Iris dataset

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Introduction

Iris dataset probably is one of the most famous dataset. The dataset can be found here. However, the CSV format can be found here.

Getting started

Loading the dataset

```r
iris = read.csv("iris.csv")
```

Take a quick look

```r
str(iris)
```

```
## 'data.frame':    150 obs. of  6 variables:
##  $ X           : int  1 2 3 4 5 6 7 8 9 10 ...
##  $ Sepal.Length: num  5.1 4.9 4.7 4.6 5 5.4 4.6 5 4.4 4.9 ...
##  $ Sepal.Width : num  3.5 3 3.2 3.1 3.6 3.9 3.4 3.4 2.9 3.1 ...
##  $ Petal.Length: num  1.4 1.4 1.3 1.5 1.4 1.7 1.4 1.5 1.4 1.5 ...
##  $ Petal.Width : num  0.2 0.2 0.2 0.2 0.2 0.4 0.3 0.2 0.2 0.1 ...
##  $ Species     : Factor w/ 3 levels "setosa","versicolor",..: 1 1 1 1 1 1 1 1 1 1 ...
```

There are 150 lines, i.e. 150 instances in the dataset, 4 columns (4 features), and 3 classes.

We might want to divide train/test dataset (or using cross-validation as later).

```r
require(caTools)
```

```
## Loading required package: caTools
```

```r
# 75% for train and 25% for test
sample = sample.split(iris$Species, SplitRatio = 0.75)
train = subset(iris, sample == TRUE)
test = subset(iris, sample == FALSE)
```

Test the division

```r
nrow(train)
```

```
## [1] 114
```

```r
nrow(test)
```

```
## [1] 36
```

Check for NA values

```r
sum(is.na(df))
```

```
## Warning in is.na(df): is.na() applied to non-(list or vector) of type
## 'closure'
```

```
## [1] 0
```

Classification

Multinomial Logistic Regression

```r
require(caret)
```

```
## Loading required package: caret
```

```
## Loading required package: lattice
```

```
## Loading required package: ggplot2
```

```r
# train
train.multinom = train(Species ~ Sepal.Length + Sepal.Width +
    Petal.Length + Petal.Width, data = train, method = "multinom")
```

```
## Loading required package: nnet
```

```r
# predict with test data
predict.multinom = predict(train.multinom, newdata = test)

# check the result
table.multinom = table(predict.multinom, test$Species)

# full result
table.multinom
```

```
##                 
## predict.multinom setosa versicolor virginica
##       setosa         12          0         0
##       versicolor      0         12         1
##       virginica       0          0        11
```

```
# accuracy
sum(diag(table.multinom))/sum(table.multinom)
```

```
## [1] 0.9722222
```

Well, quite cool. The accuracy is 97%. How about other algorithms?

SVM

```
library(e1071)
library(caret)
train.svm = train(Species ~ Sepal.Length + Sepal.Width + Petal.Length +
    Petal.Width, data = train, method = "svmLinear")
```

```
# predict with test data
predict.svm = predict(train.svm, newdata = test)

# check the result
table.svm = table(predict.svm, test$Species)

# full result
table.svm
```

```
##
## predict.svm  setosa versicolor virginica
##   setosa         12          0         0
##   versicolor      0         12         0
##   virginica       0          0        12
```

```
# accuracy
sum(diag(table.svm))/sum(table.svm)
```

```
## [1] 1
```

Again, the accuracy score is 97.2%.

Decision tree

```
library(e1071)
library(caret)
train.rpart = train(Species ~ Sepal.Length + Sepal.Width + Petal.Length +
    Petal.Width, data = train, method = "rpart")
```

```
# predict with test data
predict.rpart = predict(train.rpart, newdata = test)

# check the result
```

```
table.rpart = table(predict.rpart, test$Species)

# full result
table.rpart
```

```
##
## predict.rpart setosa versicolor virginica
##    setosa         12          0         0
##    versicolor      0         11         2
##    virginica       0          1        10
```

```
# accuracy
sum(diag(table.rpart))/sum(table.rpart)
```

```
## [1] 0.9166667
```

Not very good this time. Only 91%.

