

## R Code

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♠ library(MASS)
lda(), qda() ≈ lm()
♠ library(class)
knn(train, test, cl, k = 1, l = 0, prob = FALSE, use.all = TRUE)
♠ library(boot)
cv.glm(data, glmfit, cost, K)
boot(data, statistic, R, sim = "ordinary")
♠ library(leaps)
## S3 method for class 'formula'
regsubsets(x=, data=, nvmax=8, force.in=NULL, force.out=NULL, intercept=TRUE, method=c("exhaustive", "backward", "forward", "stepAIC"))
♠ library(glmnet)
glmnet(x, y, family=c("gaussian", "binomial", "poisson", "multinomial", "cox", "mgaussian"), alpha = 1, lambda=NULL)
alpha: The elasticnet mixing parameter, with  $\alpha = 1$  the lasso penalty, and  $\alpha = 0$  the ridge penalty.
 $(1 - \alpha)/2 \|\beta\|_2^2 + \alpha \|\beta\|_1$ .
'alpha=1' is the lasso penalty, and 'alpha=0' the ridge penalty.
## S3 method for class 'glmnet'
predict(object, newx, s = NULL, type=c("link", "response", "coefficients", "nonzero", "class"), exact = FALSE, offset, ...)
newx: Matrix of new values for 'x' at which predictions are to be made. Must be a matrix; can be sparse as in 'Matrix' package. This argument is not used for 'type=c("coefficients", "nonzero")'
♠ library(pls)
mvr(formula, ncomp, data, subset, method = pls.options()$mvralg, scale = FALSE, validation = c("none", "CV", "LOO"), model = TRUE, x = FALSE, y = FALSE, ...)
pls(..., method = pls.options()$plsr)
pcr(..., method = pls.options()$pcr)
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♠ library(splines)
bs(x, df = NULL, knots = NULL, degree = 3, intercept = FALSE, Boundary.knots = range(x))
ns(x, df = NULL, knots = NULL, intercept = FALSE, Boundary.knots = range(x))
smooth.spline(x, y = NULL, w = NULL, df, spar = NULL, cv = FALSE, all.knots = FALSE, nknots = .nknots.smspl, keep.data = TRUE, df.offset = 0, penalty = 1, control.spar = list(), tol = 1e-6 * IQR(x))
♠ library(gam)
gam(formula, family = gaussian, data, weights, subset, na.action, start, etastart, mustart, control = gam.control(...), model=TRUE, method, x=FALSE, y=TRUE, ...)
lo(..., span=0.5, degree=1)
gam.lo(x, y, w, span, degree, ncols, xeval)
♠ library(gam)
tree(formula, data, weights, subset, na.action = na.pass, control = tree.control(nobs, ...), method = "recursive.partition", split = c("deviance", "gini"), model = FALSE, x = FALSE, y = TRUE, wts = TRUE, ...)
prune.tree(tree, k = NULL, best = NULL, newdata, nwts, method = c("deviance", "misclass"), loss, eps = 1e-3)
cv.tree(object, rand, FUN = prune.tree, K = 10, ...)
♠ library(randomForest)
## S3 method for class 'formula'
randomForest(formula, data=NULL, ..., subset, na.action=na.fail)
## Default S3 method:
randomForest(x, y=NULL, ntree=500, mtry=if (!is.null(y) && !is.factor(y)) max(floor(ncol(x)/3), 1) else floor(sqrt(ncol(x))), importance=FALSE, proximity, oob.prox=proximity)
## S3 method for class 'randomForest'
importance(x, type=NULL, class=NULL, scale=TRUE, ...)
♠ library(gbm)
gbm(formula = formula(data), distribution = "bernoulli", data = list(), n.trees = 100, interac-
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tion.depth = 1, n.minobsinnode = 10, shrinkage = 0.001, cv.folds=0, verbose = "CV")
```

Currently available options are "gaussian" (squared error), "laplace" (absolute loss), "tdist" (t-distribution loss), "bernoulli" (logistic regression for 0-1 outcomes), "huberized" (huberized hinge loss for 0-1 outcomes), "multinomial" (classification when there are more than 2 classes), "adaboost" (the AdaBoost exponential loss for 0-1 outcomes), "poisson" (count outcomes), "coxph" (right censored observations), "quantile", or "pairwise" (ranking measure using the LambdaMart algorithm).

## Nouns

cross-entropy(deviance)  
feedforward neural network  
back propagation algorithm  
Markov random field  
Restricted Boltzman Machines  
energy function  
contrastive divergence  
generalized cross-validation  
Adaboost.M1 algorithm  
forward stagewise additive modeling  
PRSS, Penalized sum of squares  
backfitting  
classification Error rate(Misclassification rate)  
Gini Index  
Cross-Entropy or Deviance  
softmax function  
Parzen estimate(Kernel)  
varying coefficient model  
Nadaraya-Watson kernel-weight average  
locally weighted linear regression  
Epanechnikov/Tri-Cube kernel  
Gaussian kernel  
Nearest Neighbor kernel  
locally polynomial regression  
stochastic search variable selection(SSVS)