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Return of Super Learner

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Machine Learning 2022

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Learning Outcomes

After completing today's session, you will

- understand the basic idea of Super Learner (SL)
- understand the 3 important choices to be made for using SL
- be able to apply SL in a practical example
- know how to use cross-validation to measure the performance of a SL

Why Super Learner?

Optimality: the oracle property

- We define the ‘oracle’ selector as estimator that minimises the risk under the true data-generating distribution.
- SL has same expected risk difference as the oracle selector (up to a second order term) asymptotically
- i.e. we do not ‘lose’ anything by using the SL even if we know a situation is best suited to a particular estimator (just add it in the library!)

Conditions

- L , number of candidate learners in the library can grow at most polynomial in sample size n
 - to avoid over-fitting: estimated risk is close to true expected loss
- SL rate of convergence is $\log(n)/n$ (for a sufficiently large sample size) if it includes a parametric model which includes the truth

Empirical performance

Performance

- SL is a (meta-)learner (e.g runs a meta NNLS regression) as such, its performance should be studied via CV
- Computer intensive:
 - we can parallelise it (extra material computer lab)
 - we can run a scalable version (not covered)

Cross-validated Super Learner

- Estimate cross-validated risk of the SL itself to study the SL performance
- This requires an "external" CV layer (nested CV)
- Requires setting aside a separate holdout sample not used to fit the SL, and test the SL predictions on it
- A loss function to evaluate SL needs to be specified
- This external CV procedure incorporate F folds
- In the lab today, we use 3-5 outer/external folds of CV, usually 10.

Time for some more practice!

Interpretability

- Super Learner is a "black box" algorithm
 - The contribution of each variable is unclear
- Obtain variable importance metrics: quantifying marginal association between each predictor and outcome after adjusting for the others
 - A large contribution means strongly associated (can be confounding)

Advanced topics (not covered today)

- Select a loss function that is appropriate for the parameter to be estimated (change the method in R function)
- Variable importance for the SL and using this to select the learners
- Feature screening: Select a subset of available covariates and pass only those variables to the modelling algorithm.

Summary

What you have learnt

- Super Learner can help us choose the single best learner
- But usually, we want the best weighted combination
- ML models are not necessarily going to be always better than parametric models
 - ...but we don't usually know when there is a gain
- Key contribution of SL is that it is guaranteed to attain the performance of the best algorithm considered (oracle property)
- SL helps with transparency by pre-specifying the analysis strategy while being data-adaptive
 - attenuates model mis-specification
 - uses CV to avoid over-fitting
- Important choices : loss functions and meta-learner, library

SuperLearner, the R package

- Allows different loss functions and meta-learner functions (via `method`)
- Nested CV built-in
- Many machine algorithms have been included (with default hyper-parameters!!)
- CV can be used to tune these
- Parallel implementations
- Several other R implementations available (e.g. `sl3` in active development)
- Python implementation in `mlens` (I have not played with this, though!)

Links to practical guides and alternative software

- <https://cran.r-project.org/web/packages/SuperLearner/vignettes/Guide-to-SuperLearner.html>
- <https://tlverse.org/tlverse-handbook/sl3.html>
- <http://ml-ensemble.com> (Python)

Further reading and references

- van der Laan, M. J., and Rose, S. (2011) Targeted learning: causal inference for observational and experimental data. Springer Science & Business Media (Ch 3)
- van der Laan, MJ and Rose S. (2018) Targeted Learning in Data Science, Springer Series in Statistics (Ch 18)
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- Naimi A and Balzer L. Stacked generalization: an introduction to super learning. European Journal of Epidemiology (2018) 33:459–464
- Bühlmann, P. (Ed.), Drineas, P. (Ed.), Kane, M. (Ed.), van der Laan, M. (Ed.). (2016). Handbook of Big Data. New York: Chapman and Hall/CRC, (Chapter 19)