Working with Data

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Contents

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1 Introduction

These notes are a work in progress meant to supplement material in Fox and Weisberg (2019). The focus is using data to answer simple questions that only require simple tools.

There is a collection of exercises on R, many of which are related to this material.

Questions, links and discussions concerning this material can take place on Piazza. There's a copy of this document on Piazza that you can edit to

- correct errors
- improve or add to the presentation
- add relevant exercises. To add exercises, precede them with a 'level 3' heading: '### Exercises'

We use the following packages in this script which you may need to install if you haven't already:

```r
if(FALSE) {
  # install these manually if you need to:
  install.packages('haven')
  install.packages('tidyverse')  # might take a long time
  install.packages('readxl')
  install.packages('devtools')
  install.packages('car')
  install.packages('magrittr')
  install.packages('latticeExtra')
  install.packages('alr4')
  devtools::install_github('gmonette/spida2')
}
```

Play with the basic R functions listed in Hadley Wickham's chapter on vocabulary. Write a script that illustrates the use of these functions.

2 Data Input

2.1 From a package

The Davis data set in the 'car' package on measured versus reported height:

```r
library("car") # loads car and carData packages
```

```
Loading required package: carData
```

```r
class(Davis)
```

```
[1] "data.frame"
```

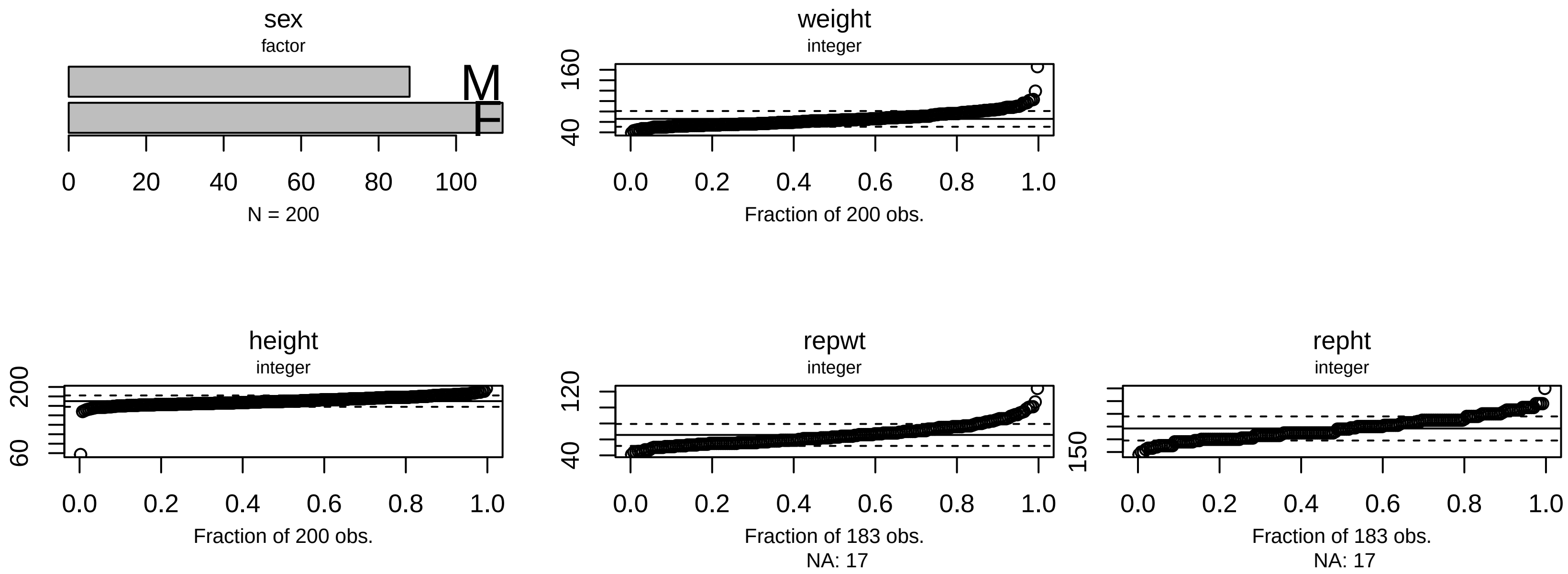
```r
brief(Davis)
```

```
200 x 5 data.frame (195 rows omitted)
    sex weight height repwt repht
    [f]    [i]    [i]   [i]   [i]
1   M       77    182    77   180
2   F       58    161    51   159
3   F       53    161    54   158
. . .
199 M       90    181    91   178
200 M       79    177    81   178
```

