A Large-Scale Neutral Comparison Study of Survival Models on Low-Dimensional Data

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July 29rd, 2024

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$\Rightarrow$ Needs comprehensive comparison!

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- 18 learners
- 2 tuning 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	3	5	7	25
Observed Events	101	194	336	1034	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**: SVM

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List of Learners (Baseline, Classical)

Name	Abbreviation	Package
Kaplan-Meier	KM	`survival`
Nelson-Aalen	NA	`survival`
Akritas	AK	`survivalmodels`
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`
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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- **Fallback**: Impute result with KM

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- We tune `cv.glmnet` for `alpha`, while it tunes itself for `lambda`

Evaluation

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- 3 types of metrics: Discrimination, Calibration, Scoring Rules
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  - Harrell's C (Discrimination)
  - Right-Censored Log Loss (Scoring Rule)

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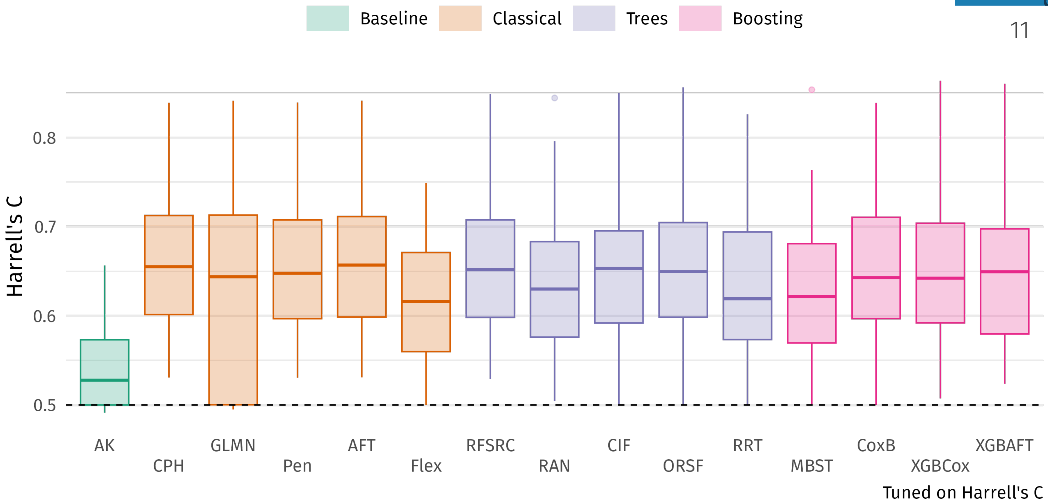
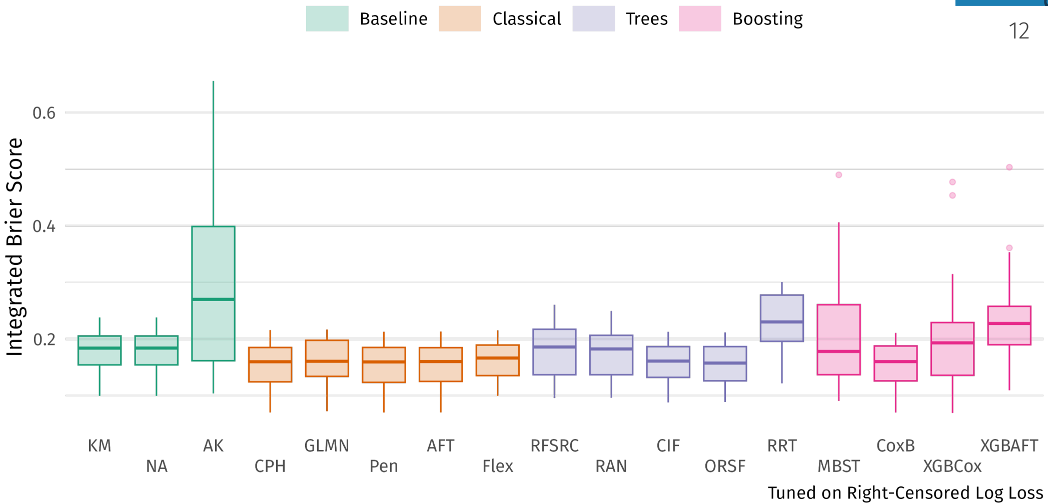
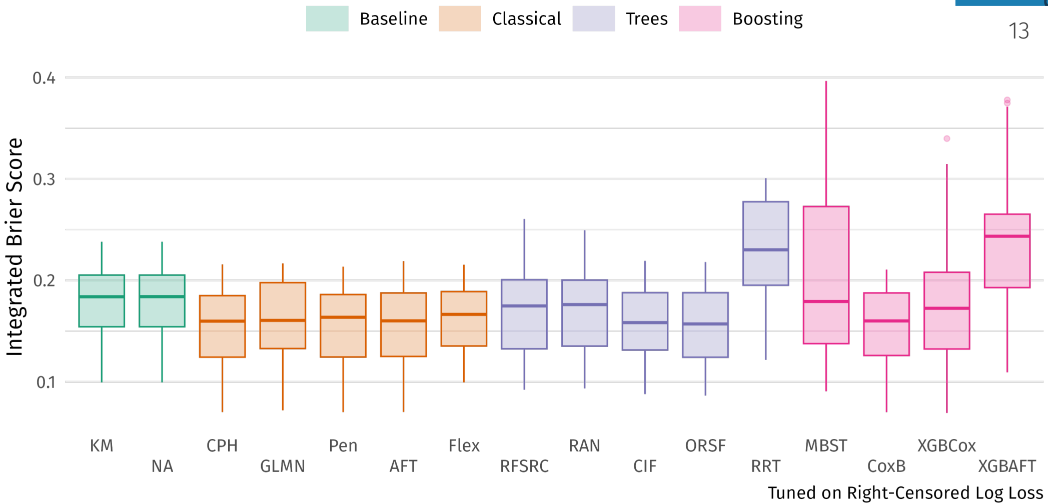
Boxplot (Harrel's C, higher is better)



