

The joint survival super learner: A super learner for right-censored data

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SUMMARY

Risk prediction models are widely used to guide real-world decision-making in areas such as healthcare and economics, and they also play a key role in estimating nuisance parameters in semiparametric inference. The super learner is a machine learning framework that combines a library of prediction algorithms into a meta-learner using cross-validated loss. In the context of right-censored data, careful consideration must be given to both the choice of loss function and the estimation of expected loss. Moreover, estimators such as inverse probability of censoring weighting (IPCW) require accurate modeling and an estimator of the censoring distribution. We propose a novel approach to super learning for survival analysis that jointly evaluates candidate learners for both the event-time distribution and the censoring distribution. Our method imposes no restrictions on the algorithms included in the library, accommodates competing risks, and does not rely on a single pre-specified estimator of the censoring distribution. We establish a finite-sample bound on the average price we pay for using cross-validation, and show that this price vanishes asymptotically, up to poly-logarithmic terms, provided that the size of the library does not grow faster than at a polynomial rate in the sample size. We demonstrate the practical utility of our method using prostate cancer data and compare it to existing super learner algorithms for survival analysis using synthesized data.

Some key words: competing risks; cross-validation; loss based estimation; right-censored data; super learner

1. INTRODUCTION

Accurately predicting risk from time-to-event data is a central challenge in various research fields, such as epidemiology, economics, and weather forecasting, with applications in clinical decision making and policy interventions. For instance, in prostate cancer management, clinicians often need to estimate a patient's risk of disease progression and mortality over time to make informed decisions about treatment strategies such as active surveillance versus immediate intervention. Reliable risk prediction models can help tailor care to individual patients, avoid overtreatment, and allocate healthcare resources more effectively. Super learning (van der Laan et al., 2007), also known as ensemble learning or stacked regression (Wolpert, 1992; Breiman, 1996), provides a powerful approach to this problem by combining multiple candidate prediction models to reduce the risk of bias incurred by a single potentially misspecified model. In survival analysis, a super learner may for example combine a stack of Cox regression models

with a stack of random survival forests (Gerds & Kattan, 2021, Section 8.4). Such a strategy has recently produced KDpredict (<https://kdpredict.com/>) a model which jointly predicts the risks of kidney failure and all-cause mortality at multiple time horizons based on different sets of covariates (Liu et al., 2024). To evaluate the prediction performance of the learners, the super learner behind KDpredict uses inverse probability of censoring weighting (IPCW), where the censoring distribution is estimated under the restrictive assumption that it does not depend on the covariates. This is a potential source of bias which is difficult to overcome with the currently available methods.

In this article, we propose the *joint survival super learner*, a new super learner designed to handle the specific challenges of ensemble learning with right-censored data. The joint survival super learner simultaneously learns prediction models for the event-time and censoring distributions. The joint survival super learner is based on a competing risks model for the observed data, in which censoring is included as a state of its own, such that at any time it is known in which state an individual is. We assume conditionally independent censoring and exploit well-known relationships between the observed data distribution on the one side and the partly unobserved distributions of the event time and the censoring time on the other. Learners for the event-time and censoring hazard functions are then assessed based on how well they predict the state occupation probabilities of the competing risks model over time, given baseline covariate information. Our estimation framework thus naturally incorporates competing risks, avoids restrictive assumptions on the censoring distribution, and produces an estimator for the censoring distribution. Our approach is also fully flexible with respect to the choice of learners. The latter is in contrast to other proposals which restrict the library of learners to specific model classes (Polley & van der Laan, 2011; Golmakani & Polley, 2020), as we discuss in more detail in Section 3.

To analyse the theoretical properties of the joint survival super learner, we focus on the discrete super learner, which selects the model in the library with the best estimated performance (van der Laan et al., 2007). We provide theoretical guarantees for the performance of the joint survival super learner, and in particular show that the discrete joint survival super learner is consistent, when the library of learners includes at least one consistent learner. We also derive a finite-sample oracle inequality for the discrete joint survival super learner. We demonstrate how to construct a library of learners using common methods for survival analysis and illustrate the use of the joint survival super learner using a prostate cancer data set.

The article is organized as follows. We introduce our notation and framework in Section 2. Section 3 introduces loss-based super learning and discusses other existing super learners for right-censored data. In Section 4 we define the joint survival super learner, while Section 5 provides theoretical guarantees. Section 6 reports the results of a series of numerical experiments, and Section 7 illustrates the method on prostate cancer data. We conclude with a discussion in Section 8. Proofs are collected in the Appendix. Code and an implementation of the joint survival super learner in R (R Core Team, 2024) are available at <https://github.com/amnuden/joint-survival-super-learner>.

2. NOTATION AND FRAMEWORK

In a competing risks framework (Andersen et al., 2012) with J competing risks, let T be a time to event variable, $D \in \{1, 2, \dots, J\}$ the cause of the event, and $X \in \mathcal{X}$ a vector of baseline covariates taking values in a bounded subset $\mathcal{X} \subset \mathbb{R}^p$, $p \in \mathbb{N}$. Let $\tau < \infty$ be a fixed prediction horizon. We use \mathcal{Q} to denote the collection of all probability measures on $[0, \tau] \times \{1, 2, \dots, J\} \times \mathcal{X}$ such that $(T, D, X) \sim Q$ for some unknown $Q \in \mathcal{Q}$. For $j \in \{1, 2, \dots, J\}$, the cause-specific conditional

cumulative hazard functions $\Lambda_j: [0, \tau] \times \mathcal{X} \rightarrow \mathbb{R}_+$ are defined as

$$\Lambda_j(t | x) = \int_0^t \frac{Q(T \in ds, D = j | X = x)}{Q(T \geq s | X = x)}.$$

For ease of presentation we assume from now on that $J = 2$ and that the map $t \mapsto \Lambda_j(t | x)$ is continuous for all x and j , however, all technical arguments extend naturally to the general case (Andersen et al., 2012). The event-free survival function conditional on covariates is given by

$$S(t | x) = \exp \{-\Lambda_1(t | x) - \Lambda_2(t | x)\}. \quad (1)$$

Let \mathcal{M}_τ denote the space of all conditional cumulative hazard functions on $[0, \tau] \times \mathcal{X}$. Any distribution $Q \in \mathcal{Q}$ can be characterized by

$$Q(dt, j, dx) = \{S(t- | x)\Lambda_1(dt | x)H(dx)\}^{\mathbb{1}\{j=1\}} \\ \{S(t- | x)\Lambda_2(dt | x)H(dx)\}^{\mathbb{1}\{j=2\}},$$

where $\Lambda_j \in \mathcal{M}_\tau$ for $j = 1, 2$ and H is the marginal distribution of the covariates.