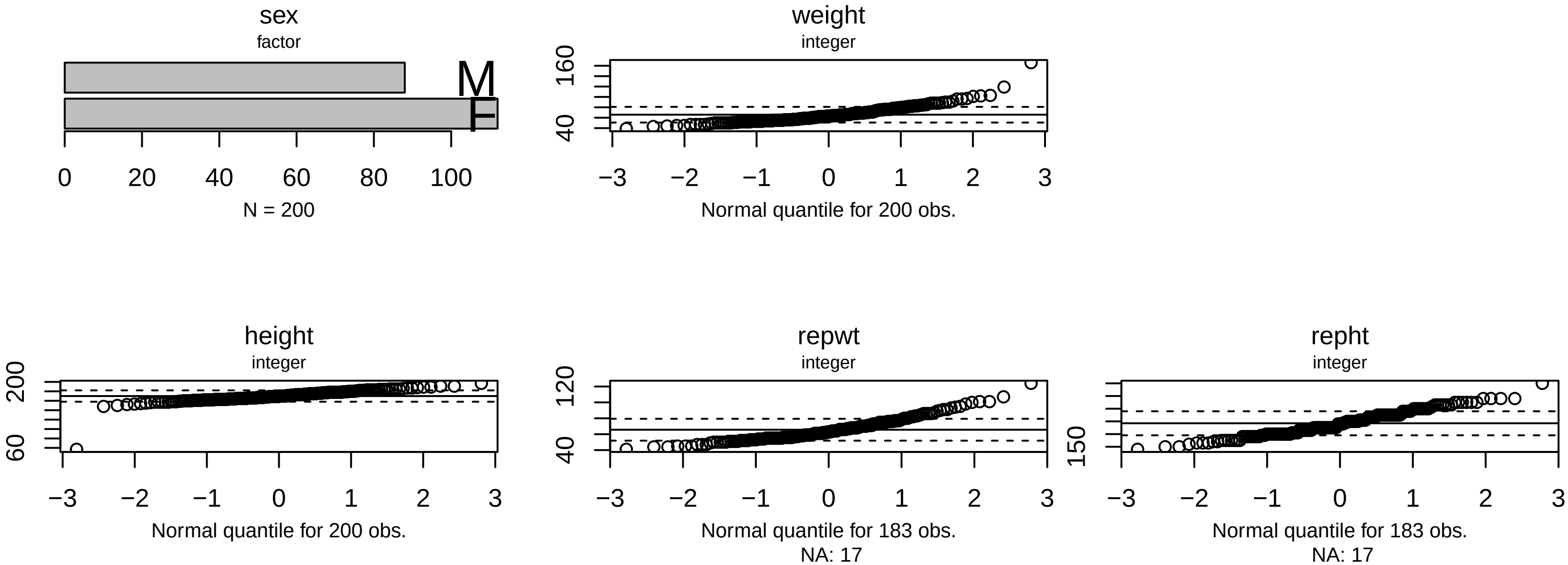
```r
library(spida2)
```

```
Attaching package: 'spida2'

The following object is masked from 'package:base':

    grepv
```

```r
xqplot(Davis, mfrow = c(2,2)) # uniform quantiles
```




```r
xqplot(Davis, mfrow = c(2,2), ptype = 'n')  # normal quantiles
```




```r
# if not installed: install.packages('alr4')
data("Challeng", package="alr4")
brief(Challeng)
```

```
23 x 7 data.frame (18 rows omitted)
         temp pres fail   n erosion blowby damage
          [i]  [i]  [i] [i]     [i]    [i]    [i]
4/12/81    66   50    0   6       0      0      0
11/12/81   70   50    1   6       1      0      4
3/22/82    69   50    0   6       0      0      0
. . .
11/26/85   76  200    0   6       0      0      0
1/12/86    58  200    1   6       1      0      4
```

2.2 From vectors

```r
cooperation <- c(49, 64, 37, 52, 68, 54, 61, 79, 64, 29,
    27, 58, 52, 41, 30, 40, 39, 44, 34, 44)

(condition <- rep(c("public", "anonymous"), c(10, 10)))
```

```
 [1] "public"    "public"    "public"    "public"    "public"
 [6] "public"    "public"    "public"    "public"    "public"
[11] "anonymous" "anonymous" "anonymous" "anonymous" "anonymous"
[16] "anonymous" "anonymous" "anonymous" "anonymous" "anonymous"
```

```r
(sex <- rep(rep(c("male", "female"), each=5), 2))
```

```
 [1] "male"   "male"   "male"   "male"   "male"   "female"
 [7] "female" "female" "female" "female" "male"   "male"
[13] "male"   "male"   "male"   "female" "female" "female"
[19] "female" "female"
```

```r
rep(5, 3)
```

```
[1] 5 5 5
```

```r
rep(c(1, 2, 3), 2)
```

```
[1] 1 2 3 1 2 3
```

```r
rep(1:3, 3:1)
```

```
[1] 1 1 1 2 2 3
```

```r
Guyer1 <- data.frame(cooperation, condition, sex)
brief(Guyer1)
```

```
20 x 3 data.frame (15 rows omitted)
   cooperation condition    sex
           [n]       [c]    [c]
1           49 public    male
2           64 public    male
3           37 public    male
. . .
19          34 anonymous female
20          44 anonymous female
```

```r
Guyer2 <- data.frame(
  cooperation = c(49, 64, 37, 52, 68, 54, 61, 79, 64, 29,
                  27, 58, 52, 41, 30, 40, 39, 44, 34, 44),
  condition = rep(c("public", "anonymous"), c(10, 10)),
  sex = rep(rep(c("male", "female"), each=5), 2)
)
identical(Guyer1, Guyer2)
```

```
[1] TRUE
```

