

Regression and Classification with R*

Yanchang Zhao

<http://www.RDataMining.com>

30 October 2014

*Presented at Australian Customs and UJAT

Outline

Introduction

Linear Regression

Generalized Linear Regression

Decision Trees with Package party

Decision Trees with Package rpart

Random Forest

Online Resources

Regression and Classification with R [†]

- ▶ build a linear regression model to predict CPI data
- ▶ build a generalized linear model (GLM)
- ▶ build decision trees with package *party* and *rpart*
- ▶ train a random forest model with package *randomForest*

[†]Chapter 4: Decision Trees and Random Forest & Chapter 5: Regression, in book *R and Data Mining: Examples and Case Studies*.

Regression

- ▶ Regression is to build a function of *independent variables* (also known as *predictors*) to predict a *dependent variable* (also called *response*).
- ▶ For example, banks assess the risk of home-loan applicants based on their age, income, expenses, occupation, number of dependents, total credit limit, etc.
- ▶ linear regression models
- ▶ generalized linear models (GLM)

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Linear Regression

- ▶ Linear regression is to predict response with a linear function of predictors as follows:

$$y = c_0 + c_1x_1 + c_2x_2 + \cdots + c_kx_k,$$

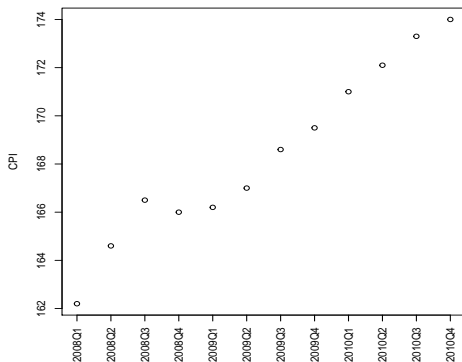
where x_1, x_2, \dots, x_k are predictors and y is the response to predict.

- ▶ linear regression with function `lm()`
- ▶ the Australian CPI (Consumer Price Index) data: quarterly CPIs from 2008 to 2010 [‡]

[‡]From Australian Bureau of Statistics, <http://www.abs.gov.au>.

The CPI Data

```
year <- rep(2008:2010, each = 4)
quarter <- rep(1:4, 3)
cpi <- c(162.2, 164.6, 166.5, 166, 166.2, 167, 168.6, 169.5, 171,
        172.1, 173.3, 174)
plot(cpi, xaxt = "n", ylab = "CPI", xlab = "")
# draw x-axis, where 'las=3' makes text vertical
axis(1, labels = paste(year, quarter, sep = "Q"), at = 1:12, las = 3)
```



Linear Regression

```
## correlation between CPI and year / quarter
cor(year, cpi)

## [1] 0.9096

cor(quarter, cpi)

## [1] 0.3738

## build a linear regression model with function lm()
fit <- lm(cpi ~ year + quarter)
fit

##
## Call:
## lm(formula = cpi ~ year + quarter)
##
## Coefficients:
## (Intercept)      year      quarter
##    -7644.49      3.89      1.17
```


With the above linear model, CPI is calculated as

$$\text{cpi} = c_0 + c_1 * \text{year} + c_2 * \text{quarter},$$

where c_0 , c_1 and c_2 are coefficients from model fit.

What will the CPI be in 2011?

```
cpi2011 <- fit$coefficients[[1]] +  
          fit$coefficients[[2]] * 2011 +  
          fit$coefficients[[3]] * (1:4)  
cpi2011  
  
## [1] 174.4 175.6 176.8 177.9
```

With the above linear model, CPI is calculated as

$$\text{cpi} = c_0 + c_1 * \text{year} + c_2 * \text{quarter},$$

where c_0 , c_1 and c_2 are coefficients from model fit.

What will the CPI be in 2011?

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  fit$coefficients[[3]] * (1:4)  
cpi2011  
  
## [1] 174.4 175.6 176.8 177.9
```

An easier way is to use function `predict()`.

More details of the model can be obtained with the code below.

