R supports several levels of parallel execution, starting with executing code on multiple cores, and going up to executing code in massively parallel Hadoop platforms. Since R Version 2.14.0 parallel has provided support for parallel computation through forking (c.f. multicore) and sockets (c.f. snow).

To illustrate parallel computation we will build rpart decision trees in parallel.

The required packages for this module include:

```r
library(parallel)
library(rpart)
```

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:

```r
?read.csv
```

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

```r
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 Weather Data

We will model the weatherAUS dataset. We choose this dataset since it is reasonably large, and takes quite a few seconds to build a decision tree.

We have a CSV version of the dataset available in the local data folder.

```
dir(path="data", pattern="*.csv")
```

The data is directly read into a data frame.

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

As always, we first check the contents of the dataset to ensure everything looks okay:

```
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
## ....
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
## ....
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 ...
## ....
summary(ds)
```

```
## Date Location MinTemp MaxTemp
## 2009-01-01: 46 Canberra: 1826 Min. :-8.5 Min. :-3.10
```
<table>
<thead>
<tr>
<th>Date</th>
<th>City</th>
<th>Count</th>
<th>1st Qu.</th>
<th>Median</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>2009-01-02</td>
<td>Sydney</td>
<td>1734</td>
<td>7.3</td>
<td>17.60</td>
<td></td>
</tr>
<tr>
<td>2009-01-03</td>
<td>Adelaide</td>
<td>1583</td>
<td>11.7</td>
<td>22.10</td>
<td></td>
</tr>
<tr>
<td>2009-01-04</td>
<td>Brisbane</td>
<td>1583</td>
<td>11.9</td>
<td>22.68</td>
<td></td>
</tr>
</tbody>
</table>
2 Prepare for Modelling

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

```r
# Load the required libraries
library(caret)  # For data splitting
library(randomForest)  # For random forest model

# Define the target variable
target <- "RainTomorrow"

# Load the dataset
data <- read.csv("weather.csv")

# Convert the target variable to a factor
data[, target] <- as.factor(data[, target])

# Summary of the target variable
summary(data[, target])
# RainTomorrow
# No :50187
# Yes :15259
# NA's: 1226

# Define the input variables
vars <- colnames(data)
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"

# Define the number of observations
nobs <- nrow(data)

# Define the dimensions of the input variables
dim(data[, vars])
# [1] 66672 21

# Define the formula for the model
(form <- formula(paste(target, " ~ .")))
# RainTomorrow ~ .

# Define the random seed for data splitting
(seed <- sample(1:1000000, 1))
# [1] 84938

# Set the seed
set.seed(seed)

# Define the training set
length(train <- sample(nobs, 0.7*nobs))
# [1] 46670

# Define the test set
length(test <- setdiff(seq_len(nobs), train))
# [1] 20002
```

---

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### 3 Build a Model

An exercise in the Functions module developed `wsrpart()` to build one or more `rpart` (Therneau and Atkinson, 2014) decision trees based on a random subset of the data and a weighted random subset of the variables. We can use this function here, and will do so to distribute computation first over multiple cores and then over multiple servers.

Each time `wsrpart()` builds a decision tree it selects a different random training dataset and a different random choice of variables to use in the tree building. The processing for each call to the function to build the decision tree (`rpart()`) will be distributed across multiple cores or servers.

Building a single model returns the model and other information.

```r
set.seed(42)
system.time(model <- wsrpart(form, ds[train, vars], ntrees=1))
## user  system elapsed
## 0.117  0.009  2.420
model[[1]]$model
## n=45816 (854 observations deleted due to missingness)
## node), split, n, loss, yval, (yprob)
## * denotes terminal node
## ....
model[[1]]$vars
## [1] "Humidity9am"  "Humidity3pm" "Cloud9am"   "Pressure9am"
## [5] "Evaporation"  "MinTemp"    "WindGustSpeed" "WindGustDir"
## [9] "Temp3pm"      "Sunshine"   "RainToday"
model[[1]]$accuracy
## NULL
```
4 Build a Second Model

We can call it again to obtain another model:

```r
set.seed(84)
system.time(model <- wsrpart(form, ds[train, vars], ntrees=1))
## user  system elapsed
## 2.368  0.068  2.369
model[[1]]$model
## n=45834 (836 observations deleted due to missingness)
## node), split, n, loss, yval, (yprob)
##  * denotes terminal node
....
model[[1]]$vars
## [1] "Cloud9am"   "Sunshine"  "MaxTemp"   "Humidity3pm"
## [5] "Rainfall"   "WindSpeed9am" "Cloud3pm"  "RainToday"
## [9] "Humidity9am" "WindSpeed3pm" "Pressure9am"
model[[1]]$oob.error
## [1] 0.1757465
```
5 Build Models in Parallel

The `parallel` package provides functions to distribute the computation across multiple cores and servers.

We first determine the number of cores available on the computer we are processing our data on:

```r
cores <- detectCores()
cores
## [1] 8
```

We can then start a parallel run of building models using `mcparallel()`. This command forks the current process to build the tree (and hence will not work on MS/Windows). Here we build one tree for each core.