The structure of a data frame:

- a **list** in which each element has the same length

```r
str(Guyer1)
```

```
'data.frame': 20 obs. of  3 variables:
 $ cooperation: num  49 64 37 52 68 54 61 79 64 29 ...
```

```
 $ condition  : chr  "public" "public" "public" "public" ...
 $ sex        : chr  "male" "male" "male" "male" ...
```

2.3 From a text file

2.3.1 From a remote site

If the the values in the file are separated by arbitrary white space use the **read.table** function.

```
Duncan <- read.table(
  file="http://www.john-fox.ca/Companion/data/Duncan.txt",
  header=TRUE)
brief(Duncan)  # a 'car' function that prints first 3 and last 2
```

```
  45 x 4 data.frame (40 rows omitted)
             type income education prestige
              [c]    [i]       [i]      [i]
  accountant prof     62        86       82
  pilot      prof     72        76       83
  architect  prof     75        92       90
  . . .
  policeman  bc       34        47       41
  waiter     bc        8        32       10
```

```
             # rows along with the type of each variable
```

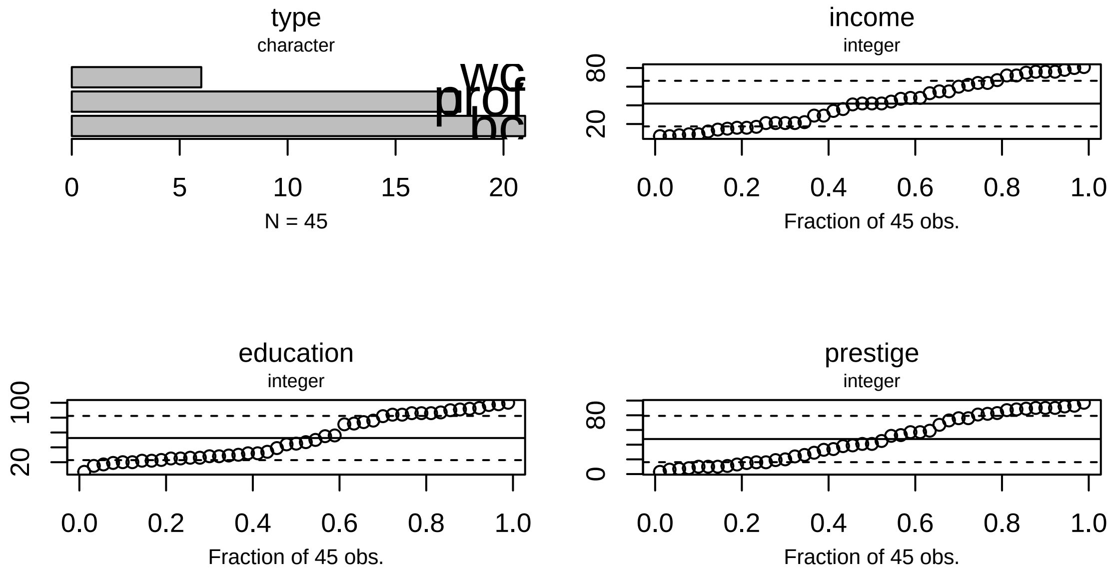
2.3.2 Locally

We're going to download this text file from John Fox's website to illustrate what it looks like when reading a local file:

```r
download.file(
  "http://www.john-fox.ca/Companion/data/Duncan.txt",
  "Duncan.txt")
Duncan <- read.table("Duncan.txt", header = TRUE)
brief(Duncan)
```

```
45 x 4 data.frame (40 rows omitted)
           type income education prestige
            [c]    [i]       [i]      [i]
accountant prof     62        86       82
pilot      prof     72        76       83
architect  prof     75        92       90
. . .
policeman  bc       34        47       41
waiter     bc        8        32       10
```

```r
xqplot(Duncan, mfrow = c(2,2))
```




```
# use: ?Duncan for more information
```

2.4 Excel files

2.4.1 CSV files

One way to read a single Excel spreadsheet is to save it from Excel as a comma-separated-values (CSV) file from Excel. You can then read it with the **read.csv** function that works like 'read.table' except that 'header = TRUE' is the default and fields are separated by commas (,). If a field contains a comma then it must be enclosed in quotes. You don't need to worry about this. Excel takes care of creating an appropriate file and 'read.csv' takes care of reading it.