Random forest

Usually random forest provide very good classification results. How about this case?

```
# we will use h2o for speeding up not really need because the
# data is small
library(h2o)
```

```
## Loading required package: statmod
```

```
##
## ----------------------------------------------------------------------
##
## Your next step is to start H2O:
##     > h2o.init()
##
## For H2O package documentation, ask for help:
##     > ??h2o
##
## After starting H2O, you can use the Web UI at http://localhost:54321
## For more information visit http://docs.h2o.ai
##
## ----------------------------------------------------------------------
```

```
##
## Attaching package: 'h2o'
```

```
## The following objects are masked from 'package:stats':
##
##     cor, sd, var
## The following objects are masked from 'package:base':
##
##     &&, %*%, %in%, ||, apply, as.factor, as.numeric, colnames,
##     colnames<-, ifelse, is.character, is.factor, is.numeric, log,
##     log10, log1p, log2, round, signif, trunc
```

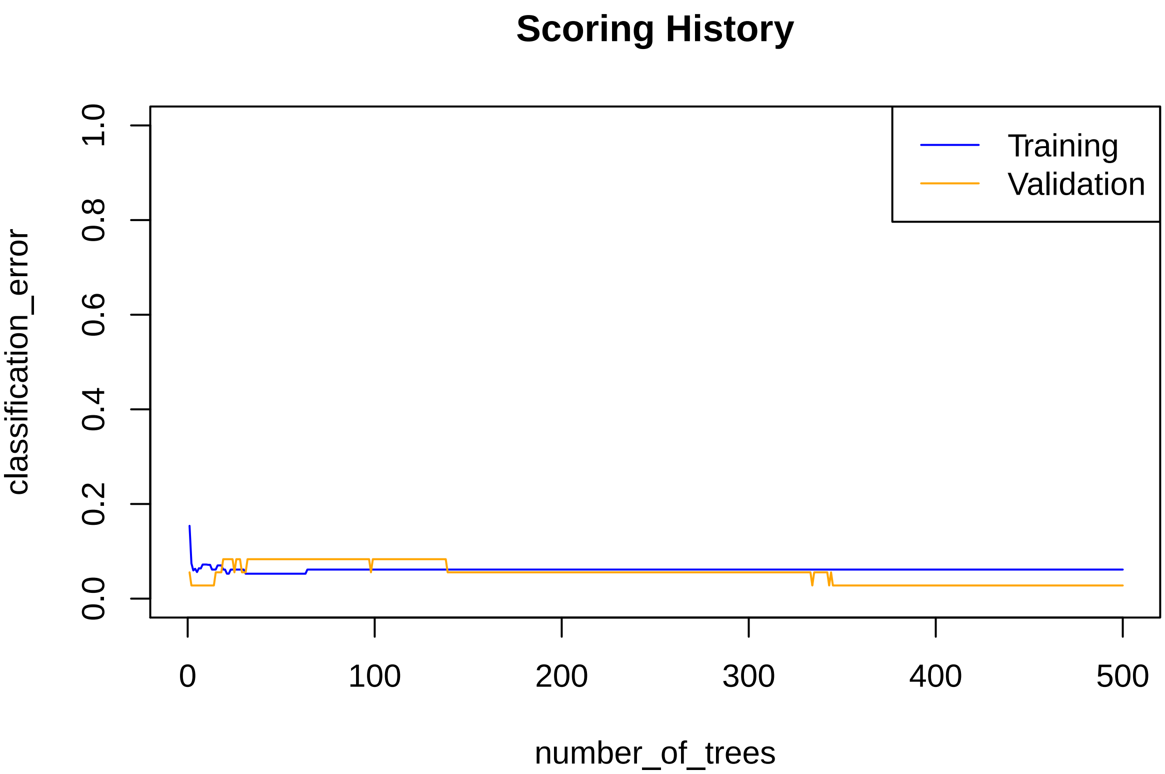
```
h2o.init()

train.rf = h2o.randomForest(y = 6, x = 2:5, training_frame = as.h2o(train),
    validation_frame = as.h2o(test), ntrees = 500)
```

```
print(train.rf)
```

```
## Model Details:
## ==============
##
## H2OMultinomialModel: drf
## Model ID:  DRF_model_R_1477488686931_1
## Model Summary:
##   number_of_trees number_of_internal_trees model_size_in_bytes min_depth
## 1             500                     1500              192663         1
##   max_depth mean_depth min_leaves max_leaves mean_leaves
## 1         9    3.24800          2         15     5.18400
##
##
## H2OMultinomialMetrics: drf
## ** Reported on training data. **
## ** Metrics reported on Out-Of-Bag training samples **
##
## Training Set Metrics:
## =====================
##
## Extract training frame with `h2o.getFrame("train")`
## MSE: (Extract with `h2o.mse`) 0.03315535
## RMSE: (Extract with `h2o.rmse`) 0.1820861
## Logloss: (Extract with `h2o.logloss`) 0.1009518
## Mean Per-Class Error: 0.06140351
## Confusion Matrix: Extract with `h2o.confusionMatrix(<model>,train = TRUE)`)
## =========================================================================
## Confusion Matrix: vertical: actual; across: predicted
##            setosa versicolor virginica  Error      Rate
## setosa         38          0         0 0.0000 =  0 / 38
## versicolor      0         35         3 0.0789 =  3 / 38
## virginica       0          4        34 0.1053 =  4 / 38
## Totals         38         39        37 0.0614 = 7 / 114
##
## Hit Ratio Table: Extract with `h2o.hit_ratio_table(<model>,train = TRUE)`
## =======================================================================
## Top-3 Hit Ratios:
##   k hit_ratio
## 1 1  0.938596
## 2 2  1.000000
## 3 3  1.000000
```

```
##
##
## H2OMultinomialMetrics: drf
## ** Reported on validation data. **
##
## Validation Set Metrics:
## =====================
##
## Extract validation frame with `h2o.getFrame("test")`
## MSE: (Extract with `h2o.mse`) 0.04260067
## RMSE: (Extract with `h2o.rmse`) 0.2063993
## Logloss: (Extract with `h2o.logloss`) 0.1526042
## Mean Per-Class Error: 0.02777778
## Confusion Matrix: Extract with `h2o.confusionMatrix(<model>,valid = TRUE)`)
## =========================================================================
## Confusion Matrix: vertical: actual; across: predicted
##            setosa versicolor virginica  Error     Rate
## setosa         12          0         0 0.0000 = 0 / 12
## versicolor      0         12         0 0.0000 = 0 / 12
## virginica       0          1        11 0.0833 = 1 / 12
## Totals         12         13        11 0.0278 = 1 / 36
##
## Hit Ratio Table: Extract with `h2o.hit_ratio_table(<model>,valid = TRUE)`
## =======================================================================
## Top-3 Hit Ratios:
##   k hit_ratio
## 1 1  0.972222
## 2 2  1.000000
## 3 3  1.000000
```

```r
plot(train.rf)
```