We consider the right-censored setting in which we observe $O = (\tilde{T}, \tilde{D}, X)$, where $\tilde{T} = \min(T, C)$ for a right-censoring time C , $\Delta = \mathbb{1}\{T \leq C\}$, and $\tilde{D} = \Delta D$. Let \mathcal{P} denote a set of probability measures on the sample space $\mathcal{O} = [0, \tau] \times \{0, 1, 2\} \times \mathcal{X}$ such that $O \sim P$ for some unknown $P \in \mathcal{P}$. We assume that the event times and the censoring times are conditionally independent given covariates, $T \perp\!\!\!\perp C | X$. This implies that any distribution $P \in \mathcal{P}$ is characterized by a distribution $Q \in \mathcal{Q}$ and a conditional cumulative hazard function for C given X (c.f., Begun et al., 1983; Gill et al., 1997). We use $\Gamma \in \mathcal{M}_\tau$ to denote the cumulative hazard function of the conditional censoring distribution given covariates. For ease of presentation we assume that $t \mapsto \Gamma(t | x)$ is continuous for all x . We let $(t, x) \mapsto G(t | x) = \exp \{-\Gamma(t | x)\}$ denote the survival function of the conditional censoring distribution. The distribution P is characterized by

$$P(dt, j, dx) = \{G(t- | x)S(t- | x)\Lambda_1(dt | x)H(dx)\}^{\mathbb{1}\{j=1\}} \\ \{G(t- | x)S(t- | x)\Lambda_2(dt | x)H(dx)\}^{\mathbb{1}\{j=2\}} \\ \{G(t- | x)S(t- | x)\Gamma(dt | x)H(dx)\}^{\mathbb{1}\{j=0\}} \quad (2) \\ = \{G(t- | x)Q(dt, j, dx)\}^{\mathbb{1}\{j \neq 0\}} \\ \{G(t- | x)S(t- | x)\Gamma(dt | x)H(dx)\}^{\mathbb{1}\{j=0\}}.$$

Hence, we may write $\mathcal{P} = \{P_{Q, \Gamma} : Q \in \mathcal{Q}, \Gamma \in \mathcal{G}\}$ for some $\mathcal{G} \subset \mathcal{M}_\tau$. We also have H -almost everywhere

$$P(\tilde{T} > t | X = x) = S(t | x)G(t | x) = \exp \{-\Lambda_1(t | x) - \Lambda_2(t | x) - \Gamma(t | x)\}.$$

We assume that there exists $\kappa < \infty$ such that $\Lambda_j(\tau- | x) < \kappa$, for $j \in \{1, 2\}$, and $\Gamma(\tau- | x) < \kappa$ for almost all $x \in \mathcal{X}$. This implies that $G(\tau- | x)$ is bounded away from zero for almost all $x \in \mathcal{X}$. Under these assumptions, the conditional cumulative hazard functions Λ_j and Γ can be identified from P by

$$\Lambda_j(t | x) = \int_0^t \frac{P(\tilde{T} \in ds, \tilde{D} = j | X = x)}{P(\tilde{T} \geq s | X = x)}, \quad (3)$$

$$\Gamma(t | x) = \int_0^t \frac{P(\tilde{T} \in ds, \tilde{D} = 0 | X = x)}{P(\tilde{T} \geq s | X = x)}. \quad (4)$$

Thus, we can consider Λ_j and Γ as operators which map from \mathcal{P} to \mathcal{M}_τ .

3. LOSS-BASED SUPER LEARNING

Loss-based super learning requires a library of learners, a cross-validation algorithm, and a loss function for evaluating predictive performance on hold-out samples. Let $\mathcal{D}_n = \{O_i\}_{i=1}^n \in \mathcal{O}^n$ be a data set of i.i.d. observations from $P \in \mathcal{P}$, and \mathcal{A} a collection of candidate learners. Let Θ be the parameter space, which in our case is a class of functions representing different models. Each learner $a \in \mathcal{A}$ is a map $a: \mathcal{O}^n \rightarrow \Theta$ which takes a data set as input and returns an estimate $a(\mathcal{D}_n) \in \Theta$. Let $L: \Theta \times \mathcal{O} \rightarrow \mathbb{R}_+$ be a loss function, representing the performance of the model $\theta \in \Theta$ at the observation $O \in \mathcal{O}$, where lower values mean better performance.

The expected loss of a learner is estimated by splitting the data set \mathcal{D}_n into K disjoint approximately equally sized subsets $\mathcal{D}_n^1, \mathcal{D}_n^2, \dots, \mathcal{D}_n^K$ and then calculating the cross-validated loss

$$\hat{R}_n(a; L) = \frac{1}{K} \sum_{k=1}^K \frac{1}{|\mathcal{D}_n^k|} \sum_{O_i \in \mathcal{D}_n^k} L(a(\mathcal{D}_n^{-k}), O_i), \quad \text{with } \mathcal{D}_n^{-k} = \mathcal{D}_n \setminus \mathcal{D}_n^k. \quad (5)$$

The subset \mathcal{D}_n^{-k} is referred to as the k 'th training sample, while \mathcal{D}_n^k is referred to as the k 'th test or hold-out sample. The discrete super learner is defined as

$$\hat{a}_n = \underset{a \in \mathcal{A}}{\operatorname{argmin}} \hat{R}_n(a; L),$$

and depends on both the library of learners and the specific partitioning of the data into cross-validation folds $\mathcal{D}_n^1, \dots, \mathcal{D}_n^K$.

When designing a super learner for right-censored data, particular care must be taken in the choice of loss function and in the estimation of the expected loss. A commonly used loss function for right-censored data is the partial log-likelihood loss (e.g., Li et al., 2016; Yao et al., 2017; Lee et al., 2018; Katzman et al., 2018; Gensheimer & Narasimhan, 2019; Lee et al., 2021; Kvamme & Borgan, 2021). This loss function is also recommended for super learning with right-censored data by Polley & van der Laan (2011), under the assumption that data are observed in discrete time. However, the partial log-likelihood loss does not work well as a general purpose measure of performance in hold-out samples when data are observed in continuous time. The reason is that the partial log-likelihood assigns an infinite value to any learner that predicts piecewise constant cumulative hazard functions, if the test set contains event times that are not observed in the training set. This problem occurs with prominent survival learners including the Kaplan-Meier estimator, random survival forests, and semi-parametric Cox regression models, and these learners cannot be included in the library of the super learner proposed by Polley & van der Laan (2011). When a proportional hazards model is assumed, the baseline hazard function can be profiled out of the likelihood (Cox, 1972). The cross-validated partial log-likelihood loss (Verweij & van Houwelingen, 1993) has therefore been suggested as a loss function for super learning by Golmakani & Polley (2020). However, this choice of loss function restricts the library of learners to include only Cox proportional hazards models, and hence excludes many learners such as, e.g., random survival forests, additive hazards models, and accelerated failure time models.