For more advanced work, look at the help file for **read.table**.

2.4.2 Reading worksheets from an Excel file

The Hadleyverse uses 'tibbles': data frames with extra information and an aversion to factors and rownames

I believe that currently the **readxl** package in CRAN may be **(but see some reservations below)** the most effective way to read Excel worksheets directly.

The 'readxl' package is part of the 'tidyverse' (which is part of what's often referred to as the 'Hadleyverse' after Hadley Wickham who started it). The Hadleyverse adds a lot of functionality to R and redoes much of R's basic functions. Some people think of it as a new dialect of R, a bit like American English compared with British English. It's controversial whether one should invest effort learning basic R or whether one should jump into the Hadleyverse from the start. Hadley Wickam's excellent on-line book, *Advanced R* whose first edition is on line explores the depths of 'base' R, which are complex enough to require an extensive treatment for anyone who aspires to be creative with the language, either in base R or in the Hadleyverse.

```
library("tidyverse")  # loads all of the tidyverse packages
```

```
-- Attaching core tidyverse packages --------- tidyverse 2.0.0 --
v dplyr     1.1.4     v readr     2.1.5
v forcats   1.0.0     v stringr   1.5.1
v ggplot2   3.5.2     v tibble    3.2.1
v lubridate 1.9.4     v tidyr     1.3.1
v purrr     1.0.4
-- Conflicts -------------------------- tidyverse_conflicts() --
x readr::cols()      masks spida2::cols()
x dplyr::filter()    masks stats::filter()
x ggplot2::labs()    masks spida2::labs()
x dplyr::lag()       masks stats::lag()
x purrr::map()       masks spida2::map()
x dplyr::recode()    masks car::recode()
x purrr::some()      masks car::some()
```

```
x lubridate::years() masks spida2::years()
i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to become errors
```

Note how 'tidyverse' masks many functions including functions in 'base' packages. This can break code that uses these functions. Having a look at the list of masked function, I notice 'some' in 'car' that I use so, to set things straight, I can redefine 'some' to make sure that we use the version in 'car':

```
some <- car::some
```

This stores a local version 'car::some' in the global environment which R searches before looking in 'tidyverse'. This is the list of places where R searches for objects when they are called from the command line:

```
search()
```

```
 [1] ".GlobalEnv"         "package:lubridate" "package:forcats"
 [4] "package:stringr"    "package:dplyr"     "package:purrr"
 [7] "package:readr"      "package:tidyr"     "package:tibble"
[10] "package:ggplot2"    "package:tidyverse" "package:spida2"
[13] "package:car"        "package:carData"   "package:stats"
[16] "package:graphics"   "package:grDevices" "package:utils"
[19] "package:datasets"   "package:methods"   "Autoloads"
[22] "package:base"
```

You can see that packages are searched in the reverse order in which they were loaded.

```
Duncan.tibble <- as_tibble(Duncan)
print(Duncan.tibble, n=5)  # note print() method
```

```
# A tibble: 45 x 4
  type  income education prestige
  <chr>  <int>     <int>    <int>
1 prof      62        86       82
```

```
  2 prof      72         76        83
  3 prof      75         92        90
  4 prof      55         90        76
  5 prof      64         86        90
  # i 40 more rows
```

```r
brief(Duncan.tibble)
```

```
  # A tibble: 45 x 4
     type  income education prestige
     <chr>  <int>     <int>    <int>
   1 prof      62        86       82
   2 prof      72        76       83
   3 prof      75        92       90
   4 prof      55        90       76
   5 prof      64        86       90
   6 prof      21        84       87
   7 prof      64        93       93
   8 prof      80       100       90
   9 wc        67        87       52
  10 prof      72        86       88
  # i 35 more rows
```

```r
brief(as.data.frame(Duncan.tibble))
```

```
  45 x 4 data.frame (40 rows omitted)
     type income education prestige
      [c]    [i]       [i]      [i]
  1  prof     62        86       82
  2  prof     72        76       83
```

```
3  prof     75         92        90
. . .
44 bc       34         47        41
45 bc        8         32        10
```

