Data Science with R
Writing Functions in R

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22nd May 2014

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The required packages for this module include:

```
library(rattle)
```

As we work through this chapter, new R commands will be introduced. Be sure to review the command's documentation and understand what the command does. You can ask for help using the `?` command as in:

```
?read.csv
```

We can obtain documentation on a particular package using the *help=* option of `library()`:

```
library(help=rattle)
```

This chapter is intended to be hands on. To learn effectively, you are encouraged to have R running (e.g., RStudio) and to run all the commands as they appear here. Check that you get the same output, and you understand the output. Try some variations. Explore.

1 Functions

This page is under development.

```
mult10 <- function(x)
{
  if (is.character(x))
  {
    result <- apply(sapply(x, rep, 10), 2, paste, collapse="")
    names(result) <- NULL
  }
  else
  {
    result <- x * 10
  }

  return(result)
}
```

2 Function Calls

This page is under development.

```
4 + 5

## [1] 9

"+"(4, 5)

## [1] 9
```

```
1 + 2 + 3 + 4 + 5

## [1] 15

Reduce("+", 1:5)

## [1] 15
```

```
cmd <- "1 + 2 + 3 + 4 + 5"
eval(parse(text=cmd))

## [1] 15
```

3 Flow Control

This page is under development.

```
for (i in 0:4)
  for (j in 5:9)
    print(paste0(i, j))

## [1] "05"
## [1] "06"
## [1] "07"
## [1] "08"
....
```

4 Exercise Dataset: WeatherAUS

For our exercises we will use the **weatherAUS** dataset from rattle (Williams, 2014). We will essentially follow the template presented in the Models module.

```
ds <- read.csv(file="data/weatherAUS.csv")
```

```
dim(ds)

## [1] 66672    24

head(ds)

##         Date Location MinTemp MaxTemp Rainfall Evaporation Sunshine
## 1 2008-12-01   Albury    13.4    22.9      0.6          NA       NA
## 2 2008-12-02   Albury     7.4    25.1      0.0          NA       NA
## 3 2008-12-03   Albury    12.9    25.7      0.0          NA       NA
## 4 2008-12-04   Albury     9.2    28.0      0.0          NA       NA
## 5 2008-12-05   Albury    17.5    32.3      1.0          NA       NA
## 6 2008-12-06   Albury    14.6    29.7      0.2          NA       NA
....

tail(ds)

##             Date Location MinTemp MaxTemp Rainfall Evaporation Sunshine
## 66667 2012-11-24   Darwin    25.5    34.1      0.0         5.0      6.2
## 66668 2012-11-25   Darwin    24.4    35.7      0.2         4.8     11.7
## 66669 2012-11-26   Darwin    25.0    35.4      0.0         7.4     11.7
## 66670 2012-11-27   Darwin    26.5    35.9      0.0         8.0     10.3
## 66671 2012-11-28   Darwin    27.4    35.0      0.0         7.8      6.5
## 66672 2012-11-29   Darwin    24.8    33.5      3.4         7.4      4.7
....

str(ds)

## 'data.frame': 66672 obs. of  24 variables:
##  $ Date         : Factor w/ 1826 levels "2007-11-01","2007-11-02",..: 397 ...
##  $ Location     : Factor w/ 46 levels "Adelaide","Albany",..: 3 3 3 3 3 3 ...
##  $ MinTemp      : num  13.4 7.4 12.9 9.2 17.5 14.6 14.3 7.7 9.7 13.1 ...
##  $ MaxTemp      : num  22.9 25.1 25.7 28 32.3 29.7 25 26.7 31.9 30.1 ...
##  $ Rainfall     : num  0.6 0 0 0 1 0.2 0 0 0 1.4 ...
##  $ Evaporation  : num  NA NA NA NA NA NA NA NA NA NA ...
....

summary(ds)

##          Date            Location        MinTemp         MaxTemp
##  2009-01-01:   46   Canberra: 1826   Min.   :-8.5   Min.   :-3.1
##  2009-01-02:   46   Sydney  : 1734   1st Qu.: 7.3   1st Qu.:17.6
##  2009-01-03:   46   Adelaide: 1583   Median :11.7   Median :22.1
##  2009-01-04:   46   Brisbane: 1583   Mean   :11.9   Mean   :22.7
##  2009-01-05:   46   Darwin  : 1583   3rd Qu.:16.6   3rd Qu.:27.5
##  2009-01-06:   46   Hobart  : 1583   Max.   :33.9   Max.   :48.1
....
```

