A Large-Scale Neutral Comparison Study of Survival Models

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$\Rightarrow$ Needs comprehensive comparison!

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- 32 tasks
- 18 learners
- 2 tuning measures
- 9 evaluation measures

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$\Rightarrow$ The largest survival benchmark to date as far as we know

Scope

The “Standard Setting”:

- Single-event outcome: $\delta_i \in \{0, 1\}$
- Low-dimensional: $2 \leq p < n$
- No time-varying covariates
- Right-censoring only
- At least 100 observed events

Tasks

32 tasks collected from R packages on CRAN

	Minimum	q25%	Median	q75%	Maximum
N	137	446	820	2378	52410
p	2	4	5	7	25
Observed Events	101	194	323	699	5616
Cens. %	6	32	48	74	95

Learners

18 learners implemented in R and available via the `mlr3` [1] framework

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- **Other**: Akritas, SVM

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List of Learners (Baseline, Classical)

Name	Abbreviation	Package
Kaplan-Meier	KM	`survival`
Nelson-Aalen	NA	`survival`
Cox Regression	CPH	`survival`
Penalized Cox Regression (L1, L2)	GLM	`glmnet`
Penalized Cox Regression (L1, L2)	Pen	`penalized`
Parametric (AFT)	Par	`survival`
Flexible Parametric Splines	Flex	`flexsurv`
Akritas	AK	`survivalmodels`
Survival SVM	SSVM	`survivalsvm`

List of Learners (Trees, Boosting)

Name	Abbreviation	Package
Decison Tree	RRT	`rpart`
Random Survival Forest	RFSRC	`randomForestSRC`
Random Survival Forest	RAN	`ranger`
Conditional Inference Forest	CIF	`partykit`
Oblique RSF	ORSF	`aorsf`
Model-Based Boosting	MBO	`mboost`
Likelihood-Based Boosting	CoxB	`CoxBoost`
Gradient Boosting (Cox objective)	XGBCox	`xgboost`
Gradient Boosting (AFT objective)	XGBAFT	`xgboost`

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    1. Number of evaluations: $n_{\text{evals}} = n_{\text{parameters}} \times 50$
    2. Tuning time of 150 hours ($6\frac{1}{4}$ days)

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- Tuned on 2 different measures
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  - Right-Censored Log Loss (Scoring Rule)
- Evaluation spans all 3 types

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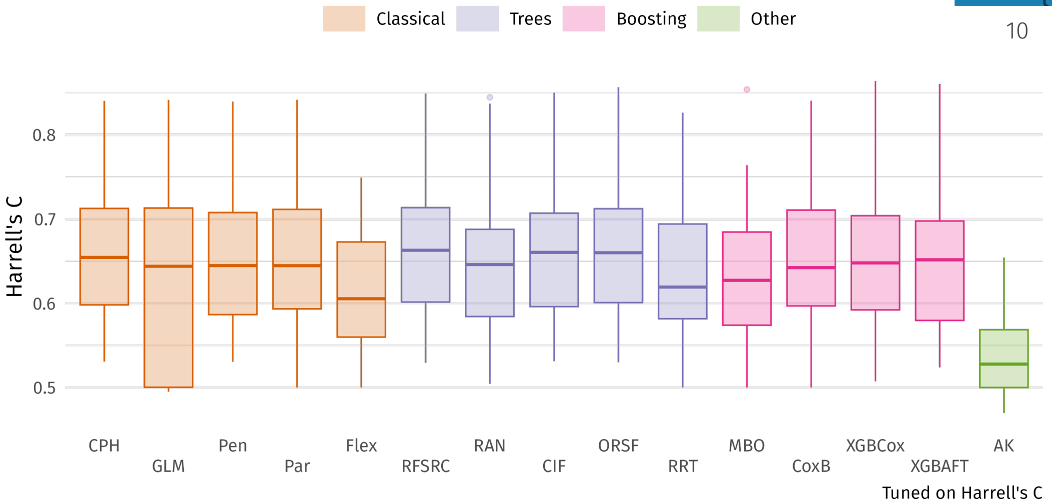
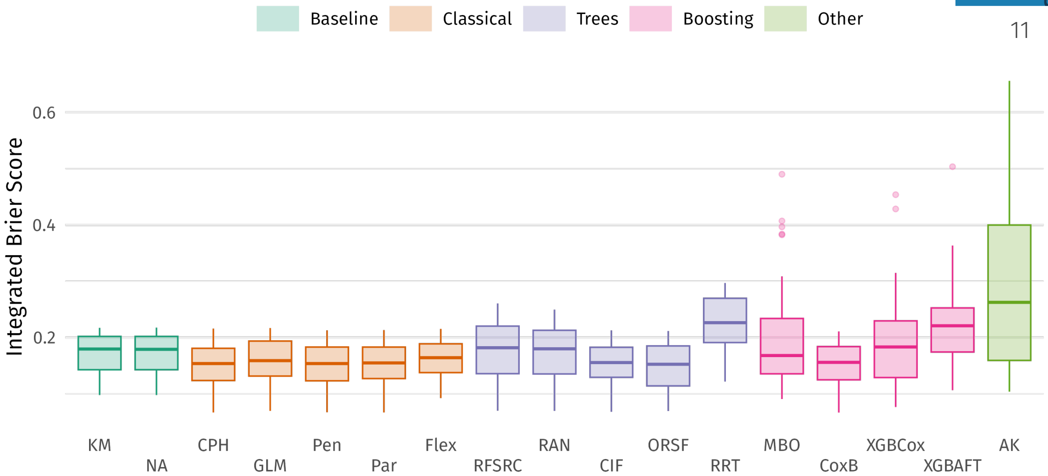
Boxplot (Harrel's C, higher is better)