```
attributes(fit)
```

```
## $names
## [1] "coefficients" "residuals"      "effects"
## [4] "rank"         "fitted.values"  "assign"
## [7] "qr"           "df.residual"    "xlevels"
## [10] "call"         "terms"          "model"
##
## $class
## [1] "lm"
```

```
fit$coefficients
```

```
## (Intercept)      year      quarter
##    -7644.488     3.888       1.167
```

Function `residuals()`: differences between observed values and fitted values

```
# differences between observed values and fitted values  
residuals(fit)
```

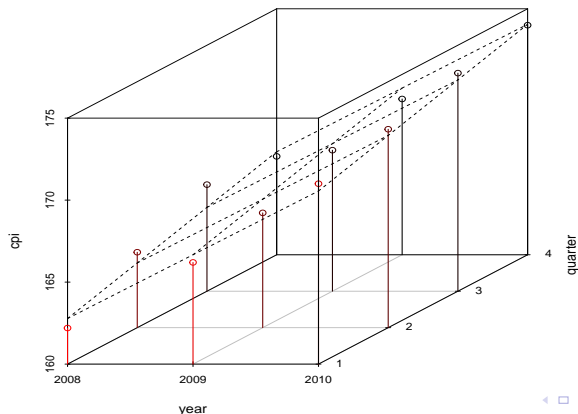
```
##           1           2           3           4           5           6           ...  
## -0.57917  0.65417  1.38750 -0.27917 -0.46667 -0.83333 -0.40...  
##           8           9          10          11          12  
## -0.66667  0.44583  0.37917  0.41250 -0.05417
```

```
summary(fit)
```

```
##  
## Call:  
## lm(formula = cpi ~ year + quarter)  
##  
## Residuals:  
##      Min       1Q   Median       3Q      Max   
## -0.833 -0.495 -0.167   0.421   1.387   
##  
## Coefficients:  
##              Estimate Std. Error t value Pr(>|t|)      
## (Intercept) -7644.488    518.654  -14.74  1.3e-07 ***  
## year          3.888       0.258   15.06  1.1e-07 ***
```

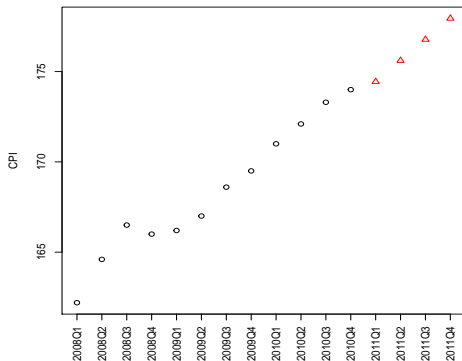
3D Plot of the Fitted Model

```
library(scatterplot3d)
s3d <- scatterplot3d(year, quarter, cpi, highlight.3d = T, type = "h",
  lab = c(2, 3)) # lab: number of tickmarks on x-/y-axes
s3d$plane3d(fit) # draws the fitted plane
```



Prediction of CPIs in 2011

```
data2011 <- data.frame(year = 2011, quarter = 1:4)
cpi2011 <- predict(fit, newdata = data2011)
style <- c(rep(1, 12), rep(2, 4))
plot(c(cpi, cpi2011), xaxt = "n", ylab = "CPI", xlab = "", pch = style,
     col = style)
axis(1, at = 1:16, las = 3, labels = c(paste(year, quarter, sep = "Q"),
    "2011Q1", "2011Q2", "2011Q3", "2011Q4"))
```



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Generalized Linear Model (GLM)

- ▶ Generalizes linear regression by allowing the linear model to be related to the response variable via a link function and allowing the magnitude of the variance of each measurement to be a function of its predicted value
- ▶ Unifies various other statistical models, including linear regression, logistic regression and Poisson regression
- ▶ Function `glm()`: fits generalized linear models, specified by giving a symbolic description of the linear predictor and a description of the error distribution

Build a Generalized Linear Model

