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.

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
```

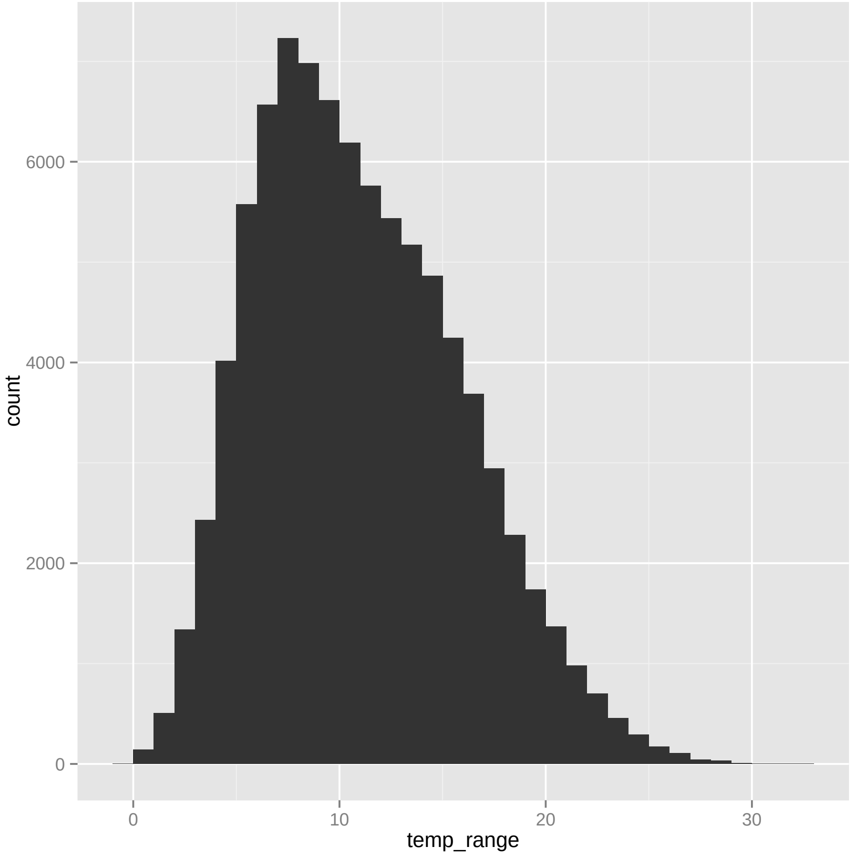
5 Data Frame: Add a Column

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 ...
....
```

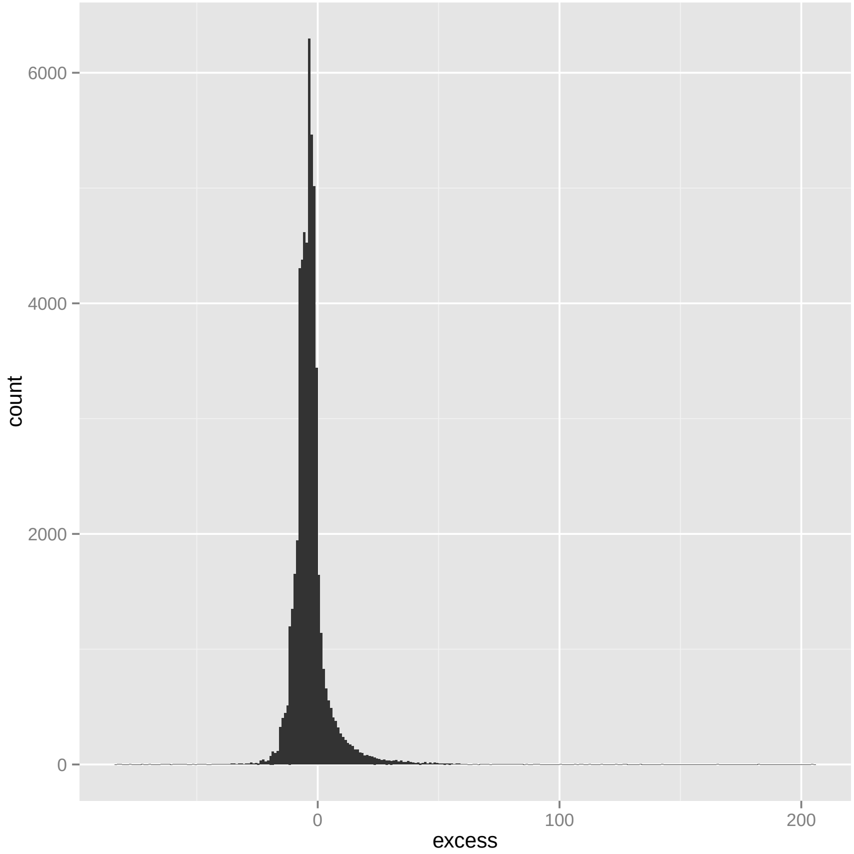
```
p <- ggplot(ds, aes(x=temp_range))
p <- p + geom_bar(binwidth=1)
p
```



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. It's 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`.

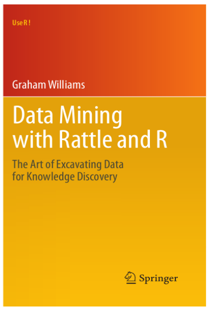
```
library(reshape2)
dssm <- melt(dss, c("date", "location"))

## 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


Use R!
Graham Williams
Data Mining with Rattle and R
The Art of Excavating Data for Knowledge Discovery
Springer

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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