Alternative approaches for super learning with right-censored data use an inverse probability of censoring weighted (IPCW) loss function (Graf et al., 1999; van der Laan & Dudoit, 2003; Molinaro et al., 2004; Keles et al., 2004; Hothorn et al., 2006; Gerds & Schumacher, 2006; Gonzalez Ginestet et al., 2021), censoring unbiased transformations (Fan & Gijbels, 1996; Steingrimsson et al., 2019), or pseudo-values (Andersen et al., 2003; Mogensen & Gerds, 2013; Sachs et al., 2019). All these methods rely on an estimator of the censoring distribution, and their drawback is that this estimator has to be pre-specified. Recent work by Han et al. (2021) and Westling et al. (2021) circumvents the need to pre-specify a censoring model by iterating between

estimation of the outcome and censoring models. However, this iterative procedure is in general not guaranteed to converge to the true data-generating mechanism (Munch, 2024, Appendix A.4).

4. THE JOINT SURVIVAL SUPER LEARNER

The main idea of the joint survival super learner is to specify libraries of learners for the hazard functions Λ_1 , Λ_2 , and Γ , and to exploit the relations in equation (2) to define a joint loss function. The joint survival super learner thus evaluates a tuple of learners for $(\Lambda_1, \Lambda_2, \Gamma)$ based on how well they jointly predict the observed data and the discrete joint survival super learner chooses the best performing tuple. To formally introduce the joint survival super learner, we define the process

$$\eta(t) = \mathbb{1}\{\tilde{T} \leq t, \tilde{D} = 1\} + 2 \mathbb{1}\{\tilde{T} \leq t, \tilde{D} = 2\} - \mathbb{1}\{\tilde{T} \leq t, \tilde{D} = 0\}, \quad \text{for } t \in [0, \tau],$$

which takes values in $\{-1, 0, 1, 2\}$. The four values represent four mutually exclusive states. Specifically, value 0 represents the state where the individual is still event-free and uncensored, value 1 the state where the event of interest has occurred, value 2 the state where a competing risk has occurred, and value -1 the state where the observation is right-censored. The state occupation probabilities given baseline covariates X are given by the function

$$F(t, l, x) = P(\eta(t) = l \mid X = x), \quad (6)$$

for all $t \in [0, \tau]$, $l \in \{-1, 0, 1, 2\}$, and $x \in \mathcal{X}$.

The joint survival super learner is a super learner for the function-valued parameter $\theta(P) = F$ which is identified through equation (6). Under conditional independent censoring, each tuple $(\Lambda_1, \Lambda_2, \Gamma, H)$ characterizes a distribution $P \in \mathcal{P}$, c.f. equation (2), which in turn determines (F, H) . Hence, a learner for F can be constructed from learners for Λ_1 , Λ_2 , and Γ as follows:

$$\begin{aligned} F(t, 0, x) &= P(\tilde{T} > t \mid X = x) = \exp\{-\Lambda_1(t \mid x) - \Lambda_2(t \mid x) - \Gamma(t \mid x)\}, \\ F(t, 1, x) &= P(\tilde{T} \leq t, \tilde{D} = 1 \mid X = x) = \int_0^t F(s-, 0, x) \Lambda_1(ds \mid x), \\ F(t, 2, x) &= P(\tilde{T} \leq t, \tilde{D} = 2 \mid X = x) = \int_0^t F(s-, 0, x) \Lambda_2(ds \mid x), \\ F(t, -1, x) &= P(\tilde{T} \leq t, \tilde{D} = 0 \mid X = x) = \int_0^t F(s-, 0, x) \Gamma(ds \mid x). \end{aligned} \quad (7)$$

Equation (7) implies that a library for the joint survival super learner can be build from three libraries of learners: \mathcal{A}_1 , \mathcal{A}_2 , and \mathcal{B} , where \mathcal{A}_1 and \mathcal{A}_2 contain learners for the conditional cause-specific cumulative hazard functions Λ_1 and Λ_2 , respectively, and \mathcal{B} contains learners for the conditional cumulative hazard function of the censoring distribution. Taking the Cartesian product of these libraries, we obtain a library \mathcal{F} of learners for F :

$$\mathcal{F}(\mathcal{A}_1, \mathcal{A}_2, \mathcal{B}) = \{\varphi_{a_1, a_2, b} : a_1 \in \mathcal{A}_1, a_2 \in \mathcal{A}_2, b \in \mathcal{B}\}, \quad (8)$$

where in correspondence with the relations in equation (7),

$$\begin{aligned}
\varphi_{a_1, a_2, b}(\mathcal{D}_n)(t, 0, x) &= \exp \{-a_1(\mathcal{D}_n)(s | x) - a_2(\mathcal{D}_n)(s | x) - b(\mathcal{D}_n)(s | x)\}, \\
\varphi_{a_1, a_2, b}(\mathcal{D}_n)(t, 1, x) &= \int_0^t \varphi_{a_1, a_2, b}(\mathcal{D}_n)(s-, 0, x) a_1(\mathcal{D}_n)(ds | x), \\
\varphi_{a_1, a_2, b}(\mathcal{D}_n)(t, 2, x) &= \int_0^t \varphi_{a_1, a_2, b}(\mathcal{D}_n)(s-, 0, x) a_2(\mathcal{D}_n)(ds | x), \\
\varphi_{a_1, a_2, b}(\mathcal{D}_n)(t, -1, x) &= \int_0^t \varphi_{a_1, a_2, b}(\mathcal{D}_n)(s-, 0, x) b(\mathcal{D}_n)(ds | x).
\end{aligned} \tag{9}$$

175 Notably, the libraries \mathcal{A}_1 , \mathcal{A}_2 , and \mathcal{B} can be constructed using standard software for survival analysis. For example, in the R software we can specify various ways to include covariates in a Cox regression model and fit learners of the hazard functions using the `survival`-package (Therneau, 2022), and we can specify hyper parameters of a random survival forest and derive learners of the hazard functions using the `randomForestSRC`-package (Ishwaran & Kogalur, 180 2025).

To evaluate how well a function F predicts the process η we use the integrated Brier score (Graf et al., 1999) evaluated at time τ :

$$\bar{B}_\tau(F, O) = \int_0^\tau \sum_{l=-1}^2 (F(t, l, X) - \mathbb{1}\{\eta(t) = l\})^2 dt.$$

Here the integrand is the average Brier score at time t across the four states (Brier et al., 1950). Based on a split of a data set \mathcal{D}_n into K disjoint approximately equally sized subsets (c.f., Section 3), each learner $\varphi_{a_1, a_2, b}$ in the library $\mathcal{F}(\mathcal{A}_1, \mathcal{A}_2, \mathcal{B})$ is evaluated using the cross-validated loss, 185

$$\hat{R}_n(\varphi_{a_1, a_2, b}; \bar{B}_\tau) = \frac{1}{K} \sum_{k=1}^K \frac{1}{|\mathcal{D}_n^k|} \sum_{O_i \in \mathcal{D}_n^k} \bar{B}_\tau(\varphi_{a_1, a_2, b}(\mathcal{D}_n^{-k}), O_i),$$

and the discrete joint survival super learner is best performing tuple of hazard functions:

$$(\hat{\Lambda}_{1n}, \hat{\Lambda}_{2n}, \hat{\Gamma}_n) = \underset{(a_1, a_2, b) \in \mathcal{A}_1 \times \mathcal{A}_2 \times \mathcal{B}}{\operatorname{argmin}} \hat{R}_n(\varphi_{a_1, a_2, b}; \bar{B}_\tau). \tag{10}$$

