

Evaluating ML models

## Evaluating machine learning models: Introduction

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# AP1.2: "Evaluation der Prädiktionsgüte in komplexen Situationen"

- PI: Prof. Dr. Anne-Laure Boulesteix
- Staff: Dr. Roman Hornung, H. Schulz-Kümpel, S. Fischer
- Area: Supervised learning (prediction) using ML algorithms
- Focus: Evaluation of prediction performance
- Methods: Resampling-based procedures (e.g., cross-validation)
- Addressed issues:
  - Evaluation of prediction performance in case of violation of the i.i.d. assumption
  - Confidence intervals for performance estimated through resampling



### Output: Two reviews/comparison studies

- Hornung, R., Nalenz, N., Schneider, L., Bender, A., Bothmann, L., Bischl, B., Augustin, A., Boulesteix, A.-L., 2023. Evaluating machine learning models in non-standard settings: An overview and new findings. arXiv:2310.15108. Statistical Science (to appear).
- H. Schulz-Kümpel\*, S. Fischer\*, R. Hornung, A.-L. Boulesteix, Thomas Nagler, Bernd Bischl. Constructing confidence intervals for 'the' generalization error – a comprehensive benchmark study. arXiv:2409.18836. Data-Centric Machine Learning Research (to appear). \*contributed equally.



## A basic resampling procedure: K-fold cross-validation

| Data D                                      |
|---|
| Test-data $\mathcal{D}_{	ext{test}}^{(1)}$  |
| Test-data $\mathcal{D}_{\text{test}}^{(2)}$ |
| Test-data $\mathcal{D}_{	ext{test}}^{(3)}$  |
| Test-data $\mathcal{D}_{test}^{(4)}$        |
| Test-data $\mathcal{D}_{	ext{test}}^{(5)}$  |

- In K-fold cross-validation, the dataset is randomly partitioned into K subsets of (nearly) equal size, termed "folds".
- Each fold serves once as the testing set, while the remaining folds collectively form the training set.
- More broadly, resampling involves the random and repeated **splitting** of data into distinct training and testing sets.



## Project 1: Complex structures beyond i.i.d.

- Machine learning (ML) applications in official statistics frequently deal with complex data structures most of which violate the standard i.i.d. assumption:
  - clustered data
  - spatial data
  - unequal sampling probabilities
  - concept drift
- The presence of these complex structures can introduce bias in generalization error (GE) estimates derived from ordinary resampling methods like cross-validation.
- Tailored resampling techniques are necessary for each data structure to obtain (largely) unbiased GE estimates.



## Project 2: Confidence intervals

- Imagine an accuracy of, say, 90% is estimated using a resampling technique.
- As all estimators, this estimator has a variance. How reliable is it?
- To interpret it, we need a confidence interval.
- Naive approach: Consider the K-folds as i.i.d. observations to derive a confidence interval in the "usual way".
- Problem: The results for the K folds are not i.i.d.!
- More sophisticated techniques are necessary.