Data Splitting

ML Basics

In-sample prediction error

Estimating the test error with training data

ullet Setup: Add training optimism $\hat{\omega}$ to training error

$$\widehat{\mathsf{Err}}_{\mathsf{in}} = \overline{\mathsf{err}} + \hat{\omega}$$

Corrected fit measure for OLS regression

$$C_p = \overline{\operatorname{err}} + 2\frac{d}{n}\hat{\sigma}_{\varepsilon}^2$$

Corrected fit measures for ML-based methods

$$AIC = -\frac{2}{n}LL + 2\frac{d}{n}$$

$$BIC = -2LL + \log(n)d$$

Training set & test set

- Estimate prediction error on new data
 - 1 Fit model using one part of training data
 - 2 Compute test error for the excluded section
- \rightarrow Model assessment

Training set, validation set & test set

- Compare models and estimate prediction error
 - 1 Fit models using training part of training data
 - ② Choose best model using validation set
 - 3 Evaluate final model using test set
- $\rightarrow \ \mathsf{Model} \ \mathsf{tuning} \ \& \ \mathsf{assessment}$

Figure: 80/20 train-test split

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Figure: 50/25/25 Train-validation-test split

Training set & test set

- Estimate prediction error on new data
 - Fit model using one part of training data
 - 2 Compute test error for the excluded section

 \rightarrow Model assessment

Training set, validation set & test set

- Compare models and estimate prediction error
 - 1 Fit models using training part of training data
 - 2 Choose best model using validation set
 - Evaluate final model using test set
- \rightarrow Model tuning & assessment

Figure: 80/20 train-test split

Train Test

Figure: 50/25/25 Train-validation-test split

Leave test data untouched until the end of analysis!

Cross-Validation

- LOOCV (Leave-One-Out Cross-Validation)
 - 1 Fit model on training data while excluding one case
 - 2 Compute test error for the excluded case
 - 3 Repeat step 1 & 2 n times
- k-Fold Cross-Validation
 - Fit model on training data while excluding one group
 - 2 Compute test error for the excluded group
 - 3 Repeat step 1 & 2 k times (e.g. k = 5, k = 10)
- Outlook: nested CV, repeated CV, ...

$$CV(\hat{f}) = \frac{1}{n} \sum_{i=1}^{n} L(y_i, \hat{f}^{-\kappa(i)}(x_i))$$

Standard Errors for CV

$$\frac{1}{\sqrt{K}}\operatorname{sd}\{CV_1(\hat{f}^{-(1)}),...,CV_K(\hat{f}^{-(K)})\}$$

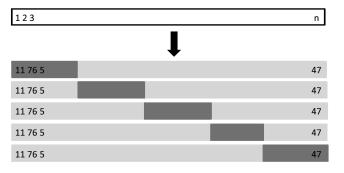
Model selection using k-Fold Cross-Validation

- Choose model with smallest cross-validated error
- Choose smallest model within one standard error of the smallest cross-validated error (1-SE Rule)

More on data splitting

- Simple random splits
 - General approach for "unstructured" data
 - Typically 75% or 80% go into training set
- Stratified splits
 - For classification problems with class imbalance
 - Sampling within each class of Y to preserve class distribution
- Splitting by groups
 - For (temporal) structured data
 - Use specific groups (temporal holdouts) for validation

Figure: 5-Fold Cross-Validation with training set and validation set (example)



James et al. (2013)

Learning curves

How much data is needed?

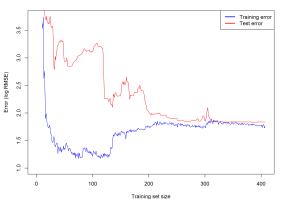
- Idea: Plot training and validation error against training set size
- Allows to study the gain of adding more data
 - Convergence of validation error curve towards training curve
- Can also be used as a diagnosis tool to asses
 - High bias (Underfitting): Curves converge at a high value
 - High variance (Overfitting): Large gap between curves

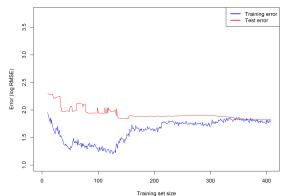
Learning curves

Figure: Learning curves

(a) Linear regression

(b) Regression trees





Performance measures for regression

- Learning curves
- 1 Performance measures for regression
- 2 Software Resources
- 3 References

Performance measures for regression

 r^2 score:

$$r^2 = \operatorname{corr}(y_i, \hat{f}(x_i))^2$$

Residual Sum of Squares (RSS):

$$\sum_{i=1}^n (y_i - \hat{f}(x_i))^2$$

Mean of squared errors (MSE):

$$\frac{1}{n}\sum_{i=1}^{n}(y_{i}-\hat{f}(x_{i}))^{2}$$

Root mean squared error (RMSE):

$$\sqrt{\frac{1}{n}\sum_{i=1}^n(y_i-\hat{f}(x_i))^2}$$

Performance measures for regression

Mean of absolute errors (MAE):

$$\frac{1}{n}\sum_{i=1}^n|(y_i-\hat{f}(x_i))|$$

Median of absolute errors (MEDAE):

median
$$(|y_1 - \hat{f}(x_1)|, ..., |y_n - \hat{f}(x_n)|)$$

Median of squared errors (MEDSE):

$$median((y_1 - \hat{f}(x_1))^2, ..., (y_n - \hat{f}(x_n))^2)$$

Software Resources

Resources for R

- Overview
 - https://cran.r-project.org/web/views/MachineLearning.html
- caret
 - http://topepo.github.io/caret/index.html
- mlr
 - https://mlr-org.github.io/mlr-tutorial/devel/html/
- H2O
 - http://docs.h2o.ai/

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- Domingos, P. (2012). A few useful things to know about machine learning. *Communications of the ACM* 55(10), 78–87.
- Hastie, T., Tibshirani, R., Friedman, J. (2009). The Elements of Statistical Learning: Data Mining, Inference, and Prediction. New York, NY: Springer.
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