

Maintainer: Torsten Hothorn

Contact: Torsten.Hothorn at R-project.org

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Several add-on packages implement ideas and methods developed at the borderline between computer science and statistics - this field of research is usually referred to as machine learning. The packages can be roughly structured into the following topics:

- *Neural Networks* : Single-hidden-layer neural network are implemented in package [nnet](#) (shipped with base R). Package [RSNNS](#) offers an interface to the Stuttgart Neural Network Simulator (SNNS). An interface to the FCNN library allows user-extensible artificial neural networks in package [FCNN4R](#).
- *Recursive Partitioning* : Tree-structured models for regression, classification and survival analysis, following the ideas in the CART book, are implemented in [rpart](#) (shipped with base R) and [tree](#). Package [rpart](#) is recommended for computing CART-like trees. A rich toolbox of partitioning algorithms is available in [Weka](#), package [RWeka](#) provides an interface to this implementation, including the J4.8-variant of C4.5 and M5. The [Cubist](#) package fits rule-based models (similar to trees) with linear regression models in the terminal leaves, instance-based corrections and boosting. The [C50](#) package can fit C5.0 classification trees, rule-based models, and boosted versions of these.
Two recursive partitioning algorithms with unbiased variable selection and statistical stopping criterion are implemented in package [party](#). Function `ctree()` is based on non-parametrical conditional inference procedures for testing independence between response and each input variable whereas `mob()` can be used to partition parametric models. Extensible tools for visualizing binary trees and node distributions of the response are available in package [party](#) as well.
Tree-structured varying coefficient models are implemented in package [verpart](#).
For problems with binary input variables the package [LogicReg](#) implements logic regression. Graphical tools for the visualization of trees are available in package [maptree](#).
Trees for modelling longitudinal data by means of random effects is offered by package [REEMtree](#). Partitioning of mixture models is performed by [RPM](#).
Computational infrastructure for representing trees and unified methods for prediction and visualization is implemented in [partykit](#). This infrastructure is used by package [evtree](#) to implement evolutionary learning of globally optimal trees. Oblique trees are available in package [oblique.tree](#).
- *Random Forests* : The reference implementation of the random forest algorithm for regression and classification is available in package [randomForest](#). Package [ipred](#) has bagging for regression, classification and survival analysis as well as bundling, a combination of multiple models via ensemble learning. In addition, a random forest variant for response variables measured at arbitrary scales based on conditional inference trees is implemented in package [party](#). [randomForestSRC](#) implements a unified treatment of Breiman's random forests for survival, regression and classification problems. Quantile regression forests [quantregForest](#) allow to regress quantiles of a numeric response on exploratory variables via a random forest approach. For binary data, [LogicForest](#) is a forest of logic regression trees (package [LogicReg](#)). The [varSelRF](#) and [Boruta](#) packages focus on variable selection by means for random forest algorithms. For large data sets, package [bigRF](#) computes random forests in parallel and uses large memory objects to store the data.
- *Regularized and Shrinkage Methods* : Regression models with some constraint on the parameter estimates can be fitted with the [lasso2](#) and [lars](#) packages. Lasso with simultaneous updates for groups of parameters (groupwise lasso) is available in package [grplasso](#); the [gprreg](#) package implements a number of other group penalization models, such as group MCP and group SCAD. The L1 regularization path for generalized linear models and Cox models can be obtained from functions available in package [glmnet](#), the entire lasso or elastic-net regularization path (also in [elasticnet](#)) for linear regression, logistic and multinomial regression models can be obtained from package [glmnet](#). The [penalized](#) package provides an alternative implementation of lasso (L1) and ridge (L2) penalized regression models (both GLM and Cox models). Package [RXshrink](#) can be used to identify and display TRACEs for a specified shrinkage path and to determine the appropriate extent of shrinkage. Semiparametric additive hazards models under lasso penalties are offered by package [ahaz](#). A generalisation of the Lasso shrinkage technique for linear regression is called relaxed lasso and is available in package [relaxo](#). Fisher's LDA projection with an optional LASSO penalty to produce sparse solutions is implemented in package [penalizedLDA](#). The shrunk centroids classifier and utilities for gene expression analyses are implemented in package [pamr](#). An implementation of multivariate adaptive regression splines is available in package [earth](#). Variable selection through clone selection in SVMs in penalized models (SCAD or L1 penalties) is implemented in package [penalizedSVM](#). Various forms of penalized discriminant analysis are implemented in packages [hda](#), [rda](#), and [sda](#). Package [Liblinear](#) offers an interface to the LIBLINEAR library. The [ncvreg](#) package fits linear and logistic regression models under the SCAD and MCP regression penalties using a coordinate descent algorithm. High-throughput ridge regression (i.e., penalization with many predictor variables) and heteroskedastic effects models are the focus of the [bigRR](#) package. An implementation of bundle methods for regularized risk minimization is available from package [bmm](#).
- *Boosting* : Various forms of gradient boosting are implemented in package [gbm](#) (tree-based functional gradient descent boosting). The Hinge-loss is optimized by the boosting implementation in package [bst](#). Package [GAMBoost](#) can be used to fit generalized additive models by a boosting algorithm. An extensible boosting framework for generalized linear, additive and nonparametric models is available in package [mboost](#). Likelihood-based boosting for Cox models is implemented in [CoxBoost](#) and for mixed models in [GMMBoost](#). GAMLSS models can be fitted using boosting by [gamboostLSS](#).
- *Support Vector Machines and Kernel Methods* : The function `svm()` from [e1071](#) offers an interface to the LIBSVM library and package [kernlab](#) implements a flexible framework for kernel learning (including SVMs, RVMs and other kernel learning algorithms). An interface to the SVMlight implementation (only for one-against-all classification) is provided in package [klaR](#). The relevant dimension in kernel feature spaces can be estimated using [rdetools](#) which also offers procedures for model selection and prediction.
- *Bayesian Methods* : Bayesian Additive Regression Trees (BART), where the final model is defined in terms of the sum over many weak learners (not unlike ensemble methods), are implemented in package [BayesTree](#). Bayesian nonstationary, semiparametric nonlinear regression and design by treed Gaussian processes including Bayesian CART and treed linear models are made available by package [tgp](#).
- *Optimization using Genetic Algorithms* : Packages [rgp](#) and [regenoud](#) offer optimization routines based on genetic algorithms. The package [Rnalschains](#) implements memetic algorithms with local search chains, which are a special type of evolutionary algorithms, combining a steady state genetic algorithm with local search for real-valued parameter optimization.
- *Association Rules* : Package [arules](#) provides both data structures for efficient handling of sparse binary data as well as interfaces to implementations of Apriori and Eclat for mining frequent itemsets, maximal frequent itemsets, closed frequent itemsets and association rules.
- *Fuzzy Rule-based Systems* : Package [fibs](#) implements a host of standard methods for learning fuzzy rule-based systems from data for regression and classification. Package [RoughSets](#) provides comprehensive implementations of the rough set theory (RST) and the fuzzy rough set theory (FRST) in a