```
data("bodyfat", package="TH.data")
myFormula <- DEXfat ~ age + waistcirc + hipcirc + elbowbreadth +
  kneebreadth
bodyfat.glm <- glm(myFormula, family = gaussian("log"), data = bodyfat)
summary(bodyfat.glm)
```

##

Call:

glm(formula = myFormula, family = gaussian("log"), data = b...

##

Deviance Residuals:

##	Min	1Q	Median	3Q	Max
##	-11.569	-3.006	0.127	2.831	10.097

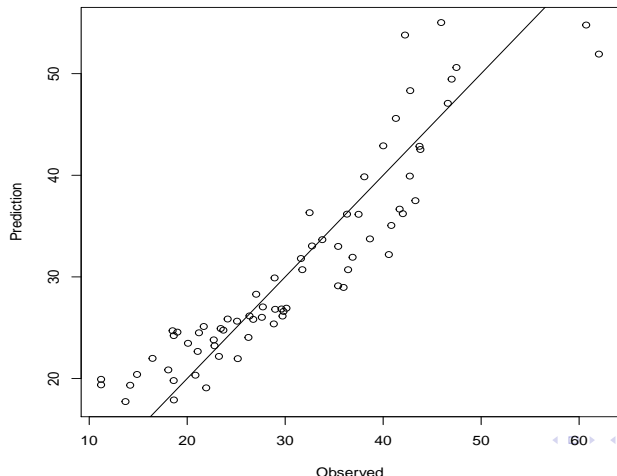
##

Coefficients:

##	Estimate	Std. Error	t value	Pr(> t)	
## (Intercept)	0.73429	0.30895	2.38	0.0204	*
## age	0.00213	0.00145	1.47	0.1456	
## waistcirc	0.01049	0.00248	4.23	7.4e-05	***
## hipcirc	0.00970	0.00323	3.00	0.0038	**
## elbowbreadth	0.00235	0.04569	0.05	0.9590	
## kneebreadth	0.06319	0.02819	2.24	0.0284	*

Prediction with Generalized Linear Regression Model

```
pred <- predict(bodyfat.glm, type = "response")  
plot(bodyfat$DEXfat, pred, xlab = "Observed", ylab = "Prediction")  
abline(a = 0, b = 1)
```



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The iris Data

```
str(iris)

## 'data.frame': 150 obs. of  5 variables:
##  $ 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...
##  $ Petal.Width  : num  0.2 0.2 0.2 0.2 0.2 0.4 0.3 0.2 0.2 0...
##  $ Species      : Factor w/ 3 levels "setosa","versicolor",....

# split data into two subsets: training (70%) and test (30%); set
# a fixed random seed to make results reproducible
set.seed(1234)
ind <- sample(2, nrow(iris), replace = TRUE, prob = c(0.7, 0.3))
train.data <- iris[ind == 1, ]
test.data <- iris[ind == 2, ]
```

Build a ctree

- ▶ Control the training of decision trees: MinSplit, MinBusket, MaxSurrogate and MaxDepth
- ▶ Target variable: Species
- ▶ Independent variables: all other variables