```r
jobs <- lapply(1:cores,
  function(x) mcparallel(wrpart(form, ds[train,vars], ntrees=1),
                        name=sprintf("dt%02d", x)))
```

We can inspect the first two processes:

```r
jobs[1:2]
## [[1]]
## $pid
## [1] 2879
##
## $fd
## [1] 4 7
##
## $name
## [1] "dt01"

## attr(,"class")
## [1] "parallelJob" "childProcess" "process"

## [[2]]
## $pid
## [1] 2880
##
## $fd
## [1] 5 9
##
## $name
## [1] "dt02"

## attr(,"class")
## [1] "parallelJob" "childProcess" "process"
```
6 Collect Results

We now wait for the jobs to finish:

```r
system.time(model <- mccollect(jobs, wait=TRUE))
## user system elapsed
## 4.710 0.588 6.813
```

The decision trees will then be available in the resulting list:

```r
length(model)
## [1] 8
model[[1]][[1]]$model
## n=45845 (825 observations deleted due to missingness)
## node), split, n, loss, yval, (yprob)
## * denotes terminal node
##
## 1) root 45845 10809 No (0.7642273 0.2357727)
## 2) Humidity3pm< 71.5 37958 5782 No (0.8476737 0.1523263) *
## 3) Humidity3pm>=71.5 7887 2860 Yes (0.3626220 0.6373780)
## 6) Humidity3pm< 82.5 4314 2111 No (0.5106630 0.4893370)
## 12) Pressure9am>=1013.95 2746 1101 No (0.5990532 0.4009468) *
## ...

model[[2]][[1]]$model
## n=45826 (844 observations deleted due to missingness)
## node), split, n, loss, yval, (yprob)
## * denotes terminal node
##
## 1) root 45826 10773 No (0.7649151 0.2350849)
## 2) Humidity3pm< 68.5 36052 5140 No (0.8574282 0.1425718) *
## 3) Humidity3pm>=68.5 9774 4141 Yes (0.4236751 0.5763249)
## 6) Humidity3pm< 82.5 6277 2793 No (0.5550422 0.4449578)
## 12) RainToday=No 3688 1298 No (0.6480477 0.3519523) *
## ...
```
7 Exercise: Multiple Cores

Our exercise here is to write a function to build decision trees on multiple cores. We will modify the function `wsrpart` we built in the Models module. It will use multiple cores in building the forest of trees in parallel. We specify the number of trees to build (`ntrees=`) and optionally the maximum number of cores to use (`parallel=`). At most, and by default, one less than the number of available cores (but at least 1) will be used. Thus, that many trees will be built in parallel at any time. More trees than cores can be specified, and as trees finish being built across the cores, further trees can start being built. We do this to allow the user to decide how best to manage the parallel execution across the cores, without swamping the server with too many processes.

The actual solution will produce the following output, showing also some timings:

```r
system.time(model <- wsrpart(form, ds, ntrees=4, parallel=2))
## user  system elapsed
##  6.257  0.293  4.210
num.trees <- cores
set.seed(42)
system.time(model <- wsrpart(form, ds, ntrees=num.trees, parallel=2))
## user  system elapsed
## 17.404  0.516 10.381
model[[1]]$model
## n=65476 (1196 observations deleted due to missingness)
## node), split, n, loss, yval, (yprob)
##   * denotes terminal node
```

We might do some more timings:

```r
set.seed(42)
system.time(model <- wsrpart(form, ds, ntrees=num.trees, parallel=2))
## user  system elapsed
## 20.149  0.595 12.374
set.seed(42)
system.time(model <- wsrpart(form, ds, ntrees=num.trees, parallel=2))
## user  system elapsed
## 16.564  0.600  8.221
```
8 Parallel Processes Through Local Sockets

Before we proceed to run parallel processes over a network of workers (remote servers) we will do the same, but have a single node cluster (the current server). We use `makeCluster()` from `parallel` to do this.

We begin with a simple example. Here we create a cluster of as many nodes as there are cores on the local host.

