Data Science with R
Multivariate Adaptive Regression Splines

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MARS, or Multivariate Adaptive Regression Splines, constructs a linear combination of basis functions for logistic regression.

The required packages for this chapter include:

```
library(rattle)         # The weather dataset and normVarNames().
library(randomForest)   # Impute missing values using na.roughfix().
library(dplyr)          # Data munging: tbl_df(), %>%.
library(ROCR)           # Use prediction() to convert to measures.
library(earth)          # An implementation of mars.
```

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 Data Preparation—Load and Configure

We use the **weather** dataset from rattle (Williams, 2014) to illustrate. Refer to Chapter Data for details.

```
library(rattle)          # Provides weather and normVarNames().
library(dplyr)           # Provides %>% and tbl_df().

dsname     <- "weather"
ds         <- get(dsname) %>% tbl_df()
names(ds)  <- normVarNames(names(ds))
vars       <- names(ds)
target     <- "rain_tomorrow"
risk       <- "risk_mm"
id         <- c("date", "location")
```

```
ds

## Source: local data frame [366 x 24]
##
##          date location min_temp max_temp rainfall evaporation sunshine
## 1  2007-11-01 Canberra      8.0     24.3      0.0         3.4      6.3
## 2  2007-11-02 Canberra     14.0     26.9      3.6         4.4      9.7
## 3  2007-11-03 Canberra     13.7     23.4      3.6         5.8      3.3
## 4  2007-11-04 Canberra     13.3     15.5     39.8         7.2      9.1
## 5  2007-11-05 Canberra      7.6     16.1      2.8         5.6     10.6
## 6  2007-11-06 Canberra      6.2     16.9      0.0         5.8      8.2
## 7  2007-11-07 Canberra      6.1     18.2      0.2         4.2      8.4
## 8  2007-11-08 Canberra      8.3     17.0      0.0         5.6      4.6
## 9  2007-11-09 Canberra      8.8     19.5      0.0         4.0      4.1
## 10 2007-11-10 Canberra      8.4     22.8     16.2         5.4      7.7
## ..        ...      ...      ...      ...      ...         ...      ...
## Variables not shown: wind_gust_dir (fctr), wind_gust_speed (dbl),
##   wind_dir_9am (fctr), wind_dir_3pm (fctr), wind_speed_9am (dbl),
##   wind_speed_3pm (dbl), humidity_9am (int), humidity_3pm (int),
##   pressure_9am (dbl), pressure_3pm (dbl), cloud_9am (int), cloud_3pm
##   (int), temp_9am (dbl), temp_3pm (dbl), rain_today (fctr), risk_mm (dbl),
##   rain_tomorrow (fctr)
```

2 Data Preparation—Variables to Ignore

Here we identify variables that we probably do not want to play a part in the modelling.

```
# Ignore the IDs and the risk variable.
ignore     <- union(id, if (exists("risk")) risk)

# Ignore variables that look like identifiers.
ids        <- which(sapply(ds, function(x) length(unique(x))) == nrow(ds))
ignore     <- union(ignore, names(ids))

# Ignore variables which are completely missing.
mvc        <- sapply(ds[vars], function(x) sum(is.na(x))) # Missing value count.
mvn        <- names(ds)[(which(mvc == nrow(ds)))]         # Missing var names.
ignore     <- union(ignore, mvn)

# Ignore variables that are mostly missing - e.g., 70% or more missing
mvn        <- names(ds)[(which(mvc >= 0.7*nrow(ds)))]
ignore     <- union(ignore, mvn)

# Ignore variables with many levels.
factors    <- which(sapply(ds[vars], is.factor))
lvls       <- sapply(factors, function(x) length(levels(ds[[x]])))
many       <- names(which(lvls > 20))    # Factors with too many levels.
ignore     <- union(ignore, many)

# Ignore constants.
constants  <- names(which(sapply(ds[vars], function(x) all(x == x[1L]))))
ignore     <- union(ignore, constants)

# Initialise the variables
vars       <- setdiff(vars, ignore)
```

```
vars

##  [1] "min_temp"        "max_temp"        "rainfall"
##  [4] "evaporation"     "sunshine"        "wind_gust_dir"
##  [7] "wind_gust_speed" "wind_dir_9am"    "wind_dir_3pm"
## [10] "wind_speed_9am"  "wind_speed_3pm"  "humidity_9am"
## [13] "humidity_3pm"    "pressure_9am"    "pressure_3pm"
## [16] "cloud_9am"       "cloud_3pm"       "temp_9am"
## [19] "temp_3pm"        "rain_today"      "rain_tomorrow"

ignore

## [1] "date"     "location" "risk_mm"
```

3 Data Preparation—Clean and Finalise

The dataset has missing values and the implementation of the algorithm does not support missing values so we impute the missing values here.

```
ds[vars] <- na.roughfix(ds[vars])
```

