Multiplicity of design and analysis options in benchmark studies based on real data: An illustration

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Illustrating the multiplicity of design and analysis options in benchmark studies

Example benchmark study: Survival prediction using multi-omics data

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Choice	Herrmann et al. (2021)	Alternative options
Data sets	18 real data sets with 5 multi-omics groups, $n \geq 100$, $\geq 5\%$ eff. cases	
Primary performance measure	Integrated Brier score	
Missing performance values	Ad-hoc 20%-threshold rule	
Aggregation across data sets	Mean	

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Aggregation across data sets	Mean	Median, rank, best0.05

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- Multiplicity of different options when designing and analysing a benchmark study (data sets, DGPs, evaluation criteria, etc.)
- Possible consequences caused by the multiplicity of options
  - Researchers might be concerned about how their choices affect the results
  - Researchers might (subconsciously) modify the benchmark study until it yields a favourable/reasonable result $\rightarrow$ risk of optimistic bias

Exploiting the multiplicity of different design and analysis options

Choice	Herrmann et al. (2021)	Alternative options	No. of options
Data sets	18 real data sets with 5 multi-omics groups, $n \geq 100$, $\geq 5\%$ eff. cases	$n, n_e, p, clin <$ or $\geq$ than median of orig. 18 data sets	9
Primary performance measure	Integrated Brier score	Uno's C-index	2
Missing performance values	Ad-hoc 20%-threshold rule	Weighted, random, mean	4
Aggregation across data sets	Mean	Median, rank, best0.05	4
			$= 288$

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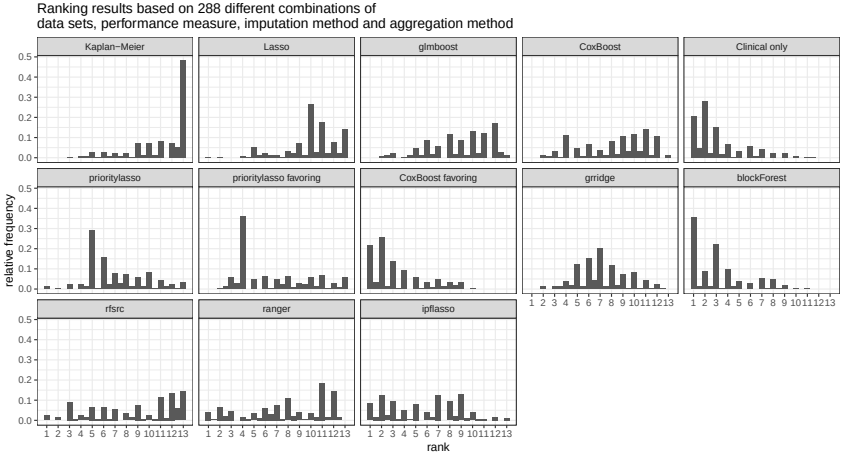
- In total: 288 combinations of design and analysis options
- Compare the resulting 288 rankings of the 13 survival prediction methods

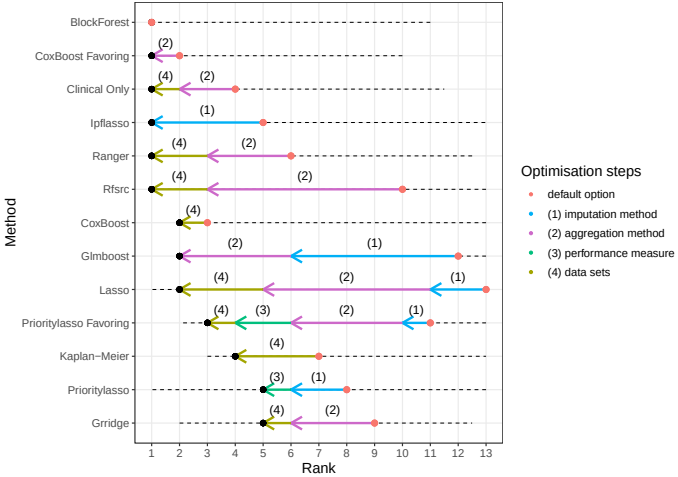
Overall variability of method rankings



→ Any method can achieve almost any rank

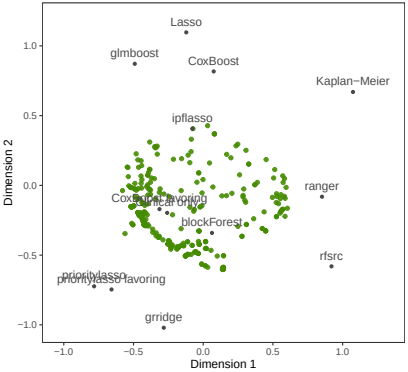
Stepwise optimisation

"No researcher would try all possibilities." → Stepwise optimisation



Assessing the impact of individual design and analysis choices

Impact of individual design and analysis choices



- Locate methods and option combinations such that distances between them correspond to ranks using multidimensional unfolding