```r
cl <- makeCluster(rep("localhost", cores))
c1
## socket cluster with 8 nodes on host 'localhost'
```

Now we ask each node of the cluster to do something. In this case we get the addition function with the additional argument 3. The 1:2 are the arguments passed to each node, so that node 1 gets 1 and node 2 gets 2.

```r
clusterApply(cl, 1:2, get("+"), 3)
## [[1]]
## [1] 4
##
## [[2]]
....
```

Because the nodes are each on the local host we don’t need to export data to the nodes. Also, each node has the current working directory set appropriately. We can use `clusterEvalQ()` to have the same expression executed on each node.

```r
clusterEvalQ(cl, getwd())
## [[1]]
## [1] "/home/gjw/projects/onepager"
##
## [[2]]
....
```

We should close the cluster once we are finished with it, though this is optional since the nodes will terminate themselves when the associated socket becomes unavailable.

```r
stopCluster(cl)
```
9 Build Models Through Local Sockets

Create a new cluster of as many nodes as there are cores on the local host.

```r
cl <- makeCluster(rep("localhost", cores))
cl
## socket cluster with 8 nodes on host 'localhost'
```

We load `rpart` and `rattle` on each node of the cluster.

```r
clusterEvalQ(cl, {library(parallel); library(rpart); library(rattle)})
```

Note that we might not have previously noticed that `library()` returns the current library search path as its value. It is returned silently and so normally we don’t see the return result. With `clusterEvalQ()` the final result is displayed.

We need to load the dataset onto each node:

```r
clusterExport(cl, c("ds", "form", "train", "vars"))
```

Now to build the decision trees. We need to export the definition of `wsrpart()` (and its support functions) to each node of the cluster. We can then call on the nodes to run the command:

```r
system.time(model <- clusterCall(cl, wsrpart, form, ds[train, vars], ntrees=4))
```

Clean up after ourselves:

```r
stopCluster(cl)
```
10 Build Models Through Multiple Servers

We call `makeCluster()` to build a cluster of servers to run our decision trees on the nodes.

```r
nodes <- paste("node", 1:10, sep="")
cl <- makeCluster(nodes)
cl
```

If there are errors, particularly about ssh askpass, then chances are you can not connect to the remote nodes using ssh without a password. You will need to set up a public ssh key (using `ssh-keygen -t dsa` without a pass phrase) on node1 and copy the resulting file `.ssh/id_dsa.pub` to each of the nodes as `.ssh/authorized_keys`.

Now we build just a single decision tree on each node:

```r
clusterEvalQ(cl, {library(parallel); library(rpart); library(rattle)})
clusterExport(cl, c("varWeights", "selectVars", "wsrpart"))
clusterExport(cl, c("varWeights", "selectVars", "wsrpart"))
system.time(model <- clusterCall(cl, wsrpart, form, ds[train, vars], ntrees=4))
stopCluster(cl)
```
11 Build Models Through Multiple Servers and Multiple Cores

We call `makeCluster()` again to build a cluster of servers to run our decision trees on the nodes. We then ask each node to use `mcparallel()` to use all cores on each node, through `mcwsrpart()`.

```r
nodes <- paste("node", 1:10, sep="")
cl <- makeCluster(nodes)
cl

clusterEvalQ(cl, {library(rpart); library(rattle)})
clusterExport(cl, "weatherDS")
clusterExport(cl, c("varWeights", "selectVars", "wsrpart", "mcwsrpart"))

system.time(forest <- clusterCall(cl, mcwsrpart, weatherDS, 8))

stopCluster(cl)
```
12 Exercise: Build Decision Trees on Multiple Servers

Extend the function \texttt{wsrpart()} to take an argument, \texttt{parallel=}, which lists a cluster of servers on which we are to build the decision trees in parallel. On each server we use as many cores as available in building trees.
13 Installing Packages Across Servers

nodes <- paste("node", 2:10, sep="")
c1 <- makeCluster(nodes)
clusterEvalQ(c1,
  install.packages("rattle",
    lib="/usr/local/lib/R/site-library",
    repos="http://rattle.togaware.com"))
stopCluster(c1)
14 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 chapter is one of many chapters available from http://HandsOnDataScience.com. In particular follow the links on the website with a * which indicates the generally more developed chapters.

Other resources include:
15 References


