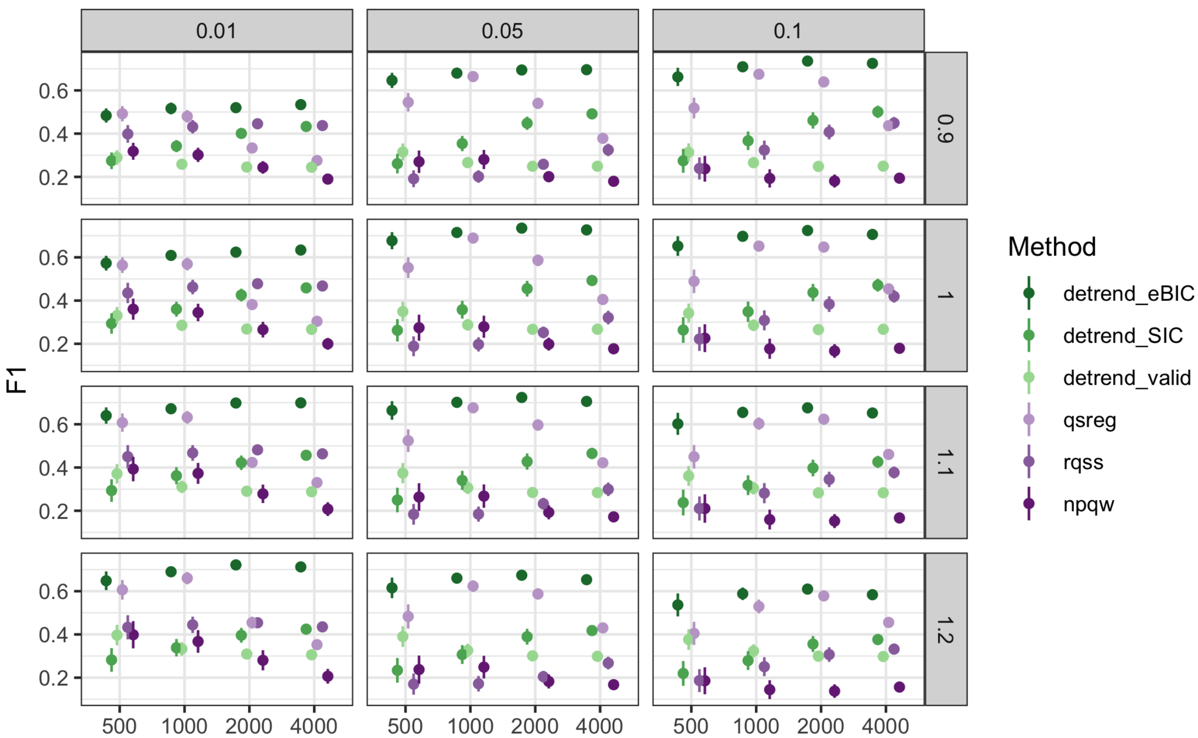
$$\phi_i^{k+1} = \arg\min_{\phi_i} \rho_\tau(\phi_i) + \lambda ||D^{(k)}(y_i - \phi_i)||_1 + \omega_i^{kT}(\phi_i - \overline{\phi_i}^k) + \frac{\gamma}{2}||\phi_i - \overline{\phi_i}^k||_2^2 \tag{19}$$

$$\omega_i^{k+1} = \omega_i^k + \gamma(\phi_i^{k+1} - \overline{\phi_i}^{k+1}) \tag{20}$$

The ϕ_i updates can be obtained using a quadratic program solver such as Gurobi and can be obtained in parallel.

2 Simulation Metrics

Figure 1: F1 score by threshold, data size, and method (1 is best 0 is worst).



3 Application Metrics

Table 1: Confusion matrices for 3 SPod nodes after baseline removal (n=6000). Node order is c, d, e. The threshold for the signal was set as the median + 3*MAD.

Method	Quantile	0,0,0	1,0,0	0,1,0	1,1,0	1,0,0	1,1,0	1,0,1	1,1,1
detrendr	0.10	5202	79	122	32	148	109	63	245
qsreg	0.10	4822	59	297	29	157	85	231	320
detrendr	0.15	5174	71	132	26	163	127	70	237
qsreg	0.15	4867	62	249	6	153	74	245	344

Table 2: Confusion matrices for 3 SPod nodes after baseline removal (n=6000). Node order is c, d, e. The threshold for the signal was set as the median + 4*MAD.

Method	Quantile	0,0,0	1,0,0	0,1,0	1,1,0	1,0,0	1,1,0	1,0,1	1,1,1
detrendr	0.10	5632	53	7	1	67	35	59	146
qsreg	0.10	5204	33	237	2	96	45	178	205
detrendr	0.15	5624	37	3	1	85	48	60	142
qsreg	0.15	5273	29	141	2	94	41	210	210

Table 3: Confusion matrices for 3 SPod nodes after baseline removal (n=6000). Node order is c, d, e. The threshold for the signal was set as the median + 5*MAD.

Method	Quantile	0,0,0	1,0,0	0,1,0	1,1,0	1,0,0	1,1,0	1,0,1	1,1,1
detrendr	0.10	5777	9	9	0	38	24	39	104
qsreg	0.10	5485	16	116	1	105	15	121	141
detrendr	0.15	5763	16	4	0	46	26	41	104
qsreg	0.15	5508	16	70	1	95	17	137	156

Figure 2: Precision by threshold, data size, and method (true positive over true positives + false positives).