```
library(party)
myFormula <- Species ~ Sepal.Length + Sepal.Width + Petal.Length +
  Petal.Width
iris_ctree <- ctree(myFormula, data = train.data)
# check the prediction
table(predict(iris_ctree), train.data$Species)
```

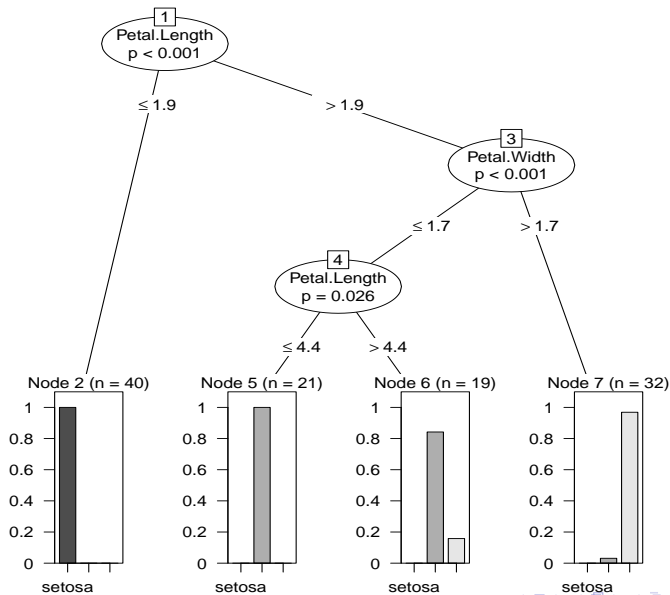
```
##
##          setosa versicolor virginica
## setosa          40           0         0
## versicolor       0          37         3
## virginica        0           1        31
```

Print ctree

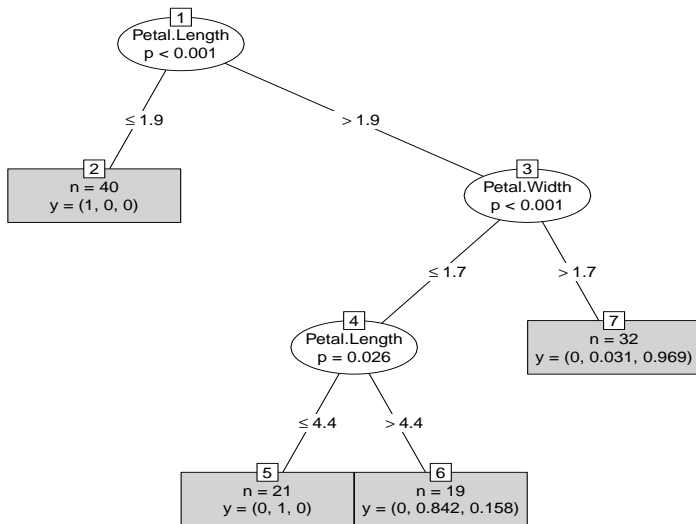
```
print(iris_ctree)

##
##   Conditional inference tree with 4 terminal nodes
##
## Response:   Species
## Inputs:   Sepal.Length, Sepal.Width, Petal.Length, Petal.Width
## Number of observations:   112
##
## 1) Petal.Length <= 1.9; criterion = 1, statistic = 104.643
##   2)* weights = 40
## 1) Petal.Length > 1.9
##   3) Petal.Width <= 1.7; criterion = 1, statistic = 48.939
##     4) Petal.Length <= 4.4; criterion = 0.974, statistic = ...
##       5)* weights = 21
##       4) Petal.Length > 4.4
##         6)* weights = 19
##     3) Petal.Width > 1.7
##       7)* weights = 32
```

```
plot(iris_ctree)
```



```
plot(iris_ctree, type = "simple")
```



Test

```
# predict on test data  
testPred <- predict(iris_ctree, newdata = test.data)  
table(testPred, test.data$Species)
```

```
##  
## testPred      setosa versicolor virginica  
##   setosa      10         0         0  
## versicolor    0        12         2  
## virginica     0         0        14
```

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The bodyfat Dataset

```
data("bodyfat", package = "TH.data")  
dim(bodyfat)
```

```
## [1] 71 10
```

```
# str(bodyfat)  
head(bodyfat, 5)
```

```
##      age DEXfat waistcirc hipcirc elbowbreadth kneebreadth  
## 47  57  41.68    100.0    112.0           7.1           9.4  
## 48  65  43.29     99.5    116.5           6.5           8.9  
## 49  59  35.41     96.0    108.5           6.2           8.9  
## 50  58  22.79     72.0     96.5           6.1           9.2  
## 51  60  36.42     89.5    100.5           7.1          10.0  
##      anthro3a anthro3b anthro3c anthro4  
## 47      4.42      4.95      4.50      6.13  
## 48      4.63      5.01      4.48      6.37  
## 49      4.12      4.74      4.60      5.82  
## 50      4.03      4.48      3.91      5.66  
## 51      4.24      4.68      4.15      5.91
```

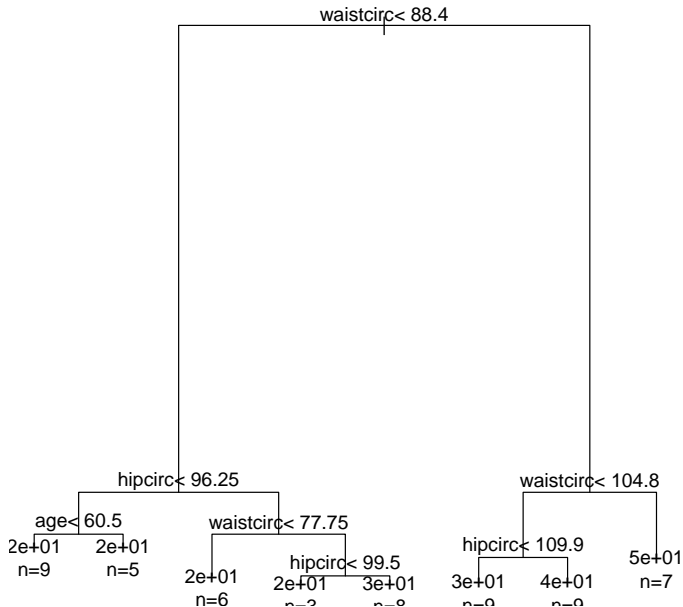
Train a Decision Tree with Package rpart