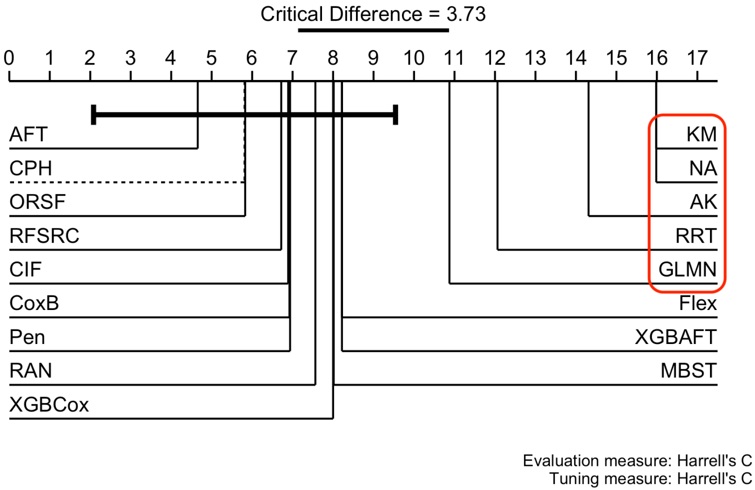
Boxplot (IBS, lower is better)



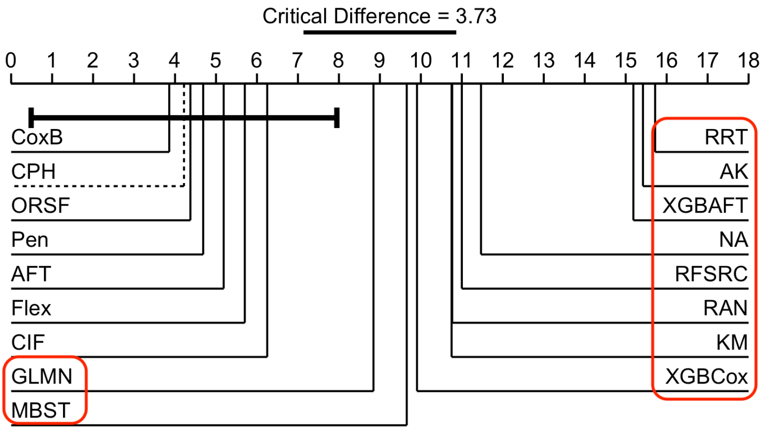
Boxplot (IBS, truncated)



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



Critical Difference: Bonferroni-Dunn (IBS/RCLL)



Evaluation measure: Integrated Survival Brier Score (ISBS)
Tuning measure: Right-Censored Log Loss (RCLL)

Closing Remarks

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More results at **projects.lukasburk.de** and we have a **preprint** on arXiv!

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Thank you for your attention!

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References I

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