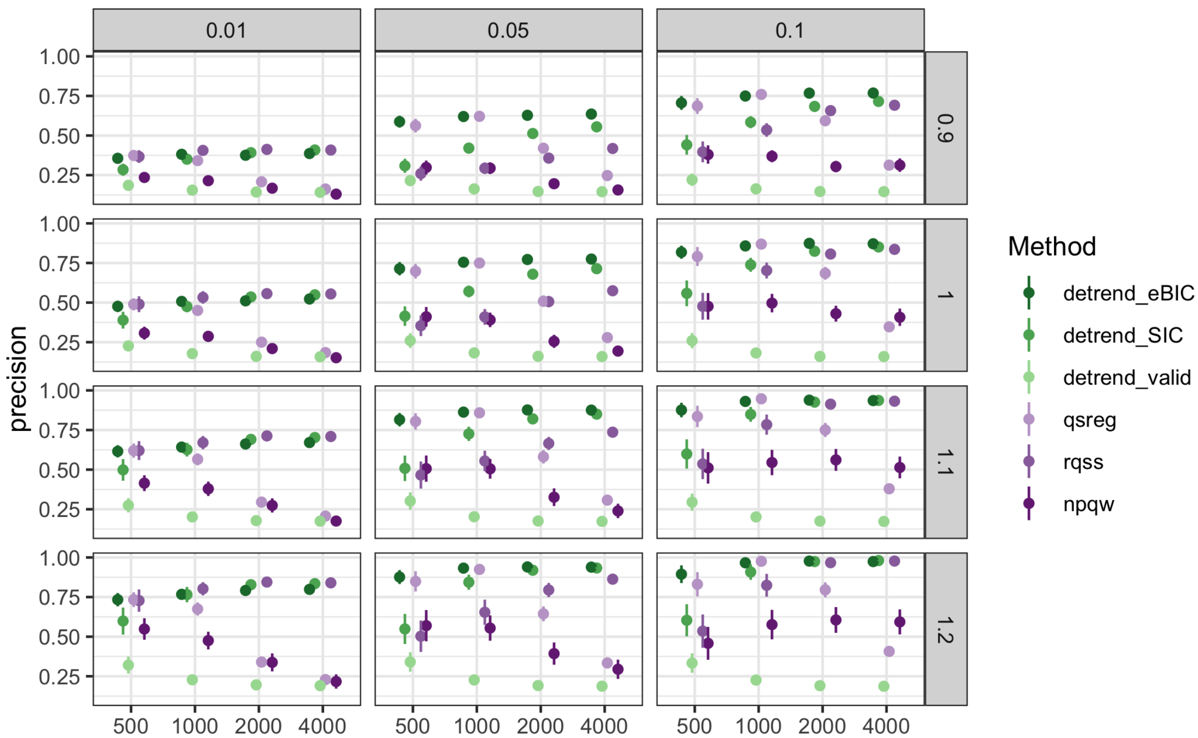


Figure 3: Recall by threshold, data size, and method (true positive over true positives + false negatives).

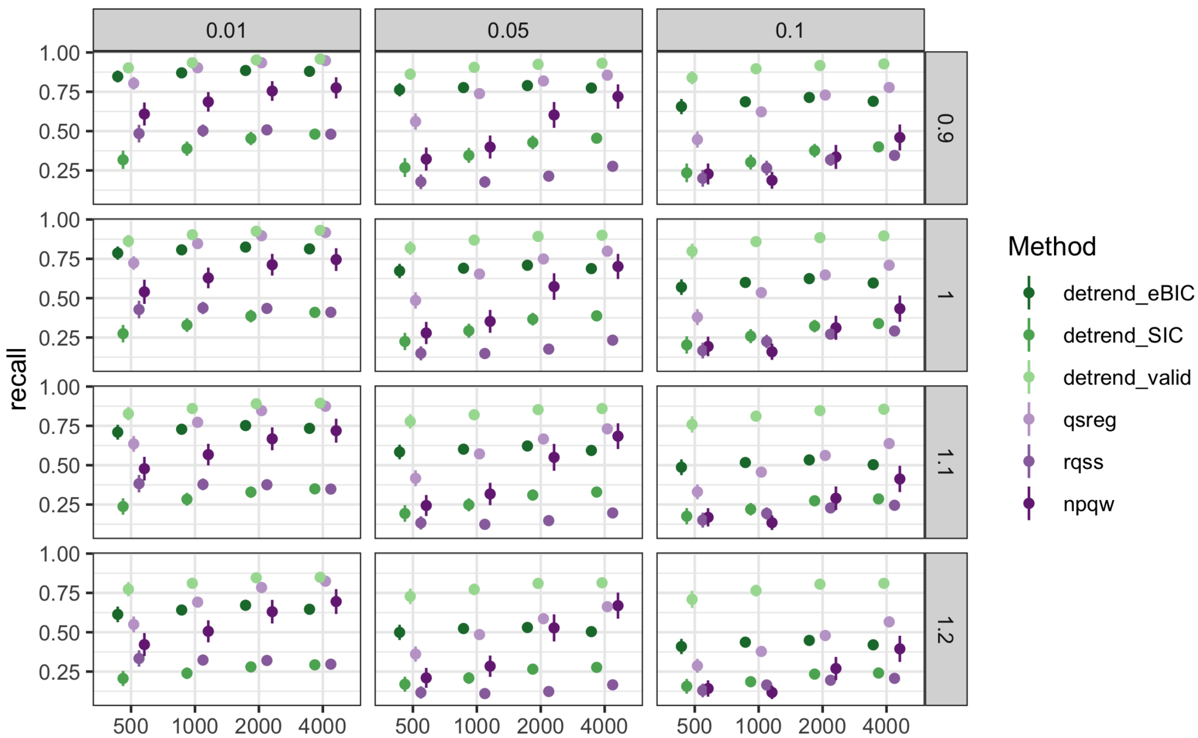


Figure 4: Miss-classification rates by threshold, data size, and method, values above the upper limit (npqw) not shown.