single package.

- *Model selection and validation* : Package [e1071](#) has function `tune()` for hyper parameter tuning and function `errorest()` ([ipred](#)) can be used for error rate estimation. The cost parameter C for support vector machines can be chosen utilizing the functionality of package [svmpath](#). Functions for ROC analysis and other visualisation techniques for comparing candidate classifiers are available from package [ROCR](#). Packages [hdi](#) and [stabs](#) implement stability selection for a range of models, [hdi](#) also offers other inference procedures in high-dimensional models.
- *Meta packages* : Package [caret](#) provides miscellaneous functions for building predictive models, including parameter tuning and variable importance measures. The package can be used with various parallel implementations (e.g. MPI, NWS etc). In a similar spirit, package [mlr](#) offers a high-level interface to various statistical and machine learning packages.
- *Elements of Statistical Learning* : Data sets, functions and examples from the book [The Elements of Statistical Learning: Data Mining, Inference, and Prediction](#) by Trevor Hastie, Robert Tibshirani and Jerome Friedman have been packaged and are available as [ElemStatLearn](#).
- *GUI* [rattle](#) is a graphical user interface for data mining in R.

[CORElearn](#) implements a rather broad class of machine learning algorithms, such as nearest neighbors, trees, random forests, and several feature selection methods. Similar, package [miner](#) interfaces several learning algorithms implemented in other packages and computes several performance measures.

CRAN packages :

- [ahaz](#)
- [arules](#)
- [BayesTree](#)
- [bigrf](#)
- [bigRR](#)
- [bmm](#)
- [Boruta](#)
- [bst](#)
- [C50](#)
- [caret](#)
- [CORElearn](#)
- [CoxBoost](#)
- [Cubist](#)
- [e1071](#) (core)
- [earth](#)
- [elasticnet](#)
- [ElemStatLearn](#)
- [evtree](#)
- [FCNN4R](#)
- [fibs](#)
- [GAMBoost](#)
- [gamboostLSS](#)
- [gbm](#) (core)
- [glmnet](#)
- [glmpath](#)
- [GMMBoost](#)
- [grplasso](#)
- [grpreg](#)
- [hda](#)
- [hdi](#)
- [ipred](#)
- [kernlab](#) (core)
- [klaR](#)
- [lars](#)
- [lasso2](#)
- [LiblineaR](#)
- [LogicForest](#)
- [LogicReg](#)
- [maptree](#)
- [mboost](#) (core)
- [mlr](#)
- [ncvreg](#)
- [nnet](#) (core)
- [oblique.tree](#)
- [pamr](#)
- [party](#)
- [partykit](#)
- [penalized](#)
- [penalizedLDA](#)
- [penalizedSVM](#)
- [quantregForest](#)

- [randomForest](#) (core)
- [randomForestSRC](#)
- [rattle](#)
- [rda](#)
- [rdetools](#)
- [REEMtree](#)
- [relaxo](#)
- [rgenoud](#)
- [rgp](#)
- [Rmalschains](#)
- [miner](#)
- [ROCR](#)
- [RoughSets](#)
- [rpart](#) (core)
- [RPMM](#)
- [RSNNS](#)
- [RWeka](#)
- [RXshrink](#)
- [sda](#)
- [stabs](#)
- [svmpath](#)
- [tgp](#)
- [tree](#)
- [varSelRF](#)
- [vcrpart](#)

Related links:

- [MLOSS: Machine Learning Open Source Software](#)
- [Boosting Research Site](#)