

Resampling & Stability selection

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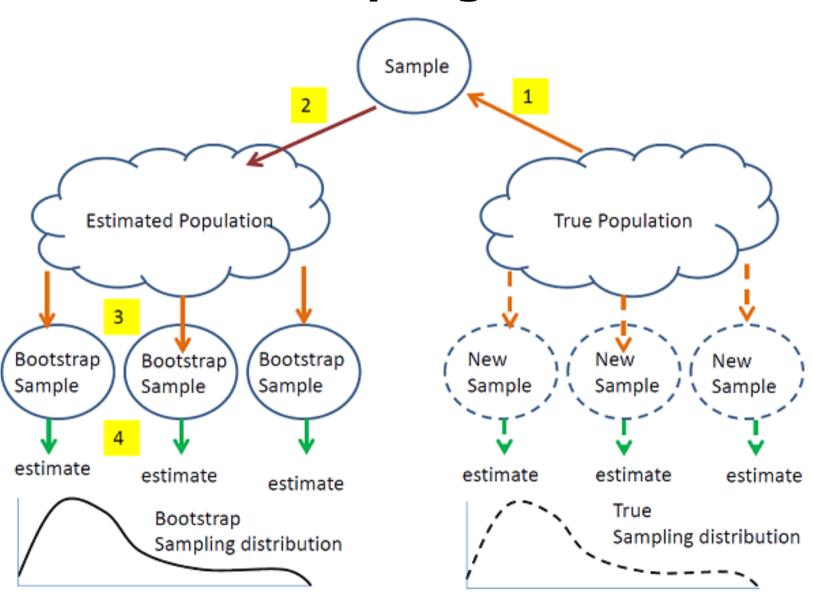




Roadmap

- What is resampling?
- Approaches to resampling:
 - Subsampling
 - Bootstrapping
- Uses of resampling:
 - Model validation: how good is the model?
 - parameter tuning/model selection
 - Model uncertainty: parameters, structure
- Application to exposome-wide analyses
 - Stability selection

What is resampling?





Resampling methods

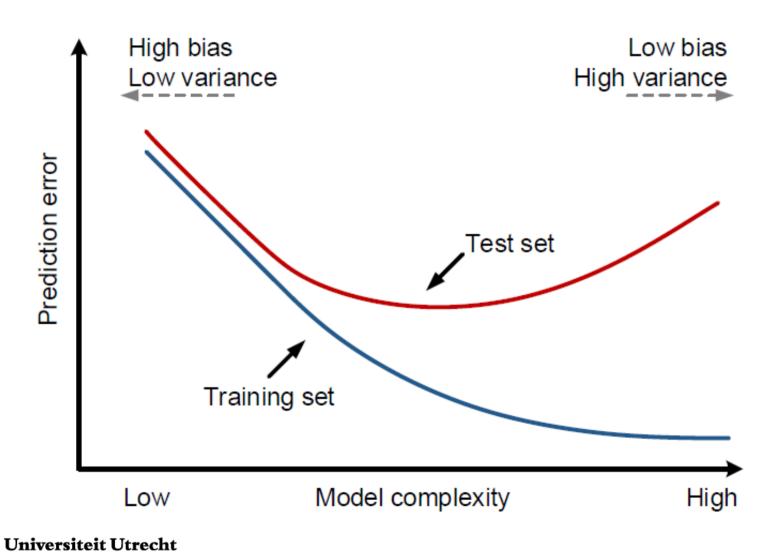
Subsampling

 Sample N* (<N) observations without replacement → new (sub)sample could have come from the original distribution. Mostly used to investigate model validity.

Bootstrapping

 Sample N* (=N) observations with replacement → new (sub)sample could have been a sample from (a discrete version of) the original distribution. Mostly used to investigate model uncertainty.

Use: prediction error





Cross-validation

K-fold cross-validation for est. prediction error:

- Repeated, systematic subsampling: divide sample in K non-overlapping folds
- K-1 folds as training sets to estimate model parameters
- other fold as test set to assess prediction error
- repeat K times and average prediction error

 $LOOCV \rightarrow K = N$

Optimal choice for #folds?