5 Exercises: Prepare for Modelling

Following the template presented in the Models module, we continue with setting up some fo the modelling parameters.

```
target <- "RainTomorrow"
risk   <- "RISK_MM"
dsname <- "weather"
```

```
ds[target] <- as.factor(ds[[target]])
summary(ds[target])

##  RainTomorrow
##  No  :50187
##  Yes :15259
##  NA's: 1226
....
```

```
vars    <- colnames(ds)
ignore  <- vars[c(1, 2, if (exists("risk")) which(risk==vars))]
vars    <- setdiff(vars, ignore)
(inputs <- setdiff(vars, target))

##  [1] "MinTemp"       "MaxTemp"       "Rainfall"      "Evaporation"
##  [5] "Sunshine"      "WindGustDir"   "WindGustSpeed" "WindDir9am"
##  [9] "WindDir3pm"    "WindSpeed9am"  "WindSpeed3pm"  "Humidity9am"
## [13] "Humidity3pm"   "Pressure9am"   "Pressure3pm"   "Cloud9am"
....

nobs   <- nrow(ds)
dim(ds[vars])

## [1] 66672    21
```

```
(form <- formula(paste(target, "~ .")))

## RainTomorrow ~ .
```

```
set.seed(142)
```

```
length(train <- sample(nobs, 0.7*nobs))

## [1] 46670

length(test  <- setdiff(seq_len(nobs), train))

## [1] 20002
```

6 Exercise: varWeights()

The first exercise is to write a function to take a dataset and return probabilities associated with each input variable in the dataset, that relate to the correlation between the input variable and the target variable.

```
varw <- varWeights(form, ds)
```

We will use the R correlation functions to calculate the correlation between each column (variable) of the **data** frame and the values of the **target** vector. Below are some hints.

```
n1 <- ds[["Temp3pm"]]
c1 <- ds[["WindGustDir"]]
t1 <- ds[[target]]

cor(as.numeric(n1), as.numeric(t1), use="pairwise.complete.obs")
## [1] -0.1857
cor(as.numeric(c1), as.numeric(t1), use="pairwise.complete.obs")
## [1] 0.04414
```

The template for the function is:

```
varWeights <- function(formula, data)
{
  ...
}
```

The actual solution will produce the following output:

```
varWeights(form, ds)
##          Date      Location       MinTemp       MaxTemp      Rainfall
##     0.0028545     0.0004961     0.0210742     0.0336550     0.0544825
##   Evaporation      Sunshine   WindGustDir WindGustSpeed    WindDir9am
##     0.0249688     0.1006235     0.0096812     0.0518932     0.0067119
....
```

It is time now to write that function.

7 Exercise: selectVars()

The next exercise is to write a function that will return n variables chosen at random from all of the variables in a dataset, but chosen with a probability proportional to the correlation of the target variable.

```
vars <- selectVars(form, ds, 3)
```

The sample() function might come in use for this function. Note the prob= argument of sample. We will, of course, also make use of the varWeights() function we defined previously.

The template for the function is:

```
selectVars <- function(formula, data, n)
{
  ...
}
```

The actual solution will produce the following output:

```
selectVars(form, ds, 3)
## [1] "Pressure3pm" "MaxTemp"     "RISK_MM"
selectVars(form, ds, 3)
## [1] "Cloud9am" "RISK_MM"  "Sunshine"
selectVars(form, ds, 3)
## [1] "WindDir9am"  "Humidity3pm" "Cloud9am"
selectVars(form, ds, 3)
## [1] "Cloud3pm"    "Evaporation" "Humidity3pm"
```

8 Exercise: wsrpart()

This exercise is to write a function to build a subspace decision tree The function `wsrpart()` (for weighted subspace rpart) will take a dataset (`data`) and return a decision tree (built using `rpart()`) that uses only a subspace of the variables available. The number of variables to use is, by default, $trunc(log_2(n+1))$ (overridden by `nvars=`) and the variables are chosen according to the weighted selection implemented through `selectVars()`.