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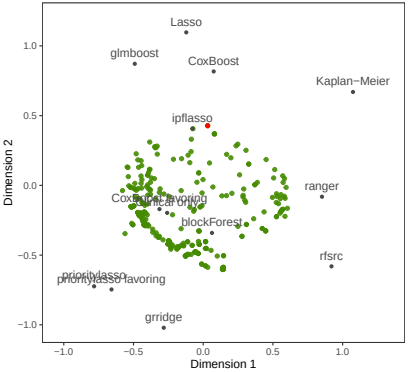

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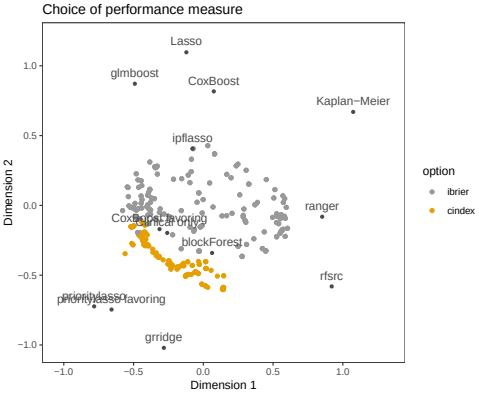

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For each design or analysis choice:

- Colour each point according to the option that was used in the respective combination

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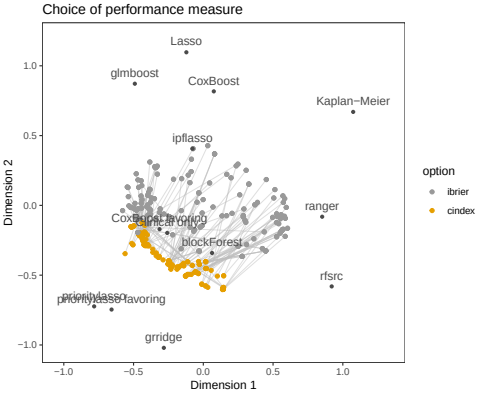

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- Connect each point representing the option used in Herrmann et al. (2021) to points representing alternative options given that the other three choices remain the same

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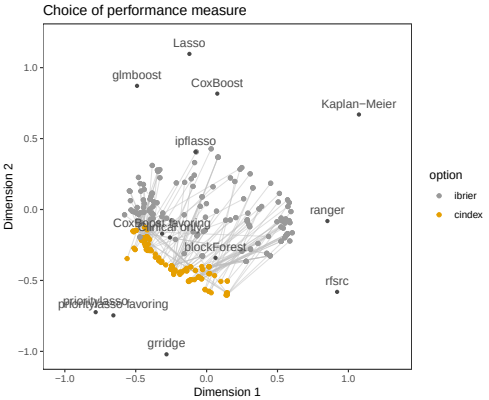

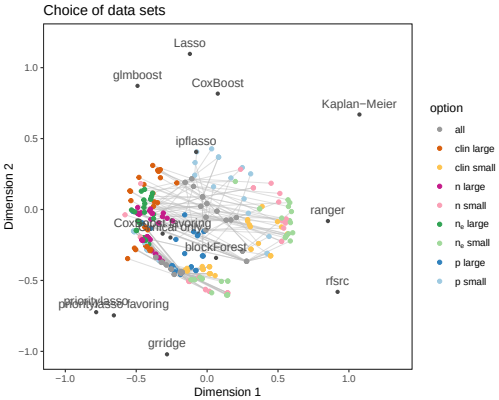

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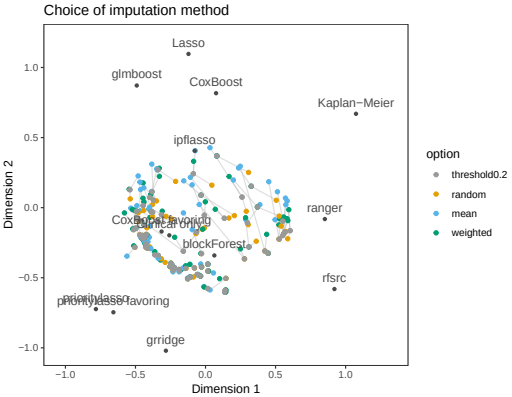

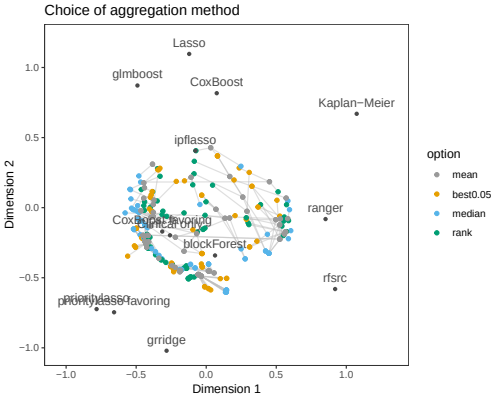

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- Results of benchmark studies can be highly variable with respect to design and analysis choices → risk of introducing an optimistic bias
- Reporting of variability using the multidimensional unfolding approach → graphical assessment of results with respect to a large number of different combinations of design and analysis options
  - Intuitive overview of the variability of results
  - Identification of critical choices that substantially affect the results and should be investigated in more detail

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Thank you!