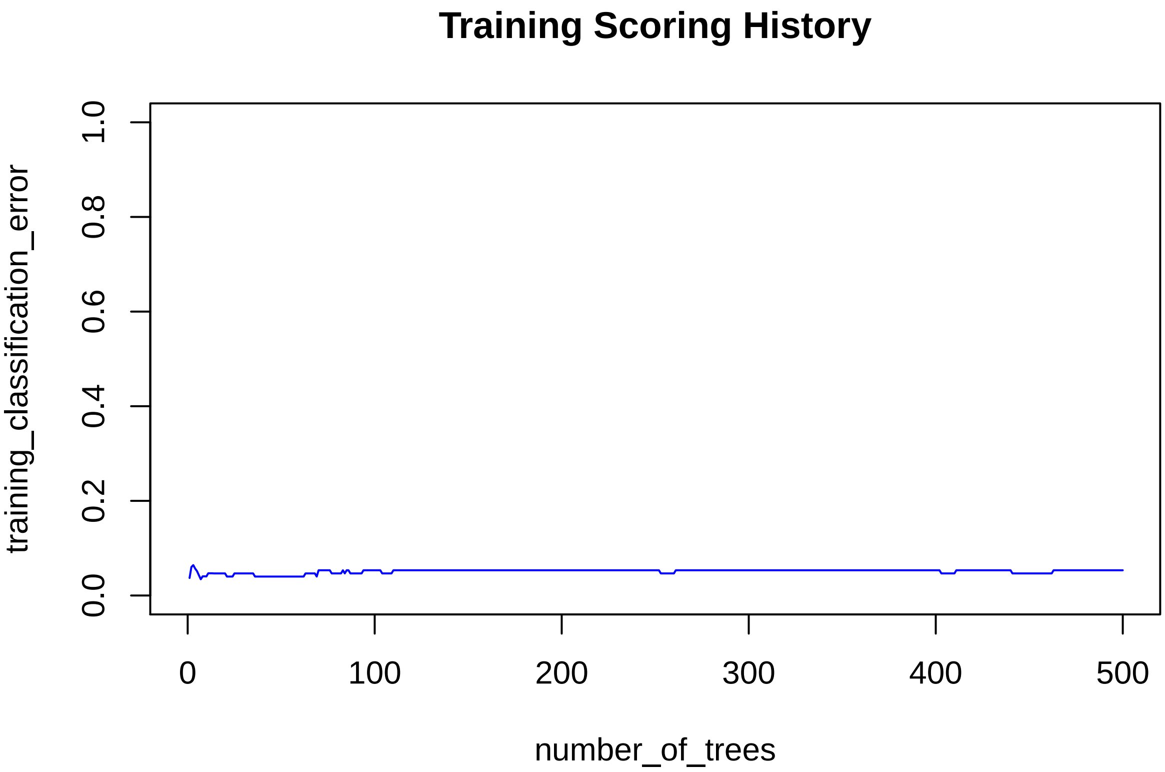
Random Forest gave us the accuracy score of 100%. So impressive. How about if we use cross-validation?

```
train.rf = h2o.randomForest(y = 6, x = 2:5, training_frame = as.h2o(iris),
    ntrees = 500, nfolds = 5)
```

```
print(train.rf)
```

```
## Model Details:
## ==============
##
## H2OMultinomialModel: drf
## Model ID:  DRF_model_R_1477488686931_2
## Model Summary:
##   number_of_trees number_of_internal_trees model_size_in_bytes min_depth
## 1             500                     1500              211853         1
##   max_depth mean_depth min_leaves max_leaves mean_leaves
## 1        11    3.71067          2         17     6.19600
##
##
## H2OMultinomialMetrics: drf
## ** Reported on training data. **
## ** Metrics reported on Out-Of-Bag training samples **
##
## Training Set Metrics:
## =====================
##
## Extract training frame with `h2o.getFrame("iris")`
## MSE: (Extract with `h2o.mse`) 0.03552398
## RMSE: (Extract with `h2o.rmse`) 0.1884781
## Logloss: (Extract with `h2o.logloss`) 0.1151747
## Mean Per-Class Error: 0.05333333
## Confusion Matrix: Extract with `h2o.confusionMatrix(<model>,train = TRUE)`)
## =========================================================================
## Confusion Matrix: vertical: actual; across: predicted
##            setosa versicolor virginica  Error      Rate
## setosa         50          0         0 0.0000 =  0 / 50
## versicolor      0         47         3 0.0600 =  3 / 50
## virginica       0          5        45 0.1000 =  5 / 50
## Totals         50         52        48 0.0533 = 8 / 150
##
## Hit Ratio Table: Extract with `h2o.hit_ratio_table(<model>,train = TRUE)`
## =======================================================================
## Top-3 Hit Ratios:
##   k hit_ratio
## 1 1  0.946667
## 2 2  1.000000
## 3 3  1.000000
##
##
##
## H2OMultinomialMetrics: drf
## ** Reported on cross-validation data. **
## ** 5-fold cross-validation on training data (Metrics computed for combined holdout predictions) **
##
## Cross-Validation Set Metrics:
## =====================