- If `file.xlsx` is an Excel file and you want to read the second worksheet that uses 'NA' for missing values, use: `dd <- read_excel('file.xlsx', sheet = 2,   na = 'NA')`
- If you want to read an Excel file on a web server (e.g. blackwell), some functions that read files, e.g. `read.csv`, will accept the URL instead of a path to a local file. However, at this time, `read_excel` requires a local path. Thus, you need to download the file before reading it with `read_excel`. The usual way to download a file within R uses the `download.file` function. However, the default way to download binary Excel files, may corrupt the file. Try using the 'curl' method as illustrated below. This may not be necessary on Macs. Please let us know on Piazza!
- There are two xlsx files on blackwell:
  - 'file.xlsx': a small Excel file with clean data except that a numerical value was entered as '$1,000.00'
  - 'file2.xlsx': same as above except that there is an 'invisible' single blank in the first column of the row after the actual data. `read_excel` will interpret this as an NA by default and create an entire row of NA values. Also, some entries are blank and some entries have been indicated as NAs by entering 'NA'. These common irregularities in Excel files can create havoc unless you are ready to deal with them.

Run this code line by line:

```r
library(readxl)
dir <- 'http://blackwell.math.yorku.ca/MATH6630/R/'
download.file(paste0(dir,'file.xlsx'),'_file.xlsx',
              method = 'curl') # download to _file.xlsx
                               # to avoid overwriting
download.file(paste0(dir,'file2.xlsx'),'_file2.xlsx',
              method = 'curl')
dt <- read_excel('_file.xlsx')
dt2 <- read_excel('_file2.xlsx')
```

```
dt
```

```
# A tibble: 5 x 3
  Name               Age Purchase
  <chr>            <dbl>    <dbl>
1 Mary Smith          25     1000
2 Chow, Vincent       42      200.
3 Mohammed, Tarik     56      123
4 O'Brien, John       21     2000
5 Jolie, Mary         33      150
```

Note that '$1,000.00' was read as a numerical value! 'read.csv' would not do this. See exercises for a way of cleaning up a numeric variable that was entered with extraneous symbols ($) and a thousands separator.

```
dt2
```

```
# A tibble: 6 x 3
  Name            Age   Purchase
  <chr>           <chr>    <dbl>
1 Mary Smith      25        1000
2 Chow, Vincent   NA         200.
3 Mohammed, Tarik 56          NA
4 O'Brien, John   <NA>      2000
5 Jolie, Mary     .          150
6 <NA>            <NA>        NA
```

Note that the '.' was interpreted as a character value and turned 'Age' into a character variable. With `read.csv` the '.' would have been interpreted as a missing data by default. See this site for the various possibilities used in different countries. It is easy to use regular expressions (see below) to fix amounts entered in a different format. Also, the symbol used for the radix (the decimal separator) can be specified as the `dec` argument to `read.csv`.

```r
dt2$Age <- as.numeric(as.character(dt2$Age))
```

```
Warning: NAs introduced by coercion
```

```r
dt2
```

```
# A tibble: 6 x 3
  Name               Age Purchase
  <chr>            <dbl>    <dbl>
1 Mary Smith          25     1000
2 Chow, Vincent       NA      200.
3 Mohammed, Tarik     56       NA
4 O'Brien, John       NA     2000
5 Jolie, Mary         NA      150
6 <NA>                NA       NA
```

To get rid of the blank row

```r
dt2 <- subset(dt2, !is.na(Name))
dt2
```

```
# A tibble: 5 x 3
  Name               Age Purchase
  <chr>            <dbl>    <dbl>
1 Mary Smith          25     1000
2 Chow, Vincent       NA      200.
3 Mohammed, Tarik     56       NA
4 O'Brien, John       NA     2000
5 Jolie, Mary         NA      150
```

The files `dt` and `dt2` are tibbles with categorical variables represented as character vectors.

```r
class(dt)
```

```
[1] "tbl_df"     "tbl"        "data.frame"
```

```r
sapply(dt, class)
```

```
       Name         Age    Purchase
"character"   "numeric"   "numeric"
```

You can turn them into data frames with factors for categorical variables as follows:

```r
dt <- as.data.frame(as.list(dt))
class(dt)
```

```
[1] "data.frame"
```

```r
sapply(dt, class)
```

```
       Name         Age    Purchase
"character"   "numeric"   "numeric"
```

```r
dt
```

```
              Name Age Purchase
1       Mary Smith  25  1000.00
2    Chow, Vincent  42   200.32
3 Mohammed, Tarik  56   123.00
4    O'Brien, John  21  2000.00
5      Jolie, Mary  33   150.00
```

```r
dt2 <- as.data.frame(as.list(dt2))
class(dt2)
```

```
[1] "data.frame"
```

```r
sapply(dt2, class)
```

```
       Name         Age    Purchase
"character"   "numeric"   "numeric"
```

```r
dt2
```

```
             Name Age Purchase
1      Mary Smith  25  1000.00
2    Chow, Vincent  NA   200.32
3 Mohammed, Tarik  56       NA
4    O'Brien, John  NA  2000.00
5     Jolie, Mary  NA   150.00
```

Sometimes, read_excel will report a warning like: … expecting numeric: got …. This happens when read_excel has decided that a column is numeric based on its inspection of the top entries but then encounters non-numeric data. The remedy is to read the file as character and to modify the entries that need to be modified. See the section below on using regular expressions to fix variables **without touching the original data**.

