

Data Science with R

Transform and Manipulate Data

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In this module we introduce approaches to manipulate and transform our data.

The required packages for this module include:

```
library(rattle)      # The weatherAUS datasets and normVarNames()
library(ggplot2)     # Visualise the transforms.
library(plyr)        # Transform using ddplyr()
library(dplyr)       # Transform using ddplyr()
library(reshape2)    # melt() and dcast()
```

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.

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1 Data

```
library(rattle)
ds      <- weatherAUS
names(ds) <- normVarNames(names(ds))  # Lower case variable names.
str(ds)

## 'data.frame': 88768 obs. of  24 variables:
## $ date      : Date, format: "2008-12-01" "2008-12-02" ...
## $ location  : Factor w/ 49 levels "Adelaide","Albany",...: 3 3 3 3 3 ...
## $ min_temp  : num  13.4 7.4 12.9 9.2 17.5 14.6 14.3 7.7 9.7 13.1 ...
## .....
```

2 Factors

3 Factors: Drop Unused Levels

The complete list of levels of a factor are maintained even when we take a subset of a dataset which contains only a subset of the original levels.

For example, suppose we subset the weather dataset on location:

```
cities <- c("Adelaide", "Brisbane", "Canberra", "Darwin")
levels(ds$location)

## [1] "Adelaide"      "Albany"        "Albury"
## [4] "AliceSprings"  "BadgerysCreek" "Ballarat"
## [7] "Bendigo"       "Brisbane"      "Cairns"
## [10] "Canberra"      "Cobar"         "CoffsHarbour"
....

summary(ds$location)

##      Adelaide      Albany      Albury      AliceSprings
##      2036         1883         1883         1883
## BadgerysCreek    Ballarat    Bendigo      Brisbane
##      1852         1883         1883         2036
....

dss <- subset(ds, location %in% cities)
levels(dss$location)

## [1] "Adelaide"      "Albany"        "Albury"
## [4] "AliceSprings"  "BadgerysCreek" "Ballarat"
## [7] "Bendigo"       "Brisbane"      "Cairns"
## [10] "Canberra"      "Cobar"         "CoffsHarbour"
....

summary(dss$location)

##      Adelaide      Albany      Albury      AliceSprings
##      2036          0          0          0
## BadgerysCreek    Ballarat    Bendigo      Brisbane
##          0          0          0         2036
....
```

Notice that the levels remain unchanged even though there are no observations of the other locations. We can re-factor the levels using `factor()`:

```
dss$location <- factor(dss$location)
levels(dss$location)

## [1] "Adelaide" "Brisbane" "Canberra" "Darwin"

summary(dss$location)

## Adelaide Brisbane Canberra Darwin
##      2036      2036      2279      2036
```