Expected test prediction error:

 $1/(N-N*) \sum_{i=1}^{n} f(N-N*) = 1/N f* \sum_{i=$



Stratified sampling

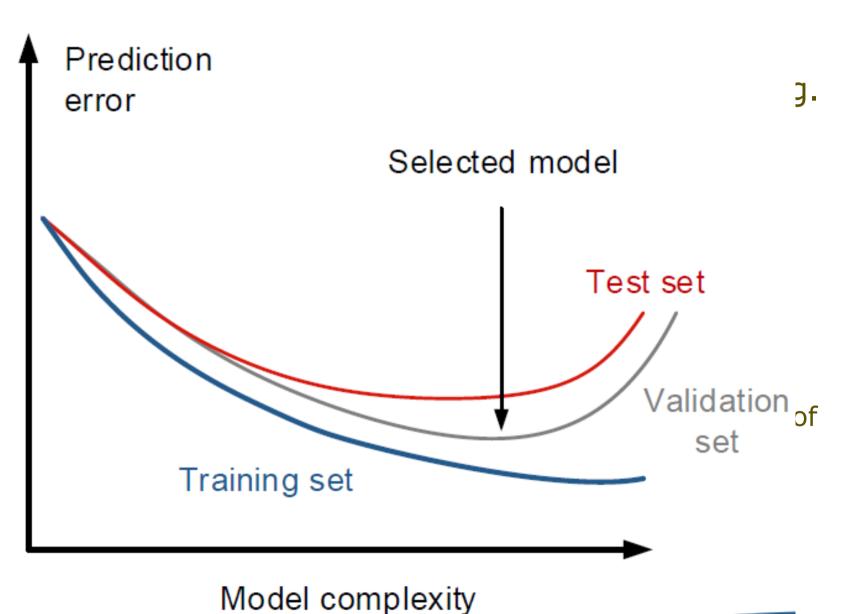
Stratified sampling

- unbalanced response classes
- unbalanced distribution of predictors
- clustered data, time series
- beware of twinning (presence of near identical cases in training and test sets)





Use: parameter tuning

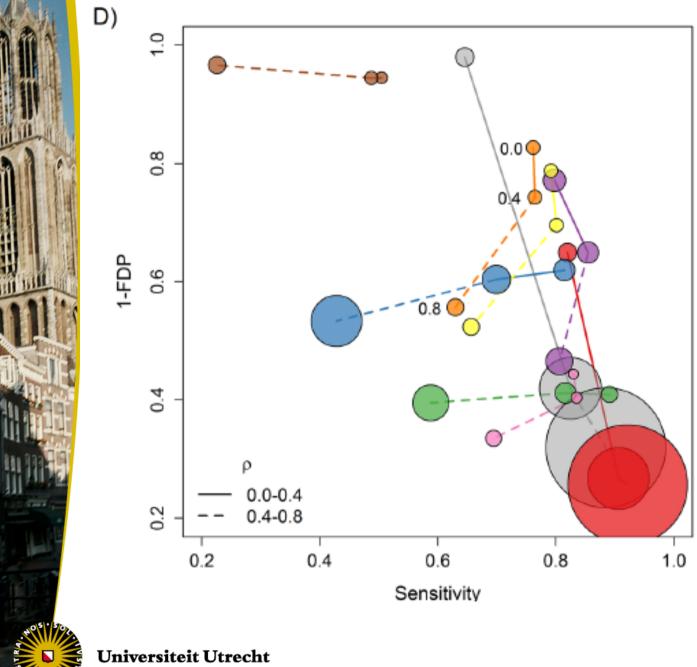




Use: model uncertainty

Model uncertainty:

- estimate variability of parameters (e.g. a slope coefficient) that results from sampling
- bootstrapping often used when analytical approaches (in the form of standard errors) are not directly available (e.g. SE for ratio of parameters)
- estimate variability (instability) of model structure (variable selection models)
- identify influential observations