Reread the data this way:

```r
dt2 <- read_excel('_file.xlsx', na = 'NA',
                  col_type = rep('text', ncol(dt2)))
dt2 <- as.data.frame(as.list(dt2))
```

All variables will now be factors. You need to go through them and modify them as needed. If a variable x, say, should be numeric, and **does not need any editing**, you can fix it with:

```r
z <- as.numeric(as.character(dd$x))  # note that 'as.character' is ESSENTIAL
z # have a look
dd$x <- z # if everything is ok
```

If a variable needs editing, for example suppose student numbers that should have 9 digits have been entered in a variety of ways: '123 456 789', or '123-456-789', or '#12346789' or with the wrong number of digits, you could do this:

```
dd$x.orig <- dd$x  # keep the original in case you need to go back and check
z <- as.character(dd$x)
# Have a look:
z
z <- gsub('[ -]','', z)  # remove all blanks and hyphens.
    # Note that the hyphen must be first or last in the brackets,
    # otherwise it denotes a range, i.e. '[A-Z]' matches any
    # capital letter.
z <- sub('^#','', z)  # remove leading # signs,'^' is an 'anchor' matching the beginning of the strin
z # have another look
table(nchar(z))
# If valid data must have a length of 9:
z9 <- nchar(z) == 9
z <- ifelse(z9, as.numeric(z), NA)
dd$x <- z # Fixed! Invalid input is NA
```

There are a number of packages to write Excel files:

- openxlsx
- writeXLS

Post your experiences on Piazza.

2.4.3 Annoyance in 'readxl'

Using read_excel to read a file with 9-digit student numbers as text because some were entered incorrectly by students converted numbers to scientific notation: '123456789E0' for no apparent reason because they were read as 'text'. The transformation back to numeric variables works correctly for 9 digits. One would need to experiment with more digits in the input. It's annoying that the string is altered in a way that seems unnecessary.

2.4.4 A wrapper for 'readxl'

From this thread on stackoverflow here is a function that reads an Excel file and make every variable a character variable to avoid problems with variables that you want to read as characters although the top of the data set contains only values that `read_excel` considers numeric. There is isn't a single argument to `read_excel` to request that all variables be read as characters. Instead, you need to know the number of variable to repeat the `col_types` argument as many times as there are columns. That is, the authors did not build in recycling! This function first finds out how many variable there are so it can then call `read_excel` with a correct `col_types` argument.

```
Read_excel<-function(file, sheet, ...)
{
  library("readxl")
  num.columns <- length(readxl:::xlsx_col_types(
    file,
    sheet = sheet, n = 1)
  )
  readxl::read_excel(
    file,
    sheet = sheet,
    col_types = rep("text", num.columns),...
  )
}
```

2.5 Read sheets from an SPSS file

SPSS files have long been a problem for R but there is a relatively recent package, 'haven', on CRAN that seems to do an excellent job. It uses R attributes to store SPSS variable labels and correctly transforms SPSS date into R objects of class 'Date'. Be aware that it is common in SPSS to have user-defined missing values. By default all these values are converted to 'NA' in R but the distinct values are likely to be informative. Use the argument, 'user_na = TRUE' to recover missing value labels. Like 'read_excel', 'read_sav' creates a 'tibble' but the trick that works with Excel files of using 'as.data.frame(as.list(...))' to turn it into a standard data frame does not work here. You might have to some surgery on the variables in some cases.

Warning: Some functions, e.g. 'lm' may treat a categorical variable as a numeric variable producing embarrassingly non-sensical results.

```
library(haven)
path <- system.file('examples', 'iris.sav', package = 'haven')
     # get the path to a system file
path
dd <- haven::read_sav(path)
head(dd)  # a tibble
class(dd)
fit <- lm(Petal.Width ~ Species, dd)
summary(fit)  # Species is numerical
ds <- as.data.frame(as.list(dd))
head(ds) # Species is still numerical
# You are not expected to understand the next line ... yet!
dd$Species <-
  factor(names(attr(dd$Species,'labels'))[dd$Species])
     # complicated fix
str(dd$Species) # now it's a factor!
fit <- lm(Petal.Width ~ Species, dd)
```

```r
    # treats 'Species' as a factor with correct levels
summary(fit)
```

2.6 Referring to variables in a data frame

Data frames have two personalities:

