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Summary of some simulation results

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1 The state learner vs IPCW super learners

We compare the state learner to two IPCW-based super learners using different estimators of the censoring distribution. As benchmark we use the (discrete) oracle. This gives the following 4 super learners.

1. The state learner (referred to as `statelearner`).
2. A super learner based on the estimated integrated Brier score, where the censoring mechanism is estimated with the Kaplan-Meier estimator (referred to as `ipcw_km`).
3. A super learner based on the estimated integrated Brier score, where the censoring mechanism is estimated with a Cox model that includes all available covariates as main effects (referred to as `ipcw_cox`).
4. The (discrete) oracle super learner, which picks the model that minimizes the Brier score in an independent data set of 10.000 uncensored samples (referred to as `oracle`).

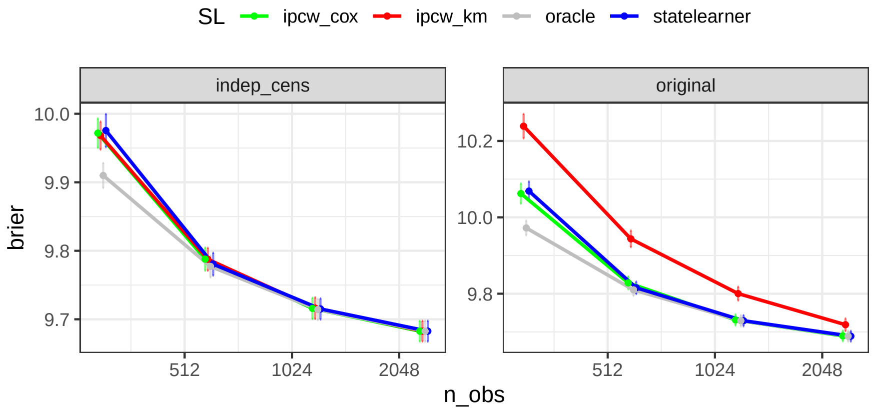
We include the following learners in all libraries:

- The Kaplan-Meier estimator
- A Cox model with main effects
- A random forest based on 50 trees

We used data generated in two different ways:

1. Data as generated in [Gerds et al., 2013] (referred to as `original`).
2. As in 1., but where censoring in completely independent of covariates (referred to as `indep_cens`).

To evaluate performance super learner, we use an independent data set of 10.000 uncensored samples and calculate the integrated Brier score in this data set. All results are based on 500 simulated data sets.

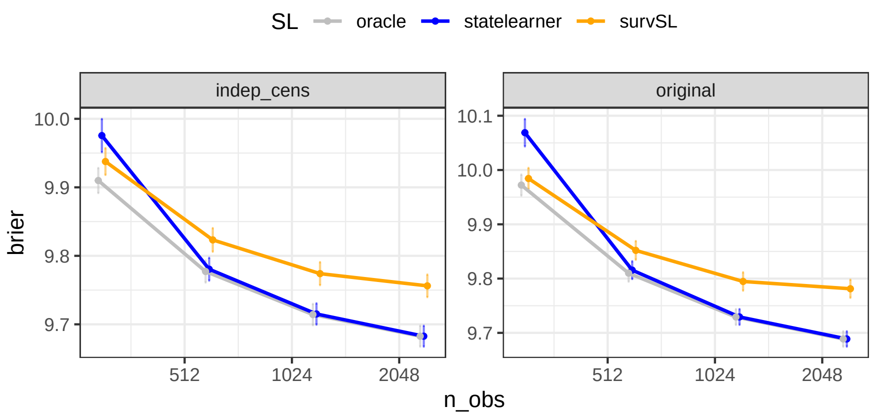

SL
ipcw_cox
ipcw_km
oracle
statelearner
indep_cens
original
brier
10.0
9.9
9.8
9.7
10.2
10.0
9.8
512
1024
2048
512
1024
2048
n_obs

2 The state learner vs SurvSL

We compare the state learner to the super learner proposed by Westling et al. [2021]. As benchmark we use again the (discrete) oracle. This gives the following 3 super learners.

1. The state learner (referred to as `statelearner`).
2. The super learner proposed in [Westling et al., 2021] (referred to as `survSL`).
3. The (discrete) oracle super learner, which picks the model that minimizes the Brier score in an independent data set of 10.000 uncensored samples (referred to as `oracle`).

We use the same data-generating mechanisms and method of evaluation as described in the section above.



3 References

T. A. Gerds, M. W. Kattan, M. Schumacher, and C. Yu. Estimating a time-dependent concordance index for survival prediction models with covariate dependent censoring. *Statistics in medicine*, 32(13):2173–2184, 2013.

T. Westling, A. Luedtke, P. Gilbert, and M. Carone. Inference for treatment-specific survival curves using machine learning. *arXiv preprint arXiv:2106.06602*, 2021.