# randomForestSRC CHEAT SHEET



### **Basics**

randomForestSRC is a fast OpenMP and memory efficient package for fitting random forests (RF) for univariate, multivariate, unsupervised, survival, competing risks, class imbalanced classification and quantile regression. A basic grow call is of the form:

#### rfsrc(formula, data, ntree, mtry, nodesize)

Grow your RF through **rfsrc**, specify your model in **formula**, provide your data frame in **data** and tune your model via **ntree**, **mtry**, **nodesize**.

### **Specify a formula**

Survival	rfsrc(Surv(time, status) ~ ., data = veteran)
Competing Risk	rfsrc(Surv(time, status) ~ ., data = wihs)
Regression	rfsrc(Ozone ~., data = airquality)
Quantile Regression	quantreg(mpg ~ ., data = mtcars)
Classification	rfsrc(Surv(time, status) ~ ., data=veteran)
Imbalanced Two-Class	imbalanced(status ~ ., data = breast)
Multivariate Regression	rfsrc(Multivar(mpg, cyl) ~., data = mtcars)
Mixed Regression	rfsrc(cbind(Species,Sepal.Length)~.,data=iris)
Quantile Regression	quantreg(cbind(mpg, cyl) ~ ., data = mtcars)
MV Mixed Quantile	quantreg(cbind(Species,Sepal.Length)~.,data=iris
Unsupervised	rfsrc(data = mtcars)
sidClustering	sidClustering(data = mtcars)
Breiman (Shi-Horvath)	sidClustering(data = mtcars, method = "sh")

### **Clean up and impute data**

a z choose your variables in **formula** and grow a tree.



your outcome(s) will be saved in <code>o\$y</code> and your predictors are in <code>o\$x</code> from <code>dta</code> without missing values. To impute your data, use

o <- impute(y ~ a + z, data = dta)

vlalblz

o <- rfsrc(y ~ a + z, data = dta, na.action = "na.impute")</pre>

# **Tune mtry and nodesize**

tune Find the optimal mtry and nodesize tuning parameter for a random forest using out-of-bag (OOB) error

0.55

0.50

0.45

0.40





### Grow

#### Convenient interface for growing a CART tree

#### Fast OpenMP parallel computing of random forests

```
rfsrc(formula, data, ntree = 500,
       mtry = NULL, ytry = NULL,
       nodesize = NULL, nodedepth = NULL,
       splitrule = NULL, nsplit = 10,
       importance = c(FALSE, TRUE, "none", "permute",
                      "random", "anti"),
       ensemble = c("all", "oob", "inbag"),
       bootstrap = c("by.root", "none", "by.user"),
       samptype = c("swor", "swr"),
       samp = NULL, membership = FALSE,
       na.action = c("na.omit", "na.impute"),
       nimpute = 1,
       ntime = 250, cause,
       proximity = FALSE, distance = FALSE,
       forest.wt = FALSE, xvar.wt = NULL,
       yvar.wt = NULL, split.wt = NULL,
       case.wt = NULL,
       forest = TRUE,
       var.used = c(FALSE, "all.trees", "by.tree"),
       split.depth = c(FALSE, "all.trees", "by.tree"),
       seed = NULL, do.trace = FALSE,
       statistics = FALSE, ...)
```

rfsrc.fast Fast approximate random forests using subsampling
with forest options set to encourage computational speed

rfsrc.anonymous Random forests carefully modified so as not to save the original training data when sharing

synthetic Synthetic random forest using synthetic features

 $\verb"imbalanced" Solutions to the two-class imbalanced problem"$ 

quantreg Univariate or multivariate quantile regression forest and returns its conditional quantile and density values

 ${\tt sidClustering} \ \ Clustering \ of unsupervised \ data$ 

# **Inference from the Forest**

#### **Ensemble Predicted Value for Training Data**

o <- rfsrc(Ozone ~ ., data = airquality)</pre>

Inbag and out-of-bag (OOB) predicted values for the training dataset are in <code>ospredicted</code> and <code>ospredicted.oob</code>

#### **Other Ensemble Values for Training Data**

• For classification problem, we also have \$class and \$class.oob for class labels

• For survival problem, we have \$survival and \$survival.oob for survival function \$chf and \$chf.oob for cumulative hazard function \$cif and \$cif.oob for cumulative incidence function

#### Prediction Error for Assessing Model Performance

o <- rfsrc(Species ~ ., data=iris, block.size=1)</pre>



o\$err.rate returns tree cumulative OOB error rate; print (o) lists OOB error rate in the bottom; plot (o) plots OOB error rate along with number of trees; get.auc(y, prob) obtains the value of AUC (area under the ROC curve)

 $\verb"get.mv.error" obtains error rate from a multivariate random forest$ 



150 200 250 300

Solar R

#### Visualization

plot.survival plots various survival estimates



#### **Tree Visualization**

get.tree extract a single tree from a forest and plot it on your browser

mtcars.unspv <- rfsrc(data = mtcars)</pre> plot(get.tree(mtcars.unspv, 5))

#### **Split Statistics**

stat.split acquires split statistic information. The end-cut preference (ECP) splitting property can be plotted

# **Predict on New Data**

o.pred <- predict(object = o, newdata)</pre>

Predicted values for the new dataset are in o.pred\$predicted

get.mv.predicted returns predicted value for multivariate regression analysis

### Restore

Restoration using the predict function makes it possible for users to acquire information from the grow forest without the computational expense of having to regrow a new forest

Examples of restore are as follows (extract: proximity, variable splitting behavior, performance over specific trees)

o <- rfsrc(Ozone ~ ., data = airquality)</pre>

predict(o, proximity = TRUE)\$proximity predict(0.obj, var.used = "by.tree")\$var.used predict(o, get.tree=10:15)\$err.rate

### **Variable Selection**

#### Variable Importance (VIMP)

o <- rfsrc(Species ~ ., iris, importance = TRUE)</pre> Or

etosa Petal.Width Petal.Lengt Sepal.Leng Sepal.Widt

gear am vs

qsec

drat

0.2 0.4 0.6 0.8

Variable Importance (Species

standardized vimp (mpg)

obj <- rfsrc(Species ~ ., data = iris)</pre> o <- vimp(obi)</pre> Petal.Width Petal.Lengt Sepal.Lengt

o\$importance returns permutation VIMP and plot (o) plots VIMP when setting importance to "permute" or "TRUE" in rfsrc or using vimp

subsample subsample forests for VIMP confidence intervals

- plot.sample plots Subsampled VIMP confidence intervals
- o <- rfsrc(mpg ~ ., mtcars)</pre>

smp.o <- subsample(reg.o, B=25,</pre> subratio=.5)

plot.subsample(smp.o)

holdout.vimp calculates hold out VIMP from the error rate of blocks of trees grown with and without a variable

get.mv.vimp returns VIMP from a multivariate random forest

#### **Minimal Depth**

max.subtree extracts minimal depth and maximal subtree information used for variable selection and identifying interactions between variables



var.select(formula, data, method) Variable selection or hunting by setting method

md	Minimal depth (default)
vh	Variable hunting
vh.vimp	Variable hunting with VIMP

### **Partial Plot**



#### **Partial Dependence Plot**

plot.variable(o, xvar.names, partial = TRUE) and partial

Categorical predictor:







get.partial.plot.data is a handy function that parses the output from "partial.rfsrc" in format suitable for plots







300

disp