4 Factors: Reorder Levels

By default the levels of a factor are ordered alphabetically. We can change the order simply by providing `levels=` to `factor()`.

```
levels(dss$location)
## [1] "Adelaide" "Brisbane" "Canberra" "Darwin"

summary(dss$location)
## Adelaide Brisbane Canberra Darwin
##      2036      2036      2279      2036

dss$location <- factor(dss$location, levels=rev(levels(dss$location)))

levels(dss$location)
## [1] "Darwin"    "Canberra" "Brisbane" "Adelaide"

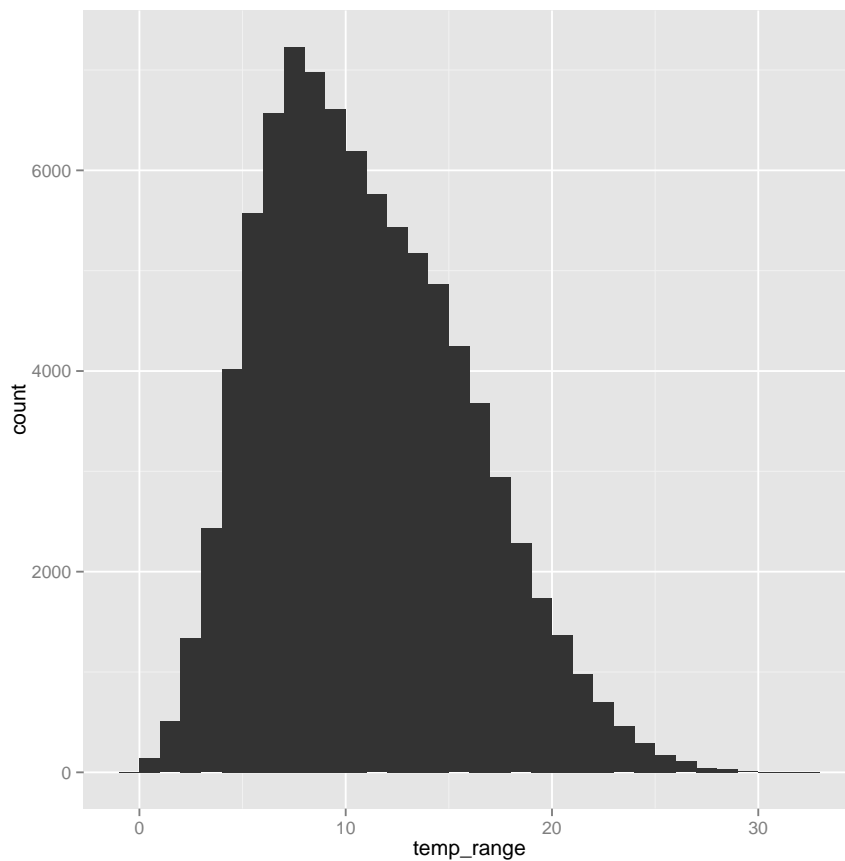
summary(dss$location)
## Darwin Canberra Brisbane Adelaide
##      2036      2279      2036      2036
```

5 Data Frame: Add a Column

Here we simply name the column as part of the data frame and it gets added to it.

```
ds$temp_range <- ds$max_temp - ds$min_temp
str(ds)

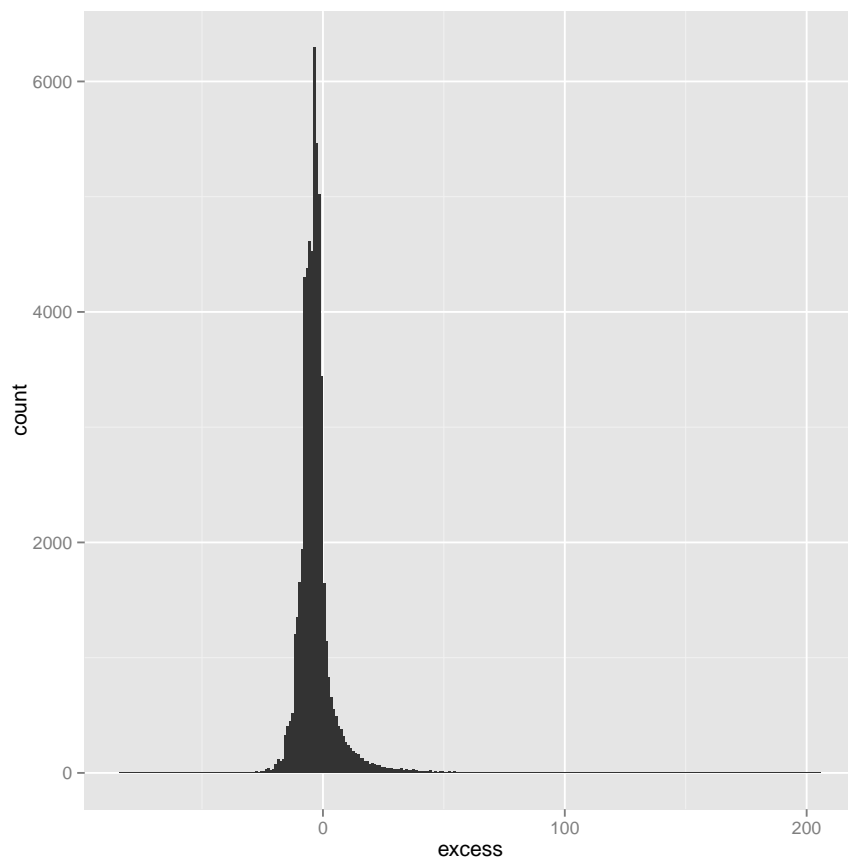
## 'data.frame': 88768 obs. of 25 variables:
## $ date      : Date, format: "2008-12-01" "2008-12-02" ...
## $ location   : Factor w/ 49 levels "Adelaide","Albany",...: 3 3 3 3 3 ...
## $ min_temp   : num 13.4 7.4 12.9 9.2 17.5 14.6 14.3 7.7 9.7 13.1 ...
## ...
p <- ggplot(ds, aes(x=temp_range))
p <- p + geom_bar(binwidth=1)
p
```