Now we finalise the meta-data.

```
# Variable roles.
inputc     <- setdiff(vars, target)
inputi     <- sapply(inputc, function(x) which(x == names(ds)), USE.NAMES=FALSE)
numi       <- intersect(inputi, which(sapply(ds, is.numeric)))
numc       <- names(numi)
cati       <- intersect(inputi, which(sapply(ds, is.factor)))
catc       <- names(cati)

# Remove all observations with a missing target.
ds         <- ds[!is.na(ds[target]),]

# Normalise factors.
factors    <- which(sapply(ds[vars], is.factor))
for (f in factors) levels(ds[[f]]) <- normVarNames(levels(ds[[f]]))

# Ensure the target is categoric.
ds[target] <- as.factor(ds[[target]])

# Number of observations.
nobs       <- nrow(ds)
```

4 Build Model

We use earth (Milborrow, 2014).

```
library(earth)          # Model builder

# Formula for modelling.
form       <- formula(paste(target, "~ ."))

# Training and test datasets.
seed       <- sample(1:1000000, 1)
set.seed(seed)
train      <- sample(nobs, 0.7*nobs)
test       <- setdiff(seq_len(nobs), train)
actual     <- ds[test, target]
risks      <- ds[test, risk]

# Build model.
m.earth    <- earth(form, data=ds[train, vars])
mtype      <- "earth"
model      <- m.earth

model

## Selected 21 of 94 terms, and 11 of 62 predictors
## Importance: wind_gust_speed, humidity_3pm, min_temp, max_temp, ...
## Number of terms at each degree of interaction: 1 20 (additive model)
## GCV 0.08528    RSS 15.4    GRSq 0.4259    RSq 0.5919
```

5 Evaluate Model with Error Matrix

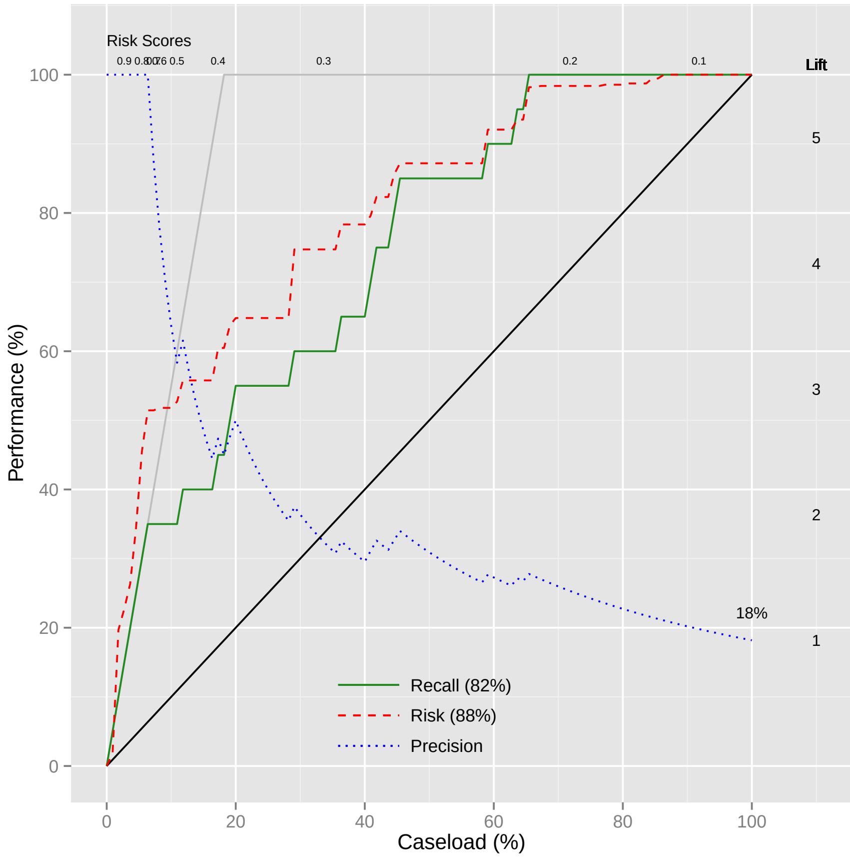
```
library(ROCR)          # prediction()

classes    <- predict(model, ds[test, vars], type="class")
acc        <- sum(classes == actual, na.rm=TRUE)/length(actual)
err        <- sum(classes != actual, na.rm=TRUE)/length(actual)
predicted  <- predict(model, ds[test, vars], type="response")
predicted  <- rescale(predicted, 0:1) # TRY THIS THEN READ DOCS
pred       <- prediction(predicted, ds[test, target])
ate        <- attr(performance(pred, "auc"), "y.values")[[1]]
```

```
round(table(actual, classes, dnn=c("Actual", "Predicted"))/length(actual), 2)

##       Predicted
## Actual   No  Yes
##    No  0.78 0.04
##    Yes 0.12 0.06
```

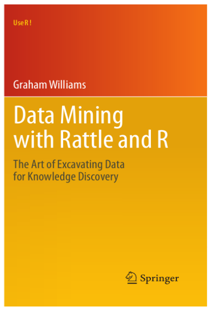
6 Evaluate Model with Riskchart




```
library(rattle)          # riskchart()

riskchart(predicted, actual, risks)
```

7 Further Reading and Acknowledgements



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:

- http://www.milbo.org/doc/earth-notes.pdf

8 References

Milborrow S (2014). *earth: Multivariate Adaptive Regression Spline Models*. R package version 3.2-7, URL http://CRAN.R-project.org/package=earth.

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 3.1.4, URL http://rattle.togaware.com/.

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