- list of variable (each of same length)
- matrix of entries like a spreadsheet so entries can be referred to by row and column

```r
str(Duncan)
```

```
'data.frame': 45 obs. of  4 variables:
 $ type     : chr  "prof" "prof" "prof" "prof" ...
 $ income   : int  62 72 75 55 64 21 64 80 67 72 ...
 $ education: int  86 76 92 90 86 84 93 100 87 86 ...
 $ prestige : int  82 83 90 76 90 87 93 90 52 88 ...
```

Fully qualified name

```r
Duncan$prestige     # using the '$' (select) operator
```

```
 [1] 82 83 90 76 90 87 93 90 52 88 57 89 97 59 73 38 76 81 45 92
[21] 39 34 41 16 33 53 67 57 26 29 10 15 19 10 13 24 20  7  3 16
[41]  6 11  8 41 10
```

3rd row, 4th columns

```r
Duncan[3, 4]
```

```
[1] 90
```

All rows, 4th column

```
Duncan[ , 4]
```

```
 [1] 82 83 90 76 90 87 93 90 52 88 57 89 97 59 73 38 76 81 45 92
[21] 39 34 41 16 33 53 67 57 26 29 10 15 19 10 13 24 20  7  3 16
[41]  6 11  8 41 10
```

Refer to column by name

```
Duncan[ , "prestige"]
```

```
 [1] 82 83 90 76 90 87 93 90 52 88 57 89 97 59 73 38 76 81 45 92
[21] 39 34 41 16 33 53 67 57 26 29 10 15 19 10 13 24 20  7  3 16
[41]  6 11  8 41 10
```

Using the 'with' function so names are interpreted within the data frame

```
with(Duncan, prestige)
```

```
 [1] 82 83 90 76 90 87 93 90 52 88 57 89 97 59 73 38 76 81 45 92
[21] 39 34 41 16 33 53 67 57 26 29 10 15 19 10 13 24 20  7  3 16
[41]  6 11  8 41 10
```

```
with(Duncan, mean(prestige))
```

```
[1] 47.68889
```

3 Subsetting data frames

`%in%` is very useful to subset rows of a data frame.

The following also illustrates inline `read.csv` and the 'magrittr' pipe: `%>%`

```r
library(spida2)
library(car)
library(magrittr)  # for pipes
```

```
Attaching package: 'magrittr'

The following object is masked from 'package:purrr':

    set_names

The following object is masked from 'package:tidyr':

    extract
```

```r
df <- read.csv(text =
'
name,    age,   sex,   height
John Smith,     32,     M,        68
Mary Smith,     36,     F,        67
Andrew Smith Edwards, 42,  M,    71
Paul Jones,     31,     M,        65
"Smith, Mary",    33,   F,        32
')
df
```

```
                  name age    sex height
1           John Smith  32      M     68
2           Mary Smith  36      F     67
3 Andrew Smith Edwards  42      M     71
```

```
4            Paul Jones  31      M     65
5           Smith, Mary  33      F     32
```

Using `subset` with `%in%`

```r
subset(df, name %in% c('John Smith','Paul Jones'))
```

```
        name age    sex height
1 John Smith  32      M     68
4 Paul Jones  31      M     65
```

Implicit drop = FALSE: The resulting factor still has the original levels (sometimes you want this)

```r
subset(df, name %in% c('John Smith','Paul Jones'))$name
```

```
[1] "John Smith" "Paul Jones"
```

Use droplevels to get drop = TRUE, and get rid of original levels.

```r
subset(df, name %in% c('John Smith','Paul Jones')) %>%
  droplevels %>%
  .$name
```

```
[1] "John Smith" "Paul Jones"
```

Using regular expressions and logical subsetting

```r
subset(df, grepl('Smith', name))   # Smith anywhere
```

```
                    name age    sex height
1             John Smith  32      M     68
2             Mary Smith  36      F     67
3 Andrew Smith Edwards  42      M     71
5            Smith, Mary  33      F     32
```

```r
subset(df, grepl('Smith$', name))  # Smith at end of string
```

```
        name age    sex height
  1 John Smith  32      M     68
  2 Mary Smith  36      F     67
```

3.1 match: associative array

%in% is a special case of **match** but it's much more intuitive. Skip this if you prefer.

match(x, table, nomatch) # returns the position of each # x matched exactly in table

```r
match(c('e','b','a','z','ee','A'), letters)
```

```
  [1]  5  2  1 26 NA NA
```

```r
match(c('e','b','a','z','ee','A'), letters, 0)
```

```
  [1]  5  2  1 26  0  0
```

```r
match(c('e','b','a','z','ee','A'), letters, 0) > 0
```

```
  [1]  TRUE  TRUE  TRUE  TRUE FALSE FALSE
```

```r
c('e','b','a','z','ee','A') %in% letters
```

```
  [1]  TRUE  TRUE  TRUE  TRUE FALSE FALSE
```

can use match to translate

```r
LETTERS [match(c('a','s','w', 'else'), letters)]
```

```
  [1] "A" "S" "W" NA
```

```r
LETTERS [match(c('a','s','w', 'else'), letters, 0)]
```

```
[1] "A" "S" "W"
```

