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Optimal Survival Trees With the Iterative Breslow Estimator and the Integrated Brier Score Objective

Iterative Breslow Estimator

Background We use dynamic programming to create the tree with the minimum training loss for a maximum depth $T(D,d) = \begin{cases} \min_{\hat{\theta}} \mathfrak{L}(D,\hat{\theta}), & d = 0\\ \min_{\hat{f}} [T(D(f), d-1) + T(D(\overline{f}, d-1)], & d > 0 \end{cases}$ $S(t) = P(T \ge t)$, where T is true time-of-event **d(t)** = deaths at time t **n(t)** = number of survivors up to and until time t *I***(***t***)** = cumulative hazard function (CHF) *N_o(t)* = baseline cumulative hazard function **θ** = risk coefficient **IBS** = Integrated Brier Score



Estimating the survival function

 $\hat{S}_i(t) = e^{-\hat{\Lambda}_i(t)}$ $\Lambda_i(t) = \theta_i \Lambda_0(t)$

Risk coefficients are estimated in leaves. The baseline CHF is the same for entire tree

The Nelson-Aalen estimator estimates the CHF by weighing every instance equally:

$$\hat{\Lambda}_0(t) = \sum_{t' \le t} \frac{d(t')}{n(t')}$$

2

3



IBS for 1 and 3 Breslow iterations





Iterative Breslow estimator on artificial data

Partial likelihood objective

The partial likelihood objective function calculates the loss by taking the difference between the log likelihoods of the estimated risk coefficient and the saturated risk coefficient:

$$\theta_i^{sat} = \frac{\delta_i}{\hat{\Lambda}_0(t_i)}$$



The partial likelihood loss judges both survival functions equally on a dataset with instances that all die at the same time. This is a flaw.

Integrated Brier Score objective

We find the tree with the optimal IBS on training data:

$$IBS = \frac{1}{t_{max}} \frac{1}{|D|} \sum_{i \in D} \int_0^{t_i} \frac{(1 - \hat{S}_i(t))^2}{\hat{G}(t)} dt + \delta_i \int_{t_i}^{t_{max}} \frac{(\hat{S}_i(t))^2}{\hat{G}(t_i)} dt$$



Intuition of the area of loss for the IBS





Comparison of IBS and Concordance Index on test data