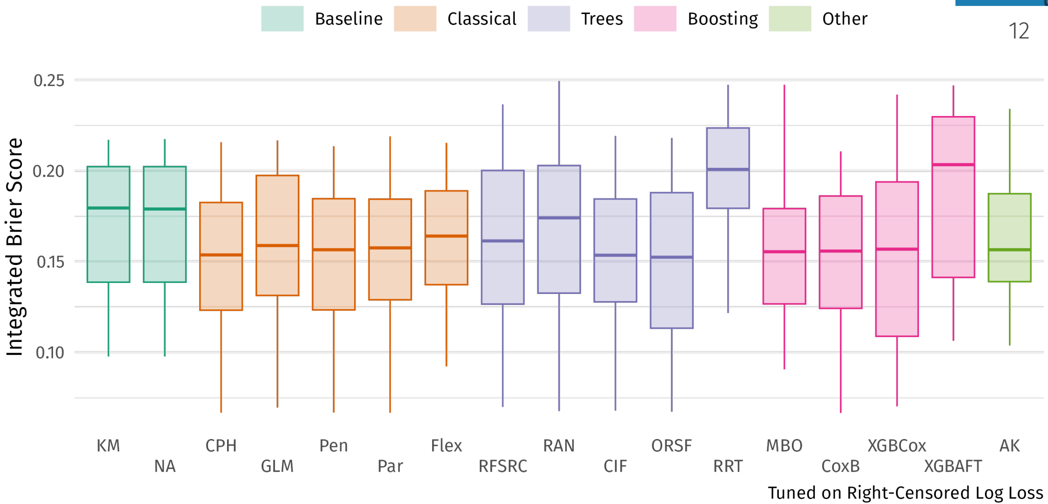


Boxplot (IBS, lower is better)

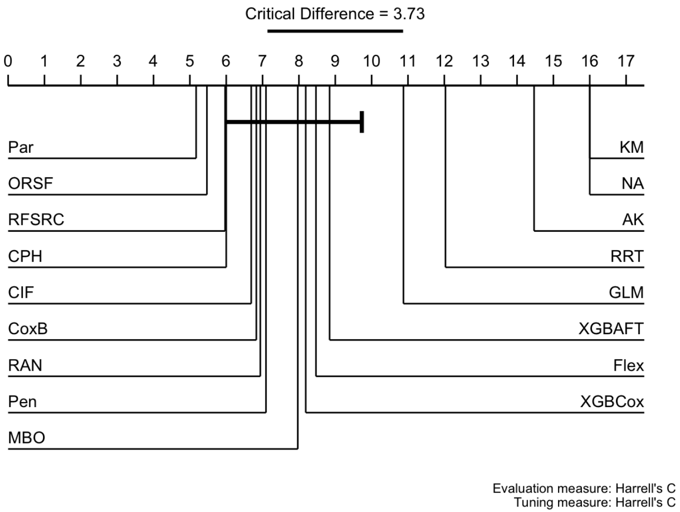


Tuned on Right-Censored Log Loss

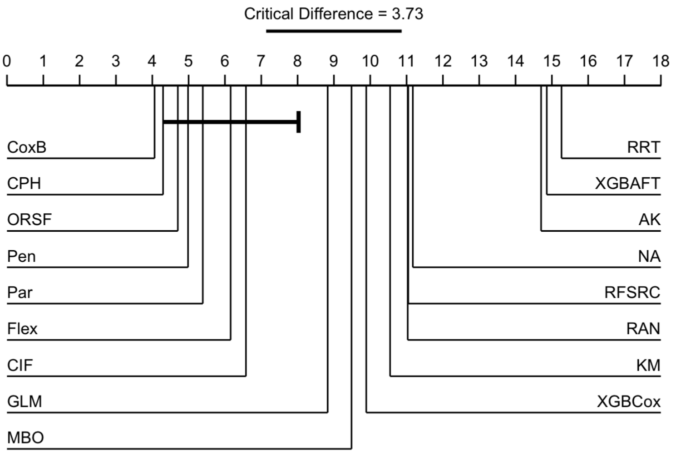
Boxplot (IBS, truncated)



Critical Difference: Bonferroni-Dunn (Harrell’s C)



Critical Difference: Bonferroni-Dunn (IBS/RCLL)



Evaluation measure: Integrated Brier Score (Improper)
Tuning measure: Right-Censored Log Loss

Closing Remarks

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- The “standard setting” $\approx$ the “do you need ML?”-setting

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Thank you for your attention!

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References I

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