```
# split into training and test subsets
set.seed(1234)
ind <- sample(2, nrow(bodyfat), replace=TRUE, prob=c(0.7, 0.3))
bodyfat.train <- bodyfat[ind==1,]
bodyfat.test <- bodyfat[ind==2,]
# train a decision tree
library(rpart)
myFormula <- DEXfat ~ age + waistcirc + hipcirc + elbowbreadth +
               kneebreadth
bodyfat_rpart <- rpart(myFormula, data = bodyfat.train,
                      control = rpart.control(minsplit = 10))
# print(bodyfat_rpart$cpstable)
print(bodyfat_rpart)
plot(bodyfat_rpart)
text(bodyfat_rpart, use.n=T)
```

The rpart Tree

```
## n= 56
##
## node), split, n, deviance, yval
##      * denotes terminal node
##
## 1) root 56 7265.0000 30.95
##    2) waistcirc< 88.4 31 960.5000 22.56
##      4) hipcirc< 96.25 14 222.3000 18.41
##        8) age< 60.5 9 66.8800 16.19 *
##        9) age>=60.5 5 31.2800 22.41 *
##      5) hipcirc>=96.25 17 299.6000 25.97
##        10) waistcirc< 77.75 6 30.7300 22.32 *
##        11) waistcirc>=77.75 11 145.7000 27.96
##          22) hipcirc< 99.5 3 0.2569 23.75 *
##          23) hipcirc>=99.5 8 72.2900 29.54 *
##    3) waistcirc>=88.4 25 1417.0000 41.35
##      6) waistcirc< 104.8 18 330.6000 38.09
##        12) hipcirc< 109.9 9 69.0000 34.38 *
##        13) hipcirc>=109.9 9 13.0800 41.81 *
##      7) waistcirc>=104.8 7 404.3000 49.73 *
```

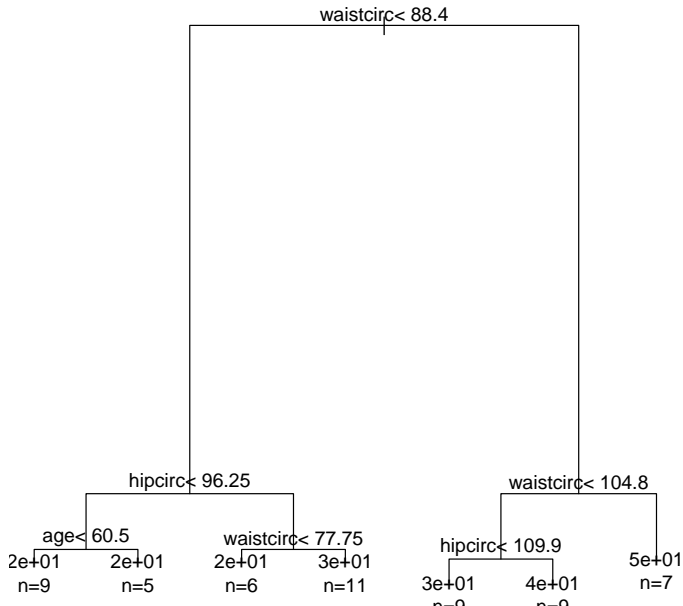
The rpart Tree



Select the Best Tree

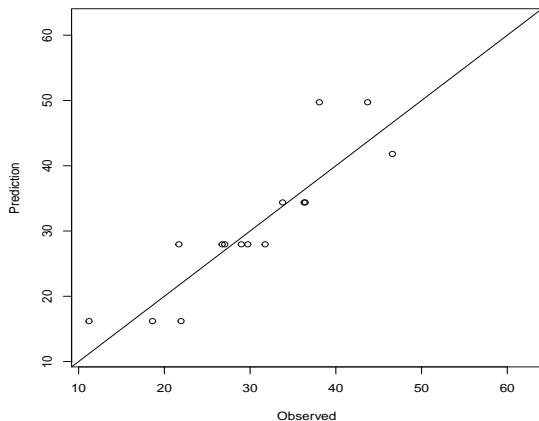
```
# select the tree with the minimum prediction error
opt <- which.min(bodyfat_rpart$cptable[, "xerror"])
cp <- bodyfat_rpart$cptable[opt, "CP"]
# prune tree
bodyfat_prune <- prune(bodyfat_rpart, cp = cp)
# plot tree
plot(bodyfat_prune)
text(bodyfat_prune, use.n = T)
```

Selected Tree



Model Evaluation