6 Transform: Add a Column

An alternative is to use `transform()` which can be neater when adding several columns, avoiding the use of the `$` nomenclature.

```
ds <- transform(ds,
                 temp_range=max_temp-min_temp,
                 excess=rainfall-evaporation)
sum(ds$excess, na.rm=TRUE)
## [1] -176068
str(ds)
## 'data.frame': 88768 obs. of 26 variables:
## $ date      : Date, format: "2008-12-01" "2008-12-02" ...
## $ location  : Factor w/ 49 levels "Adelaide","Albany",...: 3 3 3 3 3 ...
## $ min_temp  : num 13.4 7.4 12.9 9.2 17.5 14.6 14.3 7.7 9.7 13.1 ...
## ....
ggplot(ds, aes(x=excess)) + geom_bar(binwidth=1)
```



7 Subset Data

Exercise: Research the `subset()` function and illustrate its usage.

8 Transform Using DPlyR

The `plyr` ([Wickham, 2014a](#)) package provides a collection of the most useful functions for manipulating data. Its concepts, once understood, are very powerful and allow us to express numerous tasks simply and efficiently.

Like `apply()`, the `plyr` functions operate on data frames, matrices, lists, vectors or arrays. An operation is applied to some collection of items (e.g., each group of observations or group of list elements) in the input data structure, and the results are packaged into a new data structure.

Generally, the pattern is like `ddply(data, variables, function, ...)` where in this case (as indicated by the first d) the input data is a data frame and the result (the second d) is also a data frame. The rows of the data frame will be grouped by the variables identified, and for each group the function is applied to obtain the resulting data. The remaining arguments are treated as arguments to the function.

Exercise: Explore and provide examples.

9 Summarise Data Using dplyr()

dplyr (Wickham and Francois, 2014) introduces a grammar of data manipulation and processes data much more efficiently than plyr (Wickham, 2014a) (anywhere from 20 times to 1000 times faster) and other R packages through parallel processing using Rcpp (Eddelbuettel and Francois, 2014).

```
weatherAUS %>%
  group_by(Location) %>%
  summarise(total = sum(Rainfall)) %>%
  arrange(desc(total)) %>%
  head(5)

## Source: local data frame [5 x 2]
##
##      Location total
## 1      Darwin 11092
## 2 SydneyAirport 5295
## 3 MountGambier 4050
## 4      Perth 3723
## 5      Bendigo 3286
```

10 Removing Columns

```
tail(ds$excess)
## [1] NA NA NA NA NA NA

names(ds)

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

ds$excess <- NULL
tail(ds$excess)
## NULL

names(ds)

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

11 Subset Data

Exercise: Discuss the subset function.

12 Wide to Long Data

Let's take a sample dataset to illustrate the concepts of wide and long data.

```
dss <- subset(ds, date==max(date))
dim(dss)
## [1] 49 25
head(dss)
##           date      location min_temp max_temp rainfall evaporation
## 1883 2014-04-25      Albury      5.3    22.5      0.0          NA
## 3735 2014-04-25 BadgerysCreek    16.5    21.2      1.8          NA
## 5587 2014-04-25       Cobar     12.9    30.5      0.0          7.4
....
```

This data is in wide format. We can convert it to long format, which is sometimes useful when using, for example, `ggplot2` (Wickham and Chang, 2014). We use `reshape2` (Wickham, 2014b) to do this. In long format we essentially maintain a single measurement per observation. The measurement for our data are all those columns recording some measure of the weather—that is, all variables except for `date` and `location`.