Under the assumption of conditional independent censoring and positivity, as stated in Section 2, it follows from equations (3) and (4) and the definition of F that

$$\Lambda_j(t, x) = \int_0^t \frac{F(ds, j, x)}{F(s-, 0, x)}, \quad j \in \{1, 2\}. \tag{11}$$

Cause-specific risk predictions can be obtained from the joint survival super learner (10) by substituting into the well-known formula (e.g., Benichou & Gail, 1990; Ozenne et al., 2017), 190

$$\hat{Q}_n(T \leq t, D = j | X = x) = \int_0^t \exp \{-\hat{\Lambda}_{1n}(u | x) - \hat{\Lambda}_{2n}(u | x)\} \hat{\Lambda}_{jn}(du | x), \quad j \in \{1, 2\}. \tag{12}$$

Furthermore, the joint survival super learner provides an estimator of the censoring distribution:

$$\hat{G}_n(T \leq t | X = x) = \exp \{-\hat{\Gamma}_n(t | x)\}.$$

5. THEORETICAL GUARANTEES

Cross-validation is the backbone of super learning and an intuitively reasonable procedure for fair model selection without overfitting. In this section, we adapt the work of van der Laan & Dudoit (2003) and van der Vaart et al. (2006) and provide a theoretical justification for the joint survival super learner in the form of a finite-sample oracle inequality. We begin by demonstrating that minimizing the integrated Brier score, as defined in Section 4, is statistically proper, in the sense that minimization recovers the parameter of the data-generating distribution. Together with our finite-sample oracle inequality (Proposition 2 below), this implies that the joint survival super learner is consistent when it is based on a library that includes at least one consistent learner. Another consequence of our finite-sample oracle inequality is that the joint survival super learner converges (nearly) at the optimal rate achievable within the library of learners. This statement is made precise in Corollary 1 and the following discussion. Proofs are deferred to the Appendix.

A sensible loss function should attain the minimal expected value at the parameter corresponding to the data-generating distribution. Loss functions with this property are called proper, and strictly proper if the minimizer is unique (Gneiting & Raftery, 2007). Absence of properness makes it unclear why minimizing the (estimated) expected loss is interesting. Proposition 1 states that the integrated Brier score as defined in Section 4 is a strictly proper scoring rule. To establish this result, recall that the function F implicitly depends on the data-generating probability measure $P \in \mathcal{P}$ but that this was so-far suppressed in the notation. We now make this dependence explicit by writing F_P for the function determined by a given $P \in \mathcal{P}$ in accordance with equation (6). In the following we let $\mathcal{H}_{\mathcal{P}} = \{F_P : P \in \mathcal{P}\}$.

PROPOSITION 1. *If $P \in \mathcal{P}$ then*

$$F_P = \operatorname{argmin}_{F \in \mathcal{H}_{\mathcal{P}}} \mathbb{E}_P [\bar{B}_{\tau}(F, O)],$$

for all $l \in \{-1, 0, 1, 2\}$, almost all $t \in [0, \tau]$, and P -almost all $x \in \mathcal{X}$.

The discrete joint survival super learner defined in (10) provides an estimate of the function F

$$\hat{\varphi}_n = \varphi_{\hat{\Lambda}_{1n}, \hat{\Lambda}_{2n}, \hat{\Gamma}_n}$$

which is obtained by substituting $(\hat{\Lambda}_{1n}, \hat{\Lambda}_{2n}, \hat{\Gamma}_n)$ for (a_1, a_2, b) into the structural equations (9). To evaluate the performance of $\hat{\varphi}_n$ we benchmark it against the data-generating distribution F_P , which according to Proposition 1 has the smallest expected loss. Another useful theoretical benchmark is the so-called oracle learner which is the best learner included in the library of learners and formally defined by

$$\tilde{\varphi}_n = \operatorname{argmin}_{\varphi \in \mathcal{F}(\mathcal{A}_1, \mathcal{A}_2, \mathcal{B})} \tilde{R}_n(\varphi; \bar{B}_{\tau}), \quad \text{with} \quad \tilde{R}_n(\varphi; \bar{B}_{\tau}) = \frac{1}{K} \sum_{k=1}^K \mathbb{E}_P [\bar{B}_{\tau}(\varphi(\mathcal{D}_n^{-k}), O) \mid \mathcal{D}_n^{-k}],$$

where we use \mathbb{E}_P to denote the expectation under the distribution P for a new observation O which is independent of the data \mathcal{D}_n^{-k} . Like the joint survival super learner, the oracle learner depends on the library of learners and on the actual partition of the data, but unlike the joint survival super learner, it also depends on the unknown data-generating distribution. It is hence not available in practice and serves only as a theoretical benchmark.

In the following, we equip the space $\mathcal{H}_{\mathcal{P}}$ with the norm

$$\|F\|_P = \left\{ \sum_{l=-1}^2 \int_0^{\tau} \mathbb{E}_P [F(t, l, X)^2] dt \right\}^{1/2}. \quad (13)$$

This norm induces a natural performance measure, because $\|F - F_P\|_P$ is equal to the excess risk, $\mathbb{E}_P [\bar{B}_\tau(F, O)] - \mathbb{E}_P [\bar{B}_\tau(F_P, O)]$, as shown in Lemma 1 in the Appendix. For simplicity of presentation, we assume that all folds of the data partition have equal size, $|\mathcal{D}_n^{-k}| = n/K$ for a fixed number of folds K . We allow the number of learners to grow with n and write $\mathcal{F}_n = \mathcal{F}(\mathcal{A}_{1n}, \mathcal{A}_{2n}, \mathcal{B}_n)$ as short-hand notation emphasizing the dependence on the sample size. We now state a finite-sample inequality that bounds the performance of the joint survival super learner relative to that of the oracle learner.

PROPOSITION 2. *For all $P \in \mathcal{P}$, $n \in \mathbb{N}$, $k \in \{1, \dots, K\}$, and $\delta > 0$,*

$$\begin{aligned} \frac{1}{K} \sum_{k=1}^K \mathbb{E}_P [\|\hat{\varphi}_n(\mathcal{D}_n^{-k}) - F_P\|_P^2] &\leq (1 + 2\delta) \frac{1}{K} \sum_{k=1}^K \mathbb{E}_P [\|\tilde{\varphi}_n(\mathcal{D}_n^{-k}) - F_P\|_P^2] \\ &\quad + (1 + \delta) 16K\tau \left(13 + \frac{12}{\delta}\right) \frac{\log(1 + |\mathcal{F}_n|)}{n}. \end{aligned}$$

The expectation in Proposition 2 is taken with respect to the product measure P^n for the data set \mathcal{D}_n . This means that we are quantifying the average performance of the joint survival super learner across all training data of size n . A corresponding quantity was called the expected true error rate in Efron & Tibshirani (1997). As with many finite-sample oracle inequalities, this result is of little direct practical utility because the right-hand side depends on data-dependent, unknown quantities. However, it does quantify how the number of folds, the time horizon, and the number of learners in the library can be expected to influence the performance. The result has the following asymptotic consequences.