```
DEXfat_pred <- predict(bodyfat_prune, newdata = bodyfat.test)
xlim <- range(bodyfat$DEXfat)
plot(DEXfat_pred ~ DEXfat, data = bodyfat.test, xlab = "Observed",
     ylab = "Prediction", ylim = xlim, xlim = xlim)
abline(a = 0, b = 1)
```



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R Packages for Random Forest

- ▶ Package *randomForest*
 - ▶ very fast
 - ▶ cannot handle data with missing values
 - ▶ a limit of 32 to the maximum number of levels of each categorical attribute
- ▶ Package *party*: `cforest()`
 - ▶ not limited to the above maximum levels
 - ▶ slow
 - ▶ needs more memory

Train a Random Forest

```
# split into two subsets: training (70%) and test (30%)
ind <- sample(2, nrow(iris), replace=TRUE, prob=c(0.7, 0.3))
train.data <- iris[ind==1,]
test.data <- iris[ind==2,]
# use all other variables to predict Species
library(randomForest)
rf <- randomForest(Species ~ ., data=train.data, ntree=100,
                    proximity=T)
```

```
table(predict(rf), train.data$Species)
```

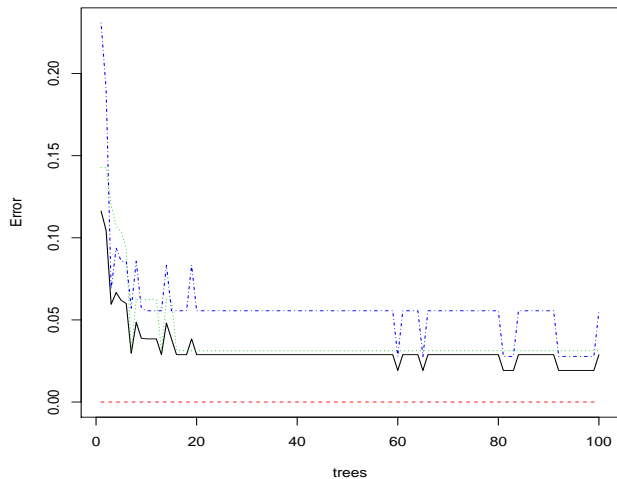
```
##
##           setosa versicolor virginica
##  setosa         36           0         0
##  versicolor      0          31         2
##  virginica       0           1        34
```

```
print(rf)
```

```
##
## Call:
##  randomForest(formula = Species ~ ., data = train.data, ntr...
##           Type of random forest: classification
##           Number of trees: 100
## No. of variables tried at each split: 2
##
##           OOB estimate of  error rate: 2.88%
## Confusion matrix:
##           setosa versicolor virginica class.error
## setosa         36           0         0  0.00000
## versicolor      0          31         1  0.03125
## virginica       0           2        34  0.05556
```

Error Rate of Random Forest

