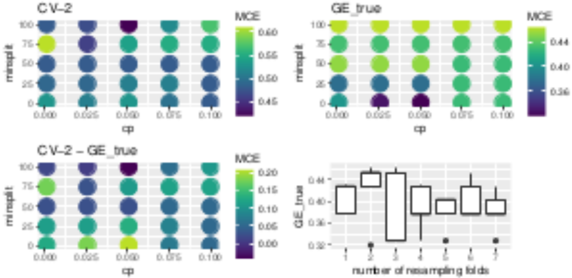
PRACTICAL ASPECTS OF HPO

- Choosing resampling
  - Nr of observations, i.i.d assumption for data sampling process
  - Higher resampling rates likely result in a better model; however they are computiationally more expensive



Tuning a CART on the `spirals` data with a k-fold CV (k=1 means here a 2/3 holdout split) using grid search and estimating the true GE with a very large test set (5 repetitions)

PRACTICAL ASPECTS OF HPO / 2

- Choosing performance measure
  - Desired implications when applying the model in practice
- Choosing a pipeline and search space
  - Numeric HPs of arbitrary size should be tuned on log scale
  - Size of search space results in different trade-offs:
    too small may miss out well performing HPCs;
    too large makes optimization more difficult

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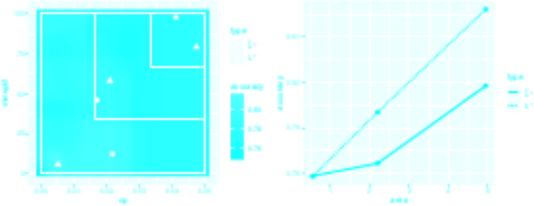

Tuning cp and minsplit for a CART on the `titanic` data over 3 increasing rectangular search spaces with random search (candidates number fixed) and comparing the result with the optimal model (found with exhaustive grid search)

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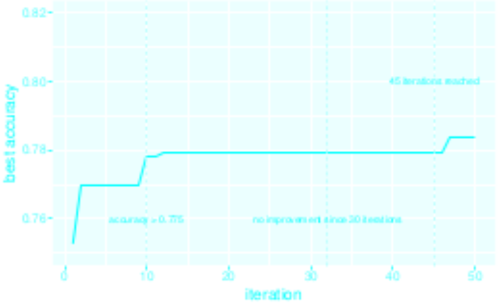
- Choosing HPO algorithm
  - For few HPS (1-3), grid search can be used
  - BO with GPs for upto 10 numeric HPs
  - BO with RFs handle mixed HP spaces
  - Random search and Hyperband work well as long as the "effective" dimension is low
  - EAs are somewhat in-between BO and RS, can handle very complex spaces, but less sample efficient than BO
  - **Also: use something that's stable and robust! More an aspect of the implementation than the algo!**

PRACTICAL ASPECTS OF HPO / 2

When to terminate HPO

- Specify a certain amount of runtime/budget beforehand
- Set a lower bound regarding $\widehat{\mathrm{GE}}$
- Terminate if performance improvement stagnates

Tuning cp and minsplit for a CART on the `titanic` data over 3 increasing rectangular search spaces with random search (candidates number fixed) and comparing the result with the optimal model (found with exhaustive grid search)



Different stopping points while tunining CART on the `titanic` data depending on which termination criterion is used

PRACTICAL ASPECTS OF HPO

- Choosing HPO algorithm
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- Warmstarts
  - Evaluations (e.g. weight sharing of neural networks)
  - Optimization (initializing with HPCs that worked well before)
- Control of execution
  - Parallelizability of HPO algorithms differs strongly
  - HPO execution can be parallelized at different levels (outer resampling, iteration, evaluation, inner resampling, model fit)