COROLLARY 1. *Assume that $|\mathcal{F}_n| = O(n^q)$, for some $q \in \mathbb{N}$ and that there exists a sequence $\varphi_n \in \mathcal{F}_n$, $n \in \mathbb{N}$, such that $\mathbb{E}_P [\|\varphi_n(\mathcal{D}_n^{-k}) - F_P\|_P^2] = C_P + O(n^{-\alpha})$, for some $\alpha \leq 1$ and $C_P \geq 0$.*

- (a) *If $\alpha = 1$, then $\frac{1}{K} \sum_{k=1}^K \mathbb{E}_P [\|\hat{\varphi}_n(\mathcal{D}_n^{-k}) - F_P\|_P^2] = C_P + O(\log(n)^{1+\varepsilon} n^{-1})$, $\forall \varepsilon > 0$.*
- (b) *If $\alpha < 1$, then $\frac{1}{K} \sum_{k=1}^K \mathbb{E}_P [\|\hat{\varphi}_n(\mathcal{D}_n^{-k}) - F_P\|_P^2] = C_P + O(n^{-\alpha})$.*

Proposition 2 thus provides a finite-sample bound on the average price we pay for using cross-validation, and Corollary 1 states that this price vanishes asymptotically, up to poly-logarithmic terms, provided that the size of the library does not grow faster than at a polynomial rate in the sample size. The situation $C_P = 0$ corresponds to a setting in which the library includes a consistent learner. Cases (a) and (b) correspond to situations where the oracle learner achieves a parametric or non-parametric asymptotic rate of convergence, respectively.

To illustrate the content of Corollary 1, consider first a situation where we use a library with an increasing number of Cox regression models. Each of these models will achieve a parametric rate of convergence, to possibly different least-false cumulative hazard functions Hjort (1992), and hence item (a) of Corollary 1 states that the joint survival super learner based on this library will achieve a near-parametric rate of convergence. C_P can be set to be the distance between the data-generating distribution and the least false model in the library, and so the joint survival super learner will approximate the least false model in the library at a near-parametric rate. Another situation appears if we add more flexible models to the library, such as Cox lasso or random survival forests. These models typically converge at slower rates, where the fastest achievable rate depends on the data-generating distribution. Item (b) of Corollary 1 shows that the joint survival super learner achieves the same convergence rate as the best-performing learner in the library, without any knowledge of the data-generating distribution.

6. NUMERICAL EXPERIMENTS

The numerical experiments have two aims. The first aim is to demonstrate that the joint survival super learner can outperform the IPCW based discrete super learners of (Gonzalez Ginestet et al., 2021) which pre-specify a potentially misspecified model for the censoring mechanism. The second aim is to show that the discrete joint survival super learner can compete and outperform the ensemble super learner proposed by Westling et al. (2021).

For the numerical experiments we have synthesized the prostate cancer data of Kattan et al. (2000) by fitting a hierarchical structural equation model under parametric assumptions. The outcome of interest is the time from randomization until the combined endpoint tumour recurrence or all-cause death. Five baseline covariates are used to predict the outcome risk: prostate-specific antigen (PSA, ng/mL), Gleason score sum (GSS, values between 6 and 10), radiation dose (RD), hormone therapy (HT, yes/no) and clinical stage (CS, six values). The study was designed such that a patient's radiation dose depended on when the patient entered the study. This in turn implies that the time of censoring depends on the radiation dose. The data were re-analysed in (Gerds et al., 2013) where a sensitivity analysis was conducted based on simulated data. Here we use the same simulation setup, where event and censoring times are generated according to parametric Cox-Weibull models (Bender et al., 2005) estimated from the original data, and the covariates are generated according to either marginal Gaussian normal or binomial distributions estimated from the original data (c.f., Gerds et al., 2013, Section 4.6). We refer to this simulation setting as 'dependent censoring'. We also considered a simulation setting where data were generated in the same way, except that censoring was generated completely independently of the covariates. We refer to this simulation setting as 'independent censoring'.

For all super learners, we use a library consisting of three learners: The Nelson-Aalen estimator (Andersen et al., 2012), a Cox regression model with additive effects of the covariates (Cox, 1972), and a random survival forest (Ishwaran et al., 2008). We use the same library to learn the cumulative hazard functions of the outcome and the censoring time, respectively. Specifically, to obtain estimates of the cumulative censoring hazard function we fit the learners to the modified data set $\{(\tilde{T}_i, 1 - \Delta_i, X_i)\}_{i=1}^n$ where the roles of censoring and outcome are exchanged.

We compare the joint survival super learner to two IPCW based super learners: The first super learner, called IPCW(Cox), uses a Cox regression model with additive effects of the five covariates to estimate the censoring probabilities, while the second super learner, called IPCW(KM), uses the Kaplan-Meier estimator to estimate the censoring probabilities. The Cox model for the censoring distribution is thus correctly specified in both simulation settings, while the Kaplan-Meier estimator only estimates the censoring model correctly in the simulation setting where censoring is independent. Both IPCW super learners are fitted using the R-package `riskRegression` (Gerds et al., 2023). The IPCW super learners use the integrated Brier score up to a fixed time horizon (36 months). The marginal risk of the event before this time horizon is $\approx 24.6\%$. Under the 'dependent censoring' setting the marginal censoring probability before the time horizon is $\approx 61.9\%$. Under the 'independent censoring' setting the marginal censoring probability before this time horizon is $\approx 38.7\%$.

Each super learner provides a learner for the cumulative hazard function for the outcome of interest. From the cumulative hazard function, we obtain a risk prediction model as described in Section 4, with the special case of $\Lambda_2 = 0$. We measure the performance of each super learner by calculating the index of prediction accuracy (IPA) (Kattan & Gerds, 2018) at a fixed time horizon (36 months) for the risk prediction model provided by the super learner. The IPA is 1 minus the ratio between the model's Brier score and the null model's Brier score, where the null model is the model that does not use any covariate information. The value of IPA is approximated using