```
plot(rf, main = "")
```



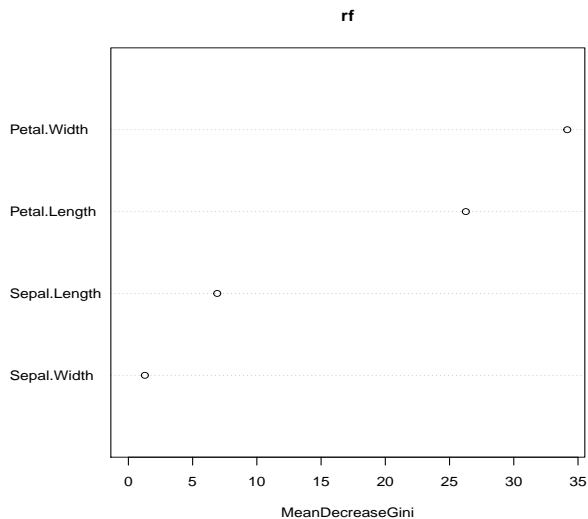
Variable Importance

```
importance(rf)
```

##	MeanDecreaseGini
## Sepal.Length	6.914
## Sepal.Width	1.283
## Petal.Length	26.267
## Petal.Width	34.164

Variable Importance

```
varImpPlot(rf)
```



Margin of Predictions

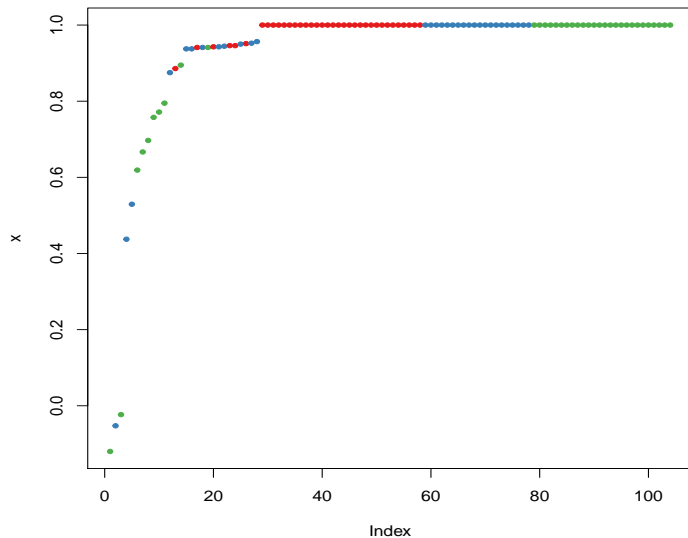
The margin of a data point is as the proportion of votes for the correct class minus maximum proportion of votes for other classes. Positive margin means correct classification.

```
irisPred <- predict(rf, newdata = test.data)
table(irisPred, test.data$Species)
```

```
##
## irisPred      setosa versicolor virginica
##   setosa         14           0           0
##   versicolor      0          17           3
##   virginica       0           1          11
```

```
plot(margin(rf, test.data$Species))
```

Margin of Predictions



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<http://www.rdatamining.com/docs/RDataMining.pdf>

- ▶ R Reference Card for Data Mining

<http://www.rdatamining.com/docs/R-refcard-data-mining.pdf>

- ▶ Free online courses and documents

<http://www.rdatamining.com/resources/>

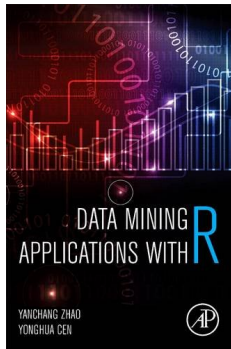
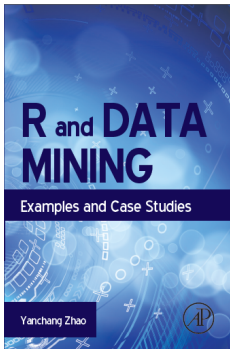
- ▶ RDataMining Group on LinkedIn (7,000+ members)

<http://group.rdatamining.com>

- ▶ RDataMining on Twitter (1,800+ followers)

@RDataMining

The End



Thanks!

Email: [yanchang\(at\)rdatamining.com](mailto:yanchang(at)rdatamining.com)