##
## Extract cross-validation frame with `h2o.getFrame("iris")`
## MSE: (Extract with `h2o.mse`) 0.033464
## RMSE: (Extract with `h2o.rmse`) 0.1829317
## Logloss: (Extract with `h2o.logloss`) 0.109004
## Mean Per-Class Error: 0.05333333
## Hit Ratio Table: Extract with `h2o.hit_ratio_table(<model>,xval = TRUE)`
## =======================================================================
## Top-3 Hit Ratios:
##   k hit_ratio
## 1 1  0.946667
## 2 2  1.000000
## 3 3  1.000000
##
##
## Cross-Validation Metrics Summary:
##                                 mean          sd  cv_1_valid   cv_2_valid
## accuracy                   0.9496956 0.018866044   0.9444444          1.0
## err                      0.050304387 0.018866044 0.055555556          0.0
## err_count                        1.6  0.56568545         2.0          0.0
## logloss                   0.10382761 0.039743733  0.14378677 0.0094938725
## max_per_class_error      0.096007325  0.03864481 0.083333336          0.0
## mean_per_class_accuracy   0.95371187 0.017162396   0.9484127          1.0
## mean_per_class_error     0.046288155 0.017162396 0.051587302          0.0
## mse                      0.031515434 0.012744342 0.045896105  3.162059E-4
## r2                         0.9513115 0.018444968    0.924516   0.99960476
## rmse                      0.16078062 0.053221356  0.21423376   0.01778218
##                          cv_3_valid  cv_4_valid  cv_5_valid
## accuracy                       0.92  0.94285715   0.9411765
## err                            0.08 0.057142857  0.05882353
## err_count                       2.0         2.0         2.0
## logloss                  0.17367926   0.1083575  0.08382064
## max_per_class_error      0.15384616         0.1  0.14285715
## mean_per_class_accuracy  0.94871795  0.94285715   0.9285714
## mean_per_class_error    0.051282052 0.057142857 0.071428575
## mse                     0.051181864 0.035247233  0.02493576
## r2                       0.93602264  0.94117457  0.95523953
## rmse                      0.2262341  0.18774246  0.15791062
```

```
plot(train.rf)
```