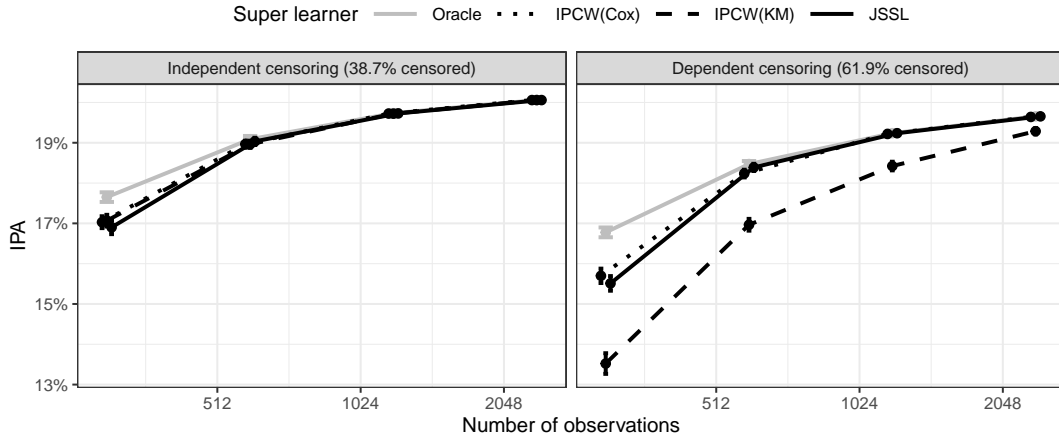


Fig. 1. For the risk prediction models provided by each of the super learners, the IPA is plotted against sample size. The results are averages across 1000 simulated data sets and the error bars are used to quantify the Monte Carlo uncertainty. JSSL denotes the joint survival super learner.

a large ($n = 20,000$) independent data set of uncensored data. As a benchmark, we calculate the performance of the risk prediction model chosen by the oracle selector, which has the highest IPA in the simulation setting.

The results for the first aim are shown in Figure 1. We see that in the scenario where censoring depends on the covariates, using the Kaplan-Meier estimator to estimate the censoring probabilities provides a risk prediction model with an IPA that is lower than the risk prediction model provided by the joint survival super learner. The performance of the risk prediction model selected by the joint survival super learner is similar to the risk prediction model selected by the IPCW(Cox) super learner which a priori uses a correctly specified model for the censoring distribution. Both these risk prediction models are close to the performance of the oracle, except for small sample sizes.

For the second aim, we consider the super learner *survSL* proposed by (Westling et al., 2021) which like the joint survival super learner does not require a pre-specified censoring model. Both methods provide estimates of the event-time and censoring distributions and hence we compare their performance with respect to both the outcome and the censoring distribution. Again we use the IPA to quantify the predictive performance.

The results for the second aim are shown in Figures 2 and 3. We see that for most sample sizes, the joint survival super learner has similar or higher IPA compared to *survSL* with respect to both the prediction of the censoring and the outcome risks. We note that the advantage of the joint survival super learner in this particular simulation setting might be due that it is a discrete super learner, whereas *survSL* combines the learners.

7. PROSTATE CANCER STUDY

We use the prostate cancer data of Kattan et al. (2000) to illustrate the use of the joint survival super learner in the presence of competing risks. We have introduced the data in Section 6. The data consist of 1,042 patients who are followed from start of followup until tumour recurrence ($n=268$), death without tumour recurrence ($n=29$), or censored ($n=745$), whatever came first. We use the joint survival super learner to rank libraries of learners for the cause-specific cumulative

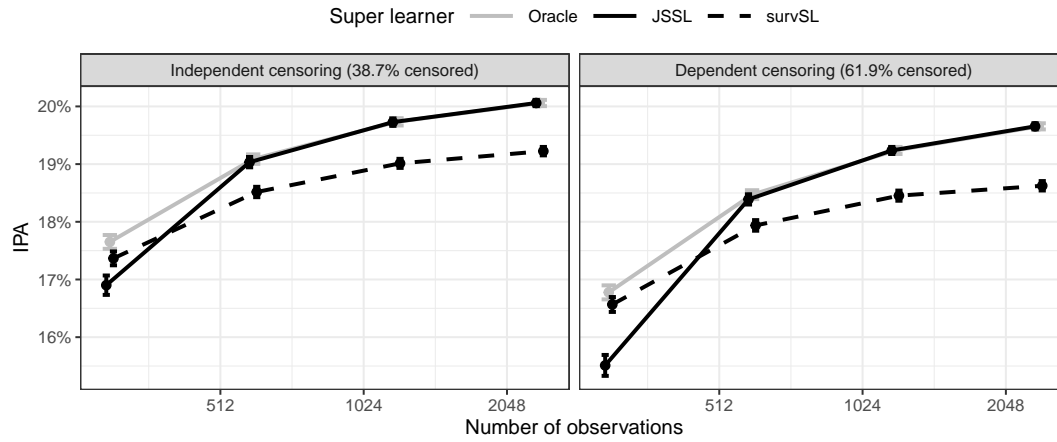


Fig. 2. For the risk prediction models of the outcome provided by each of the super learners, the IPA at the fixed time horizon is plotted against sample size. The results are averages across 1000 repetitions and the error bars are used to quantify the Monte Carlo uncertainty. JSSL denotes the joint survival super learner.

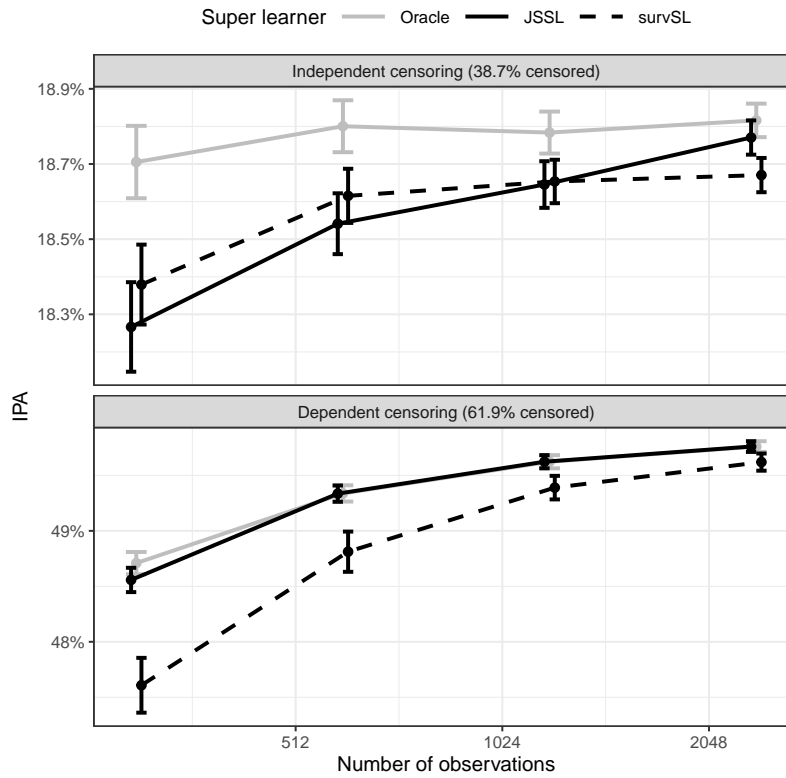


Fig. 3. For the risk prediction models of the censoring model provided by each of the super learners, the IPA at the fixed time horizon is plotted against sample size. The results are averages across 1000 repetitions and the error bars are used to quantify the Monte Carlo uncertainty. JSSL denotes the joint survival super learner.