```
library(reshape2)
dssm <- melt(dss, c("date", "location"))
## Warning: attributes are not identical across measure variables; they will be
dropped
dim(dssm)
## [1] 1127 4
head(dssm)
##           date      location variable value
## 1 2014-04-25      Albury min_temp    5.3
## 2 2014-04-25 BadgerysCreek min_temp    16.5
## 3 2014-04-25       Cobar min_temp    12.9
....
tail(dssm)
##           date      location variable value
## 1122 2014-04-25      Hobart temp_range    9.1
## 1123 2014-04-25  Launceston temp_range   17.8
## 1124 2014-04-25 AliceSprings temp_range   19.3
....
dssm[sample(nrow(dssm), 6),]
##           date location variable value
## 415 2014-04-25 Melbourne wind_dir_3pm      N
## 672 2014-04-25 Nuriootpa pressure_9am 1017.7
## 166 2014-04-25 Ballarat  evaporation    <NA>
....
```

This is now clearly long data.

13 Long to Wide Data

```
dssmc <- dcast(dssm, date + location ~ variable)
dim(dss)

## [1] 49 25

dim(dssmc)

## [1] 49 25

head(dss)

##           date      location min_temp max_temp rainfall evaporation
## 1883 2014-04-25      Albury      5.3    22.5      0.0          NA
## 3735 2014-04-25 BadgerysCreek    16.5    21.2      1.8          NA
## 5587 2014-04-25      Cobar     12.9    30.5      0.0          7.4
## 7439 2014-04-25 CoffsHarbour    14.4    25.0      0.0          3.0
## 9291 2014-04-25      Moree     17.7    30.0      0.4          NA
## 11174 2014-04-25   Newcastle    11.0    21.2     11.8          NA
##           sunshine wind_gust_dir wind_gust_speed wind_dir_9am wind_dir_3pm
## 1883          NA          NNW          22          S          NNE
## 3735          NA          NNE          20          S          ESE
## ....

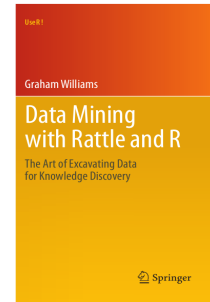
head(dssmc)

##           date      location min_temp max_temp rainfall evaporation sunshine
## 1 2014-04-25      Adelaide      9    23.3      0.2      <NA>      <NA>
## 2 2014-04-25      Albany     <NA>     21     <NA>      2.2      4.4
## 3 2014-04-25      Albury      5.3    22.5      0      <NA>      <NA>
## 4 2014-04-25 AliceSprings    10.5    29.8      0      6.6     11.1
## 5 2014-04-25 BadgerysCreek    16.5    21.2      1.8     <NA>     <NA>
## 6 2014-04-25   Ballarat      1.9    15.9      0     <NA>     <NA>
##           wind_gust_dir wind_gust_speed wind_dir_9am wind_dir_3pm wind_speed_9am
## 1          NNW          39          NE          WNW          13
## 2          <NA>          <NA>          <NA>          SSW          <NA>
## ....
```

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 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.



15 References

- Eddelbuettel D, Francois R (2014). *Rcpp: Seamless R and C++ Integration*. R package version 0.11.1, URL <http://www.rcpp.org>, <http://dirk.eddelbuettel.com/code/rcpp.html>, <https://github.com/RcppCore/Rcpp>.
- 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/>.
- Wickham H (2014a). *plyr: Tools for splitting, applying and combining data*. R package version 1.8.1, URL <http://CRAN.R-project.org/package=plyr>.
- Wickham H (2014b). *reshape2: Flexibly reshape data: a reboot of the reshape package*. R package version 1.4, URL <http://CRAN.R-project.org/package=reshape2>.
- Wickham H, Chang W (2014). *ggplot2: An implementation of the Grammar of Graphics*. R package version 1.0.0, URL <http://ggplot2.org>, <https://github.com/hadley/ggplot2>.
- Wickham H, Francois R (2014). *dplyr: dplyr: a grammar of data manipulation*. R package version 0.2, URL <http://CRAN.R-project.org/package=dplyr>.
- 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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