High-Dimensional Variable Selection for Competing Risks with Cooperative Penalized Regression

«CooPeR»

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BIPS — LMU/SLDS — MCML

2023-05-12

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- **Main goal**: Fit cause-specific model for event 1 *using shared information* from event 2

Building Blocks

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   - Idea: Some features predictive for event 1 will also be predictive for event 2

Foundation: Elastic Net

The elastic net objective function with some negative log-likelihood term:

$$\underset{\beta}{\operatorname{argmin}} \quad \mathrm{NLL}(\beta) + \lambda \sum_{j=1}^{p} \left(\alpha |\beta_j| + \frac{1-\alpha}{2} \beta_j^2 \right)$$

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$\rightarrow$ Need different approach

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Two Applications

1. Assign features to K groups w/ separate penalization weights
2. Adjust penalization weights within group

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Feature Weighting: Groups

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Interesting when e.g. $p >> 1000$ w/ 50 clinical + 5000 gene expression features

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- X_4: "Irrelevant" $\rightarrow$ stronger penalization

Feature-Weighting: New Objective Function

$$\underset{\beta}{\operatorname{argmin}} \quad \mathrm{NLL}(\beta) + \lambda \sum_{j=1}^{p} w_j(\theta) \left(\alpha |\beta_j| + \frac{1-\alpha}{2} \beta_j^2 \right)$$

Feature-Weighting: New Objective Function

$$\underset{\beta}{\operatorname{argmin}} \quad \mathrm{NLL}(\beta) + \lambda \sum_{j=1}^{p} \color{blue}{w_j(\theta)} \color{black}\left(\alpha |\beta_j| + \frac{1-\alpha}{2} \beta_j^2 \right)$$

$$\color{blue}{w_j(\theta)} \color{black}= \frac{\sum_{l=1}^{p} \exp(\mathbf{z}_l^T \theta)}{p \exp(\mathbf{z}_j^T \theta)}$$

- **Penalization weight** of β_j based on corresponding value in $\mathbf{Z}$ and parameter $\theta \in \mathbb{R}^{K \times 1}$

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  - Higher score $\rightarrow$ lower w_j, feature is "more important"

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Dubbed "Cooperative Penalized (Cox) Regression" (CooPeR)

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- Compare CooPeR, penalized Cox (glmnet), RSF (rsfrc), CoxBoost

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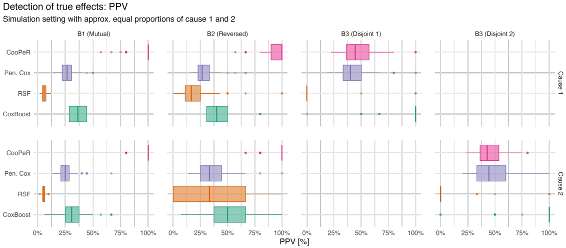
- Remaining variables: Uncorrelated noise

Positive Predictive Value



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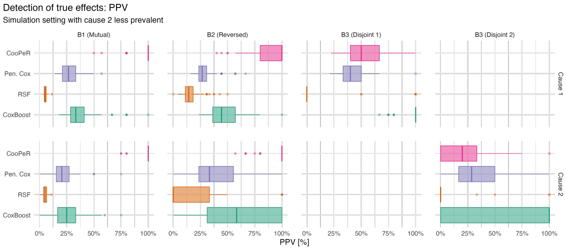

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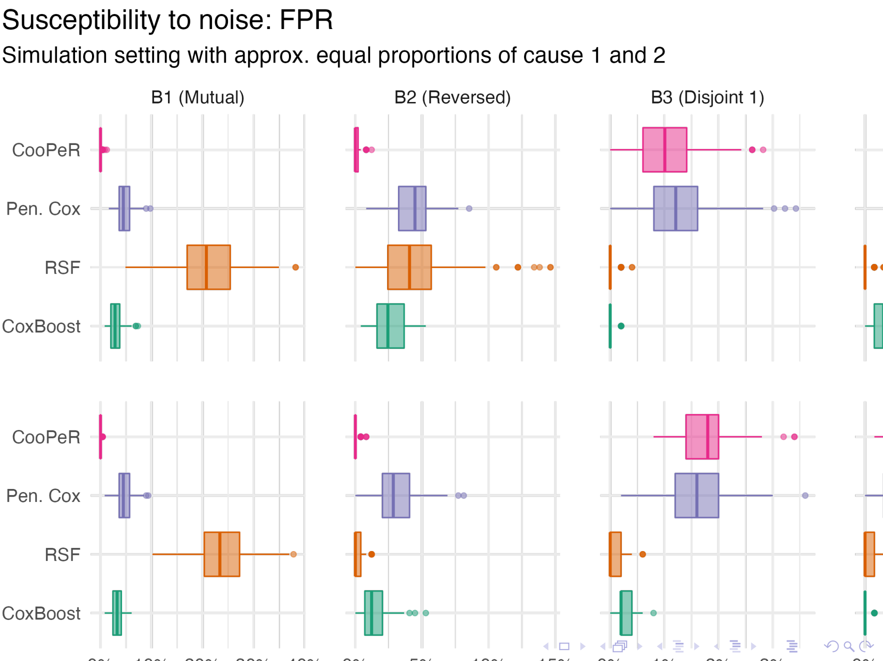

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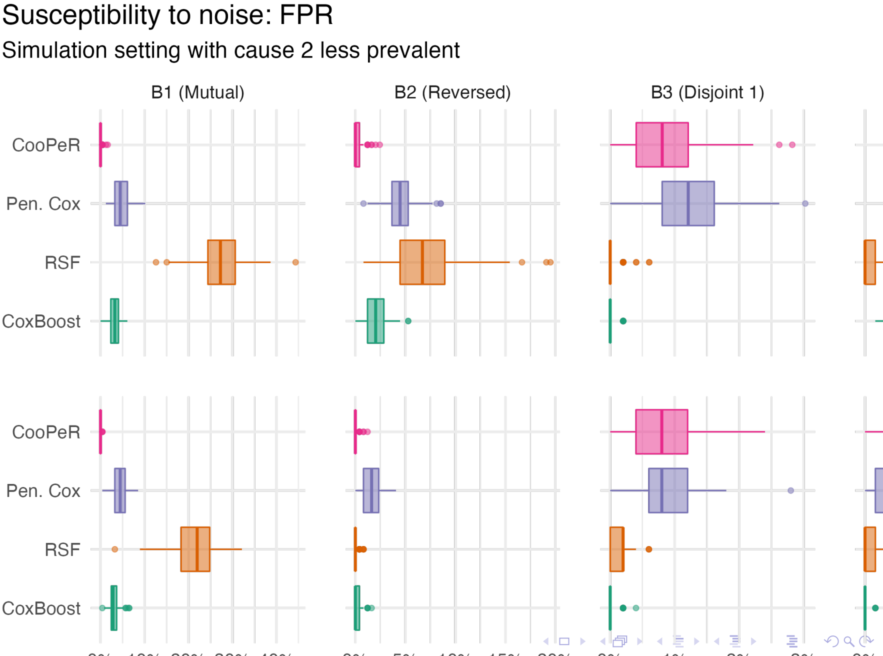

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  3. Evaluate prediction performance (tBrier, tAUC)
- Tried bladder cancer data (Dyrskjøt et al. (2005)), did not go well

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- What about $k > 2$ events? No trivial generalization

Thanks for listening!

References

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