hazard functions of tumour recurrence, death without tumour recurrence, and censoring. The three libraries of learners each include five learners: the Nelson-Aalen estimator, three Cox regression models (unpenalized, lasso, elastic net) each including additive effects of the baseline covariates, and a random survival forest. The Nelson-Aalen estimator is estimated without covariates and serves as a benchmark model which guarantees that the joint survival super learner is not worse than a model which predicts the same probability to all individuals. The other four learners use the five baseline covariates listed in Section 6 to predict the three cumulative hazard functions of time to tumour recurrence Λ_1 , time to death without tumour recurrence Λ_2 , and time to censoring Γ . The resulting library consists of $5^3 = 125$ learners. We use five folds for training and testing the models, repeat training and evaluation five times with different splits, and obtain the discrete joint survival super learner as the combination with the best average five-fold integrated Brier score across the five repetitions. Table 1 shows integrated Brier scores for the conditional state occupation probability function F as defined in Section 4, evaluated 3 years after randomization for a selection of the 125 learners. We see that among the five best combinations, the random survival forest is always selected for Γ and that the differences for different learners of Λ_1 and Λ_2 are small. To illustrate the comparative performance of the discrete joint survival super learner, we also split the data randomly into a training set with $n = 658$ individuals and a test set with the remaining $n = 384$ individuals. We fit the discrete joint survival super learner (five repetitions of five-fold cross-validation) and for comparison pre-specified cause-specific Cox regression models to the training set. In the training set, the discrete joint survival super learner chooses the unpenalized Cox regression model for tumor recurrence, the elastic net Cox regression for death without tumor recurrence, and the random survival forest for censoring. Figure 4 compares the 3-year risk predictions from the pre-specified Cox model and the discrete joint survival super learner in the test set.

Table 1. *The results of applying the 125 combinations of learners to the prostate cancer data set. Shown are the best 5 combinations and selected intermediate ranks. The “Loss” is the integrated Brier score evaluated at 3 years and “SD” is the standard deviation across the five repetitions of five-fold cross-validation. The discrete joint survival super learner chooses rank 1.*

Rank	Cause 1	Cause 2	Censored	Loss	SD
1	Elastic net	Elastic net	Random forest	7.0205	0.030977
2	LASSO	Elastic net	Random forest	7.0209	0.031035
3	Cox	Elastic net	Random forest	7.0224	0.030871
4	Elastic net	LASSO	Random forest	7.0225	0.030170
5	LASSO	LASSO	Random forest	7.0228	0.030237
25	Random forest	Random forest	LASSO	7.3845	0.026975
50	Elastic net	Random forest	LASSO	7.3974	0.021290
75	LASSO	Cox	LASSO	7.4059	0.024660
100	Nelson-Aalen	Cox	Elastic net	7.8300	0.016719
125	Nelson-Aalen	Nelson-Aalen	Nelson-Aalen	10.3298	0.003289

8. DISCUSSION

A major advantage of the joint survival super learner is that the performance of each combination of learners can be estimated without additional nuisance parameters. A potential drawback of our approach is that we are evaluating the loss of the learners on the level of the observed data

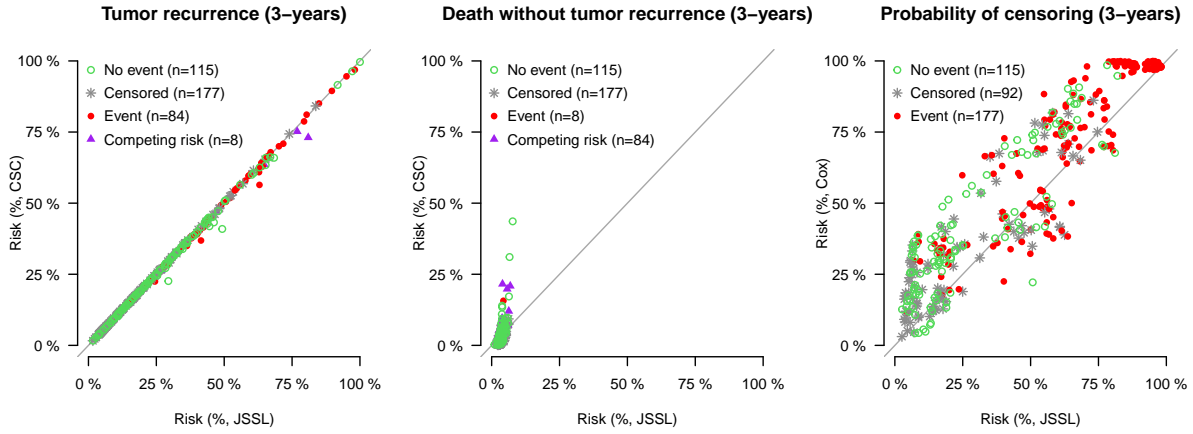


Fig. 4. Comparison of risk predictions of the discrete joint survival super learner and pre-specified Cox regressions in an independent test data set.

distribution, while the target of the analysis is either the event-time distribution, or the censoring distribution, or both.

A relevant application of the joint survival super learner is within the framework of targeted learning (van der Laan & Rose, 2011), also known as debiased machine learning (Chernozhukov et al., 2018), – a general methodology that combines flexible, data-adaptive estimation of nuisance parameters with asymptotically valid inference for low-dimensional target parameters. For example, the methods in van der Laan & Robins (2003); Rytgaard & van der Laan (2022) target the average treatment effect in a survival setting, which require estimates of the cause-specific cumulative hazard functions and the censoring cumulative hazard function. The joint survival super learner can be used to estimate these nuisance parameters and is more generally well suited for targeted and debiased machine learning with right-censored data.

We have focused on a discrete version of the joint survival super learner, but it is of interest to extend the method to a proper ensemble learner, where learners are combined, e.g., through stacking. How an ensemble should be build for tuples of learners is an interesting topic for future research.

APPENDIX

Define $\bar{B}_{\tau,P}(F, o) = \bar{B}_{\tau}(F, o) - \bar{B}_{\tau}(F_P, o)$ and $R_P(F) = \mathbb{E}_P [\bar{B}_{\tau,P}(F, O)]$, where the integrated Brier score \bar{B}_{τ} was defined in Section 4. Recall the norm $\|\cdot\|_P$ defined in equation (13).

LEMMA 1. $R_P(F) = \|F - F_P\|_P^2$.

