Reproducible Computational Research A Perspective

Manuel J. A. Eugster

Institut für Statistik Ludwig-Maximiliams-Universität München



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(*) Based on Boulesteix (2011)

Challenges of

Reproducible and/or Repeatable Validation of Algorithms on Datasets

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No Answers—Only Experiences and (a lot of) Open Questions!



INSTITUT FÜR STATISTIK



Manuel J. A. Eugster & Torsten Hothorn & Friedrich Leisch

Exploratory and Inferential Analysis of Benchmark Experiments

Technical Report Number 030, 2008 Department of Statistics University of Munich

http://www.stat.uni-muenchen.de



B. Components of the exemplar benchmark experiment

B.1. Algorithms

The candidate algorithms are:

- linear discriminant analysis: encoded as , orange; available through the function lda in package MASS.
- naive bayes classifier: encoded as , yellow; available through the function naiveBayes in package e1071.
- k-nearest neighbour classifier: encoded as purple; available through the function knn in package class. The hyperparameter k (the number of neighbours) is determined with crossvalidation between 1 and \(\overline{n}\), n the number of observations.
- classification trees: encoded as , red; available through the function rpart in package rpart. The fulled tree is pruned according to the 1-SE rule (e.g., Venables and Ripley, 2002; Hastie et al., 2001).
- support vector machines: encoded as ■, blue; available through the function svm in package e1071. We use the C-classification machine, which has two hyperparameters γ (the cost of constraints violation) and c (the kernel parameter). Following Meyer et al. (2003) the best choices are determined with a grid search over the two-dimensional parameter space (γ, c), γ ranges from 2⁻⁵ to 2¹² and c from 2⁻¹⁰ to 2⁵.
- neural networks: encoded as , yavailable through the function nnet in package nnet. The hyperparameter is the number of hidden units. The best value is searched with cross-validation between 1 and log(n), n the number of observations (following Meyer et al., 2003).

B.2. Data sets

The benchmark survey is made up of 21 binary classification problems originated from the UCI Machine Learning repository (Asuncion and Newman, 2007):

Problem		#Attributes		#Samples		Class
		nominal	continuous	complete	incomplete	distribution (%)
promotergene	A	57		106		50.00/50.00
hepatitis	В	13	6	80	75	20.65/79.35
0	~		00	000		50.05/10.00



Figure 7: Grouped box plots (Trellis display): the raw performance measures of the candidate



Figure 11: Benchmark survey graph: another representation of the distance matrix. The first 15 distance levels are shown, the color and the with of the edges represent them. Vertices are filled according to the winner algorithm if there is a unique one.

4.3. Inference

Mixed effects model. With linear mixed effects models, the assumptions on the random effects are $b_i \sim N(0, \sigma_1^2)$, $b_{ik} \sim N(0, \sigma_2^2)$ and $\epsilon_{ijk} \sim N(0, \sigma^2)$. Therefore, we estimate two parameters σ_1^2 and σ_2^2 for the effect of the data sets and the sampling within the data sets, respectively. Additionally, 1 + (K - 1) + (M - 1) + (K - 1)(M - 1) fixed effects parameters are estimated.

Example (cont.). In case of our exemplar benchmark survey these are 3 + 126 parameters, see Appendix A.2 for the parameters and a model summary. The global test with ANOVA and the F-test rejects the null hypothesis that all algorithms have the same performance on all data sets. Using Tukey contrasts we test pairwise differences and calculate simultaneous confidence intervals. Figure 12 shows the 95% family-wise confidence intervals. The only Non-significant difference is



Figure 12: Simultaneous 95% confidence intervals for multiple comparisons of means using Tukey constrast based on the mixed effects model of the example experiment.

between orange and green). An interesting aspect appears, blue is a lot better than all other algorithms. We establish the algorithm order

$$blue < red \approx orange \approx green < yellow < purple.$$

All computations are performed using R (R Development Core Team, 2008), the corresponding R functions are part of an R package for the analysis of benchmark experiments which is currently under development and will be released on CRAN in due course. Preliminary versions of the functions and all data used in this article are available from http://www.statistik.lmu.de/~eugster/.