METHOD

- univariable
- univariable-FDR
- multivariable
- stepwise
- sPLS-DA
- lasso
- elastic net
- Laplace
- boosted

avoid stent





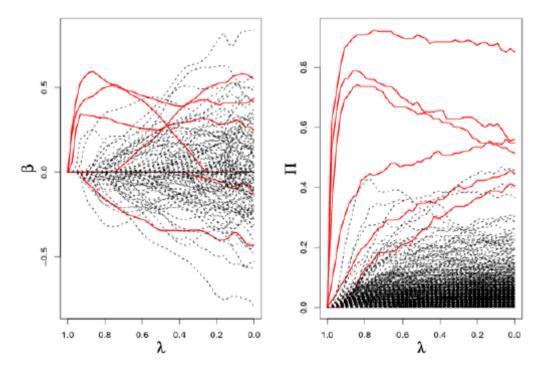




Stability selection

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- setup grid of values for tuning parameter that affects selection of features (i.e. penalties for lasso, pvalues for stepwise selection)
- repeated subsampling (1:1): estimate $P(\beta_i \boxtimes 0)$ across grid





Stability selection

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Meinshausen (2010) provides an upper bound on the number of falsely selected variables (V):

 $E(V) \le 1/2\pi \downarrow thr -1 q \downarrow \Lambda \uparrow 2 /p$

for a chosen cutoff (ϖ_{thr}) and E(V) we can choose the reqularisation region Λ so that the maximum number of non-zero coefficients q_{Λ} equals the calculated value. We then select all variables that have $\max(P\lambda(\beta i \boxtimes 0)) > \varpi_{thr}$

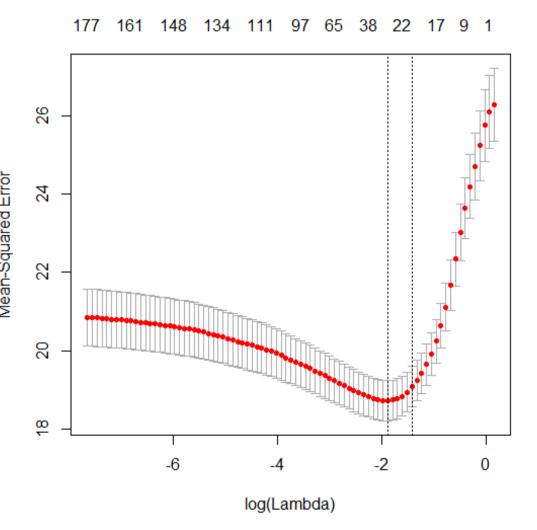


Stability selection example 4/6

- Simulated X r covariance ma measurement biomarkers)
- Outcome Y sir chosen expos

 • CV of lasso results

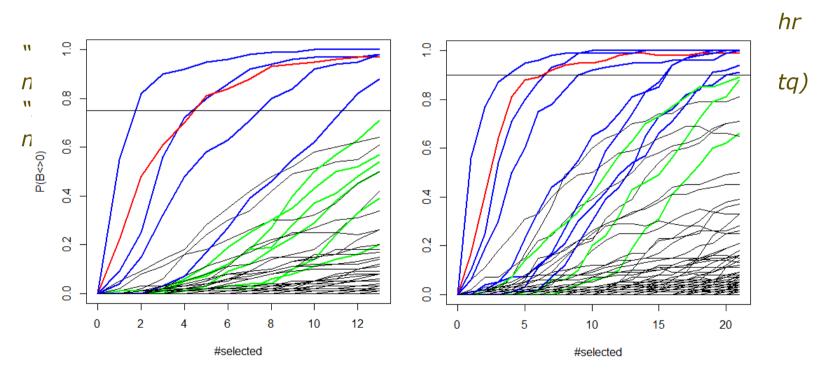
 Wean-Squared Exposers





Stability selection example 5/6

• Stability selection implemented in R packages "hdi" (Meinshausen) and "stabs" (Shah). Need to indicate X and Y, a variable selection





Stability selection example 6/6

- Stability selection does not result in a model (we can obviously fit one with the selected variables only)
- Subsampling needs to be 1:1 for the upper error bound (used here) to hold
- The theoretical conditions for the bound to hold exactly are rather restrictive.
- The bound has been found to be conservative in some practical situations and alternatives have been proposed (e.g. Shah et al. 2013).





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