Proof. For any $t \in [0, \tau]$ and $l \in \{-1, 0, 1, 2\}$ we have

$$\begin{aligned} & \mathbb{E}_P [(F(t, l, X) - \mathbb{1}\{\eta(t) = l\})^2] \\ &= \mathbb{E}_P [(F(t, l, X) - F_P(t, l, X) + F_P(t, l, X) - \mathbb{1}\{\eta(t) = l\})^2] \\ &= \mathbb{E}_P [(F(t, l, X) - F_P(t, l, X))^2] + \mathbb{E}_P [(F_P(t, l, X) - \mathbb{1}\{\eta(t) = l\})^2] \\ &\quad + 2 \mathbb{E}_P [(F(t, l, X) - F_P(t, l, X))(F_P(t, l, X) - \mathbb{1}\{\eta(t) = l\})] \\ &= \mathbb{E}_P [(F(t, l, X) - F_P(t, l, X))^2] + \mathbb{E}_P [(F_P(t, l, X) - \mathbb{1}\{\eta(t) = l\})^2], \end{aligned}$$

where the last equality follows from the tower property. Hence, using Fubini, we have

$$\mathbb{E}_P [\bar{B}_\tau(F, O)] = \|F - F_P\|_P^2 + \mathbb{E}_P [\bar{B}_\tau(F_P, O)].$$

395 *Proof of Proposition 1.* The result follows from Lemma 1. □

Recall that we use \mathcal{F}_n to denote a library of learners for the function F , and that $\hat{\varphi}$ and $\tilde{\varphi}$ denotes, respectively, the discrete super learner and the oracle learner for the library \mathcal{F}_n , c.f., Section 4.

400 *Proof of Proposition 2.* Minimizing the loss \bar{B}_τ is equivalent to minimizing the loss $\bar{B}_{\tau,P}$, so the discrete super learner and oracle according to \bar{B}_τ and $\bar{B}_{\tau,P}$ are identical. By Lemma 1, $R_P(F) \geq 0$ for any $F \in \mathcal{H}_P$, and so using Theorem 2.3 from (van der Vaart et al., 2006) with $p = 1$, we have that for all $\delta > 0$,

$$\begin{aligned} & \frac{1}{K} \sum_{k=1}^K \mathbb{E}_P [R_P(\hat{\varphi}_n(\mathcal{D}_n^{-k}))] \\ & \leq (1 + 2\delta) \frac{1}{K} \sum_{k=1}^K \mathbb{E}_P [R_P(\tilde{\varphi}_n(\mathcal{D}_n^{-k}))] \\ & \quad + (1 + \delta) \frac{16K}{n} \log(1 + |\mathcal{F}_n|) \sup_{F \in \mathcal{H}_P} \left\{ M(F) + \frac{v(F)}{R_P(F)} \left(\frac{1}{\delta} + 1 \right) \right\} \end{aligned}$$

405 where for each $F \in \mathcal{H}_P$, $(M(F), v(F))$ is some Bernstein pair for the function $o \mapsto \bar{B}_{\tau,P}(F, o)$. As $\bar{B}_{\tau,P}(F, \cdot)$ is uniformly bounded by τ for any $F \in \mathcal{H}_P$, it follows from section 8.1 in (van der Vaart et al., 2006) that $(\tau, 1.5 \mathbb{E}_P [\bar{B}_{\tau,P}(F, O)^2])$ is a Bernstein pair for $\bar{B}_{\tau,P}(F, \cdot)$. Now, for any $a, b, c \in \mathbb{R}$ we have

$$\begin{aligned} (a - c)^2 - (b - c)^2 &= (a - b + b - c)^2 - (b - c)^2 \\ &= (a - b)^2 + (b - c)^2 + 2(b - c)(a - b) - (b - c)^2 \\ &= (a - b) \{ (a - b) + 2(b - c) \} \\ &= (a - b) \{ a + b - 2c \}, \end{aligned}$$

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so using this with $a = F(t, l, x)$, $b = F_P(t, l, x)$, and $c = \mathbb{1}\{\eta(t) = l\}$, we have by Jensen's inequality

$$\begin{aligned} & \mathbb{E}_P [\bar{B}_{\tau,P}(F, O)^2] \\ & \leq 2\tau \mathbb{E}_P \left[\sum_{l=-1}^2 \int_0^\tau \{ (F(t, l, X) - \mathbb{1}\{\eta(t) = l\})^2 - (F_P(t, l, X) - \mathbb{1}\{\eta(t) = l\})^2 \}^2 dt \right] \\ & = 2\tau \mathbb{E}_P \left[\sum_{l=-1}^2 \int_0^\tau (F(t, l, X) - F_P(t, l, X))^2 \right. \\ & \quad \left. \times \{ F(t, l, X) + F_P(t, l, X) - 2\mathbb{1}\{\eta(t) = l\} \}^2 dt \right] \\ & \leq 8\tau \mathbb{E}_P \left[\sum_{l=-1}^2 \int_0^\tau (F(t, l, X) - F_P(t, l, X))^2 dt \right] \\ & = 8\tau \|F - F_P\|_P^2. \end{aligned}$$

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Thus when $v(F) = 1.5 \mathbb{E}_P [\bar{B}_{\tau,P}(F, O)^2]$ we have by Lemma 1

$$\frac{v(F)}{R_P(F)} = 1.5 \frac{\mathbb{E}_P [\bar{B}_{\tau,P}(F, O)^2]}{\mathbb{E}_P [\bar{B}_{\tau,P}(F, O)]} \leq 12\tau,$$

and so using the Bernstein pairs $(\tau, 1.5 \mathbb{E}_P [\bar{B}_{\tau,P}(F, O)^2])$ we have

$$\sup_{F \in \mathcal{H}_P} \left\{ M(F) + \frac{v(F)}{R_P(F)} \left(\frac{1}{\delta} + 1 \right) \right\} \leq \tau \left(13 + \frac{12}{\delta} \right).$$

For all $\delta > 0$ we thus have

$$\begin{aligned} \frac{1}{K} \sum_{k=1}^K \mathbb{E}_P [R_P(\hat{\varphi}_n(\mathcal{D}_n^{-k}))] &\leq (1 + 2\delta) \frac{1}{K} \sum_{k=1}^K \mathbb{E}_P [R_P(\tilde{\varphi}_n(\mathcal{D}_n^{-k}))] \\ &\quad + (1 + \delta) \log(1 + |\mathcal{F}_n|) \tau \frac{16K}{n} \left(13 + \frac{12}{\delta} \right), \end{aligned}$$

and then the final result follows from Lemma 1. \square

Proof of Corollary 1. By definition of the oracle and Lemma 1,

$$\frac{1}{K} \sum_{k=1}^K \mathbb{E}_P [\|\tilde{\varphi}_n(\mathcal{D}_n^{-k}) - F_P\|_P^2] \leq \frac{1}{K} \sum_{k=1}^K \mathbb{E}_P [\|\varphi_n(\mathcal{D}_n^{-k}) - F_P\|_P^2] = \mathbb{E}_P [\|\varphi_n(\mathcal{D}_n^{-k}) - F_P\|_P^2],$$

for all $n \in \mathbb{N}$, where the last equality follows because all the training sets \mathcal{D}_n^{-k} have the same distribution. The result then follows from Proposition 2 by letting δ grow to zero with n , for instance as $\delta_n = \log(n)^{-\varepsilon}$ for some $\varepsilon > 0$. \square

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