The idea is similar, but not identical to, the concept of random forests developed bu Leo Breiman. Note that Breiman's original random forest paper (on which this idea is based) specifies $trunc(log_2 n + 1))$ which is ambiguous in terms of being either $trunc(log_2(n+1))$ or $trunc(log_2(n)+1))$, although he probably meant then latter.

```
dt <- wsrpart(form, data)
```

The template for the function is:

```
wsrpart <- function(formula, data, nvars, ...)
{
  ...
}
```

Notice the use of "..." in the argument list. This allows us to pass other arguments on through to `rpart()`.

The actual solution will produce the following output:

```
## system.time(model <- wsrpart(form, ds[train, vars]))

##    user  system elapsed
##   0.159   0.011   2.497

model

## A multiple rpart model with 1 tree.
##
## Variables used (11): Pressure9am, Cloud3pm, Sunshine, Rainfall, WindGustDir,
##                      Humidity3pm, WindDir9am, RainToday,
....
```

9 Exercise: Multiple Decision Trees

Now extend the function `wsrpart()` to build multiple decision trees. The function will take a formula, a dataset (`data`) and a number of trees to build (`ntrees`), and returns a list of `ntrees` decision trees. Each element of the list will itself be a list, with at least one element named `model`. This is the actual rpart model. The result should be of class `mrpart` for "multiple rpart."

The actual solution will produce the following output:

```
system.time(model <- wsrpart(form, ds[train, vars], 4))

##    user  system elapsed
##  94.024   2.833  34.958

class(model)

## [1] "mrpart"

length(model)

## [1] 50

class(model[[1]]$model)

## [1] "rpart"

model[[1]]$model

## n=45731 (939 observations deleted due to missingness)
##
## node), split, n, loss, yval, (yprob)
##       * denotes terminal node
##
## 1) root 45731 10680 No (0.7665 0.2335)
##   2) RainToday=No 35102  5572 No (0.8413 0.1587) *
##   3) RainToday=Yes 10629  5106 No (0.5196 0.4804)
##     6) Cloud3pm< 6.5 4728  1531 No (0.6762 0.3238) *
##     7) Cloud3pm>=6.5 5901  2326 Yes (0.3942 0.6058) *
```

10 Exercise: `predict.mrpart()`

This page is under development.

Score a Dataset Using the Forest

Define a function **`predict.mrpart()`**. Returns the proportion of trees voting for the positive case, assuming binary classification models.

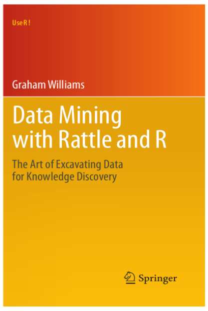
The actual solution will produce the following output:

```
predict(model, ds[test,vars])

##     8     9    12    16    19    27    36    45    46    51    55    59
##    No    No   Yes    No    No    No    No    No    No    No    No    No
##    61    62    66    68    78    83    86    87    88    89    93    95
##    No    No    No    No    No    No    No    No    No    No    No    No
....
```

11 Further Reading

The Rattle Book, published by Springer, provides a comprehensive introduction to data mining and analytics using Rattle and R. It is available from Amazon. Other documentation on a broader selection of R topics of relevance to the data scientist is freely available from `http://datamining.togaware.com`, including the Datamining Desktop Survival Guide.



This module is one of many OnePageR modules available from `http://onepager.togaware.com`. In particular follow the links on the website with a * which indicates the generally more developed OnePageR modules.

Other resources include:

12 References

R Core Team (2014). *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing, Vienna, Austria. URL http://www.R-project.org/.

Williams GJ (2009). "Rattle: A Data Mining GUI for R." *The R Journal*, **1**(2), 45–55. URL http://journal.r-project.org/archive/2009-2/RJournal_2009-2_Williams.pdf.

Williams GJ (2011). *Data Mining with Rattle and R: The art of excavating data for knowledge discovery*. Use R! Springer, New York. URL http://www.amazon.com/gp/product/1441998896/ref=as_li_qf_sp_asin_tl?ie=UTF8&tag=togaware-20&linkCode=as2&camp=217145&creative=399373&creativeASIN=1441998896.

Williams GJ (2014). *rattle: Graphical user interface for data mining in R*. R package version 3.0.4, URL http://rattle.togaware.com/.

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