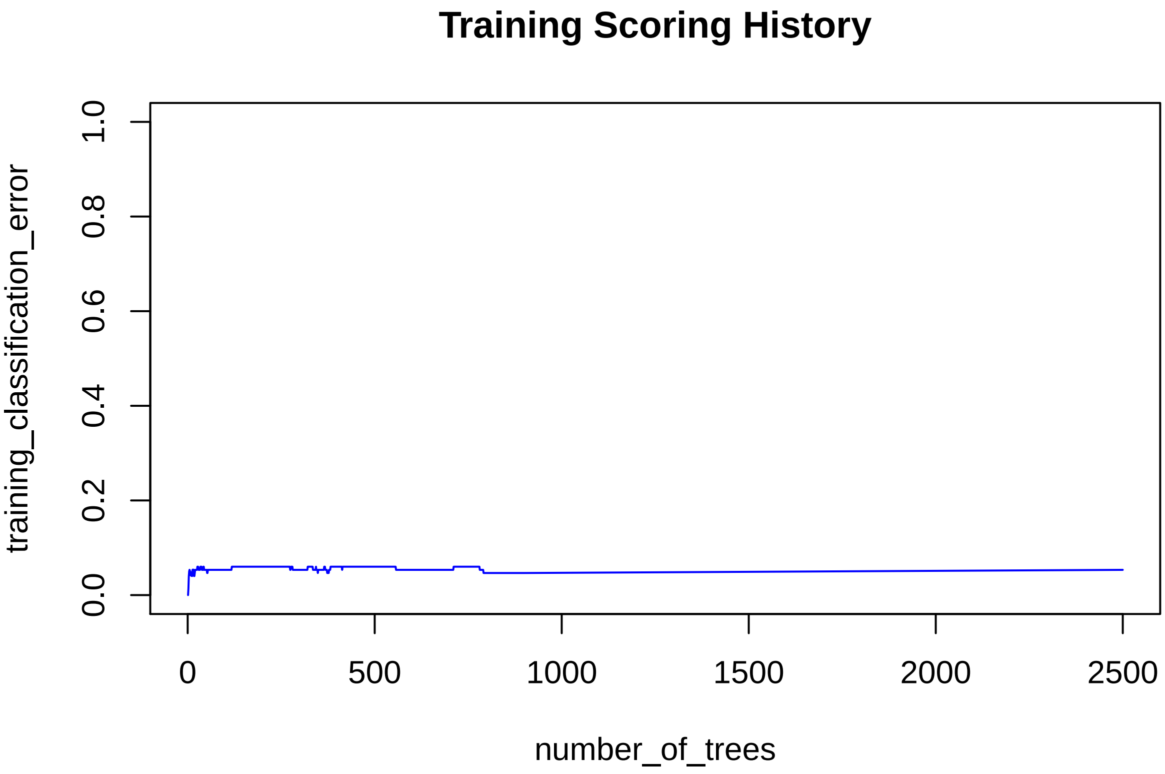
How about if we increas number of tree?

```
train.rf = h2o.randomForest(y = 6, x = 2:5, training_frame = as.h2o(iris),
    ntrees = 2500, nfolds = 5)
```

```
print(train.rf)
```

```
## Model Details:
## ==============
##
## H2OMultinomialModel: drf
## Model ID:  DRF_model_R_1477488686931_3
## Model Summary:
##   number_of_trees number_of_internal_trees model_size_in_bytes min_depth
## 1            2500                     7500             1066171         1
##   max_depth mean_depth min_leaves max_leaves mean_leaves
## 1        10    3.70453          2         18     6.20680
##
##
## H2OMultinomialMetrics: drf
## ** Reported on training data. **
## ** Metrics reported on Out-Of-Bag training samples **
##
## Training Set Metrics:
## =====================
##
## Extract training frame with `h2o.getFrame("iris")`
## MSE: (Extract with `h2o.mse`) 0.03549926
## RMSE: (Extract with `h2o.rmse`) 0.1884125
## Logloss: (Extract with `h2o.logloss`) 0.1141144
## Mean Per-Class Error: 0.05333333
## Confusion Matrix: Extract with `h2o.confusionMatrix(<model>,train = TRUE)`)
## =========================================================================
## Confusion Matrix: vertical: actual; across: predicted
##            setosa versicolor virginica  Error      Rate
## setosa         50          0         0 0.0000 =  0 / 50
## versicolor      0         47         3 0.0600 =  3 / 50
## virginica       0          5        45 0.1000 =  5 / 50
## Totals         50         52        48 0.0533 = 8 / 150
##
## Hit Ratio Table: Extract with `h2o.hit_ratio_table(<model>,train = TRUE)`
## =======================================================================
## Top-3 Hit Ratios:
##   k hit_ratio
## 1 1  0.946667
## 2 2  1.000000
## 3 3  1.000000
##
##
##
## H2OMultinomialMetrics: drf
## ** Reported on cross-validation data. **
## ** 5-fold cross-validation on training data (Metrics computed for combined holdout predictions) **
##
## Cross-Validation Set Metrics:
## =====================
##
## Extract cross-validation frame with `h2o.getFrame("iris")`
## MSE: (Extract with `h2o.mse`) 0.03793098
## RMSE: (Extract with `h2o.rmse`) 0.1947588
## Logloss: (Extract with `h2o.logloss`) 0.1208446
## Mean Per-Class Error: 0.06
## Hit Ratio Table: Extract with `h2o.hit_ratio_table(<model>,xval = TRUE)`
## =======================================================================
## Top-3 Hit Ratios:
##   k hit_ratio
## 1 1  0.940000
## 2 2  1.000000
## 3 3  1.000000
##
##
## Cross-Validation Metrics Summary:
##                                mean          sd  cv_1_valid  cv_2_valid
## accuracy                 0.94055974 0.027000353   0.8888889  0.92105263
## err                     0.059440266 0.027000353  0.11111111 0.078947365
## err_count                       1.8  0.82462114         3.0         3.0
## logloss                  0.11602521 0.047408137  0.15816341  0.20216043
## max_per_class_error      0.13600732   0.0696644         0.3  0.15384616
## mean_per_class_accuracy  0.94860363 0.025470305         0.9   0.9184149
## mean_per_class_error     0.05139638 0.025470305         0.1  0.08158508
## mse                     0.036668606 0.016380891 0.055433407 0.060977507
## r2                        0.9415697 0.026248796   0.9286026  0.90642774
## rmse                     0.17473753 0.055386845    0.235443  0.24693625
##                          cv_3_valid   cv_4_valid  cv_5_valid
## accuracy                 0.96428573          1.0   0.9285714
## err                     0.035714287          0.0 0.071428575
## err_count                       1.0          0.0         2.0
## logloss                  0.05825078   0.01971234   0.1418391
## max_per_class_error     0.083333336          0.0  0.14285715
## mean_per_class_accuracy   0.9722222          1.0  0.95238096
## mean_per_class_error    0.027777778          0.0  0.04761905
## mse                     0.017049648 0.0016997926 0.048182685
## r2                       0.97143817    0.9977452   0.9036346
## rmse                      0.1305743   0.04122854  0.21950555
```

```r
plot(train.rf)
```



Shut down h2o

```r
h2o.shutdown(FALSE)
```