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

«CooPeR»

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Introduction

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

Elastic Net

Objective function with negative log-likelihood contribution for observation i:

$$\hat{\boldsymbol{\beta}} = \underset{\boldsymbol{\beta}}{\operatorname{argmin}} \quad \sum_{i=1}^{n} \ell(y_i, \mathbf{x}_i^\top, \boldsymbol{\beta}) + \lambda \sum_{j=1}^{p} \left(\alpha |\beta_j| + \frac{1-\alpha}{2} \beta_j^2 \right)$$

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Feature-weighted elastic net[1] extends objective function:

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Individual weighting: $\mathbf{Z} \in \mathbb{R}^{5 \times 1}$

$$\mathbf{Z} = \begin{pmatrix} 1.5 \\ 1 \\ 1.2 \\ 0.7 \\ 0.3 \end{pmatrix}$$

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- $\theta \in \mathbb{R}^{K \times 1}$ fit internally
- $\theta = 0 \Rightarrow w_j = 1$

Individual Feature Weighting

- Simulation from Tay et al.: $\mathbf{Z}$ set to noisy version of true $|\boldsymbol{\beta}|$
- $|\beta_j|$ large $\Rightarrow$ weaker penalization for $\widehat{\beta}_j$
- $|\beta_j|$ small $\Rightarrow$ stronger penalization for $\widehat{\beta}_j$

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1. Set $\widehat{\beta}_1^{(0)}, \widehat{\beta}_2^{(0)}$ to elastic net solution for $(\mathbf{X}, \mathbf{y}_1), (\mathbf{X}, \mathbf{y}_2)$ with $\mathbf{y}_e := (\mathbf{t}_e, \delta_e)$

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Simulation Study

- Simulation adapted from Binder et al.[2]
- Mimics gene expression data
- Comparison with CoxBoost[3], Random Survival Forests [4]

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- Comparison with CoxBoost[3], Random Survival Forests [4]
- n = 400, p = 5000,
- 4 covariate blocks
- 4 informative variables each

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Assignment of True Effects

- Block 1 (**Mutual**): Same effect on both cause-specific hazards
- Block 2 (**Reversed**): Cause 1 (+) Cause 2 (-)
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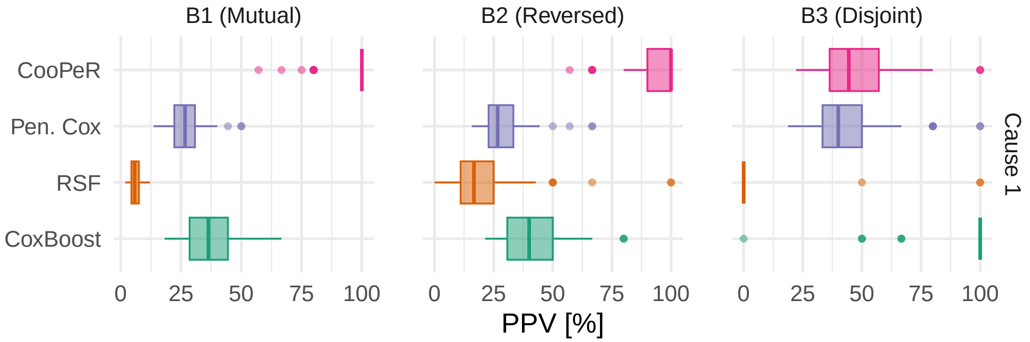
- Block 4 (**Cor. Noise**)
- Rest: Uncorrelated noise

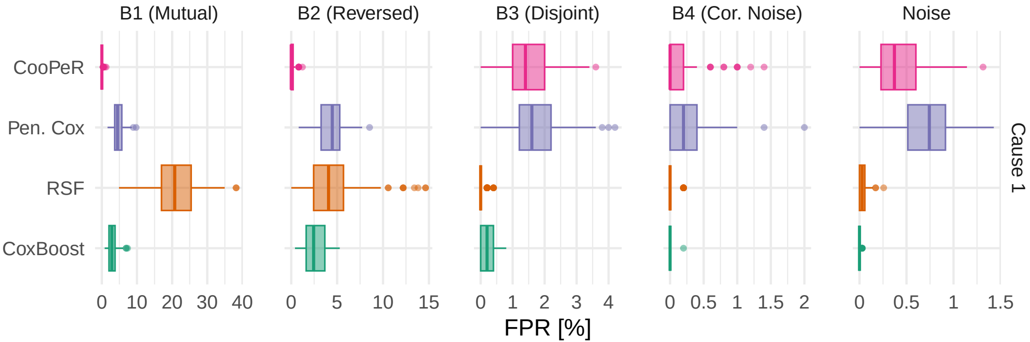
Positive Predictive Value

Probability a selected variable is informative



False Positive Rate

Proportion of noise variables falsely selected



Application on Bladder Cancer Data

- Clinical & gene expression features [5]

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  1. Apply algorithms for variable selection
  2. Fit standard cause-specific Cox model using only selected variables
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- No shared effects? Effects too small?

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Conclusion & Outlook

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- So far no promising results on real data
- Lack of readily available high-dimensional data with competing risks
- Generalization to $e > 2$ events: Unclear

Thank you for your attention!

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