2. Design of benchmark experiments

Following Hothorn et al. (2005), we set up a benchmark experiment according to their real world situation. Given is a data set $\mathfrak{L} = \{z_1, \dots, z_m\}$. We draw *B* learning samples using some resampling method, e.g. sampling with replacement (bootstrapping):

$$\mathcal{L}^{1} = \{z_{1}^{1}, \dots, z_{n}^{1}\}$$
$$\vdots$$
$$\mathcal{L}^{B} = \{z_{1}^{B}, \dots, z_{n}^{B}\}$$

Another possibility is cross-validation. Furthermore we assume that there are K > 1 candidate algorithms a_k (k = 1, ..., K) available for the solution of the underlying problem. For each algorithm a_k the function $a_k(\cdot \mid \mathcal{L}^b)$ is the fitted model based on the sample \mathcal{L}^b . This function itself has a distribution \mathcal{A}_k as it is a random variable depending on \mathcal{L}^b :

$$a_k(\cdot \mid \mathfrak{L}^b) \sim \mathcal{A}_k(\mathfrak{L}), \ k = 1, \dots, K$$

The performance of the candidate algorithm a_k when provided with the training data \mathcal{L}^b is measured by a scalar function p:

$$p_{kb} = p(a_k, \mathfrak{L}^b) \sim \mathcal{P}_k = \mathcal{P}_k(\mathfrak{L})$$

The p_{kb} are samples drawn from the distribution $\mathcal{P}_k(\mathfrak{L})$ of the performance measure of the algorithm k on the data set \mathfrak{L} .

In this paper, we illustrate the analysis of benchmark experiments by means of supervised learning problems. The observations z are of the form z = (y, x) where y denotes the response variable and x describes a vector of input variables. The aim of this learning task is to construct a learner $\hat{y} = a_k(x \mid \mathcal{L}^b)$ which, based on the input variables, provides us with information about the unknown response. The discrepancy between the true response y and the predicted response \hat{y} for one observation z is measured by a scalar loss function $L(y, \hat{y})$. The above introduced performance measure p is in this case defined by some functional μ of the distribution of the loss function:

$$p_{11} = p(q_1, \mathbf{C}^b) = \mu(I(q_1, q_1(\mathbf{x} \mid \mathbf{C}^b))) \approx \mathcal{P}_1(\mathbf{C})$$

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Analysis/Manuscript







- self-made parallelization
- nine days running time

- published R package
- Sweave



- self-made parallelization
- nine days running time

interesting

- published R package
- Sweave

easy

Challenges

Ince et al. (2012):

"The vagaries of hardware, software and natural language will always ensure that exact reproducibility remains uncertain, but withholding code increases the chances that efforts to reproduce results will fail."

Local (for me) reproducible validation:

- Clear separation between benchmark experiment and analysis/manuscript.
- Clear separation between setup and execution:
 Setup: data preparation, algorithm definition, experiment design, resampling strategy, etc.

Execution: parallel computation, cloud computing, etc.

Global (for others) reproducible validation:

- Publish data sets and source code:
 - Data set repositories
 - Licence strategies for data and code:
 - Open data and open source initiatives

- Reproducible Research Standard by Stodden (2009) for Code (GNU GPL or BSD), Media (CC BY), Data (Science Commons Database Protocol)

- Use already published data sets: e.g., UCI Machine Learning Repository (Asuncion and Newman, 2007), ArrayExpress (Parkinson et al., 2010)
- Use "standardized" benchmarking/validation software: e.g., benchmark (Eugster, 2012), caret (Kuhn, 2012), mlr (Bischl, 2012)

Repeatable validation:

- See validation/benchmarking as "real" experiments!
- Follow the rules of experimental designs: "data sets as patients and algorithms as treatments"

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Repeatable validation:

- See validation/benchmarking as "real" experiments!
- Follow the rules of experimental designs: "data sets as patients and algorithms as treatments"
- **? Future:** Validation/Benchmarking platform for randomized experiments (e.g., random assignment of data sets within a problem domain, of candidate algorithms, etc.)

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Images:

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