3.2 recycling principle

if a vector is too short, just recycle

```r
c(1, 2, 3, 4) + 1
```

```
[1] 2 3 4 5
```

```r
c(1, 2, 3, 4) + c(4, 3)     # no warning if multiple fits
```

```
[1] 5 5 7 7
```

```r
c(1, 2, 3, 4) + c(4, 3, 2)  # produces warning otherwise
```

```
Warning in c(1, 2, 3, 4) + c(4, 3, 2): longer object length is
not a multiple of shorter object length
```

```
[1] 5 5 5 8
```

```r
c(1, 2, 3, 4)[T] # T is recycled to length 4. Why?
```

```
[1] 1 2 3 4
```

```r
c(1, 2, 3, 4)[1] # But 1 is not recycled
```

```
[1] 1
```

3.3 making vectors: rep and seq

flexible: note how differently it works if the second argument is a vector:

```
rep(1:4, 5)  # recycle vector
```

```
 [1] 1 2 3 4 1 2 3 4 1 2 3 4 1 2 3 4 1 2 3 4
```

```
rep(1:4, 1:4) # repeat each element
```

```
 [1] 1 2 2 3 3 3 4 4 4 4
```

```
rep(1:4, each = 5) # repeat each element
```

```
 [1] 1 1 1 1 1 2 2 2 2 2 3 3 3 3 3 4 4 4 4 4
```

like:

```
rep(1:4, c(5,5,5,5))
```

```
 [1] 1 1 1 1 1 2 2 2 2 2 3 3 3 3 3 4 4 4 4 4
```

`seq` is similar to `:` but with more options

```
1:5
```

```
[1] 1 2 3 4 5
```

```
seq(1, 5)
```

```
[1] 1 2 3 4 5
```

```
seq(1, 5, 0.5)
```

```
[1] 1.0 1.5 2.0 2.5 3.0 3.5 4.0 4.5 5.0
```

```r
seq_along(letters) # generates a sequence of
```

```
 [1]  1  2  3  4  5  6  7  8  9 10 11 12 13 14 15 16 17 18 19 20
[21] 21 22 23 24 25 26
```

```r
                   # indices for a vector or list
```

The **seq_along** and the **seq_len** functions are useful in **for loops**. Consider the difference between using 'seq_along(x)' and '1:length(x)' if 'x' has length 0 which can easily happen inside a function.

```r
x <- 1:10
x <- x[FALSE]
x
```

```
integer(0)
```

or

```r
x <- 1:10
x <- x[0]
x
```

```
integer(0)
```

```r
1:length(x) # probably not what you want in a for loop
```

```
[1] 1 0
```

```r
seq_along(x)
```

```
integer(0)
```

4 apply and friends

`apply` is the easy one, applied to slices of a mattrix or array

`apply(m, MARGIN, FUN, ...)`; MARGIN is a vector with the dimensions to be projected onto

```
a <- array(1:24, c(2,3,4))
a
```

```
, , 1

     [,1] [,2] [,3]
[1,]    1    3    5
[2,]    2    4    6

, , 2

     [,1] [,2] [,3]
[1,]    7    9   11
[2,]    8   10   12

, , 3

     [,1] [,2] [,3]
[1,]   13   15   17
[2,]   14   16   18

, , 4

     [,1] [,2] [,3]
```

```
[1,]   19   21   23
[2,]   20   22   24
```

```r
apply(a, 1, sum)
```

```
[1] 144 156
```

```r
apply(a, c(2,3), sum)
```

```
     [,1] [,2] [,3] [,4]
[1,]    3   15   27   39
[2,]    7   19   31   43
[3,]   11   23   35   47
```

```r
a[1,1,1] <- NA
apply(a, c(2,3), sum)
```

```
     [,1] [,2] [,3] [,4]
[1,]   NA   15   27   39
[2,]    7   19   31   43
[3,]   11   23   35   47
```

```r
apply(a, c(2,3), sum, na.rm = T) # extra arguments to sum
```

```
     [,1] [,2] [,3] [,4]
[1,]    2   15   27   39
[2,]    7   19   31   43
[3,]   11   23   35   47
```

4.1 lapply: do the same thing to each element of a list

A data frame is an important example of a list.

Suppose you have a data frame with many numeric variables recording temperatures in Celsius and you need to transform them to Farenheit

```
df <- read.csv(text=
'
city,     day1,  day2,  day3
Montreal,   20,    25,    30
Toronto,    23,    26,    19
New York,   28,    35,    32
')
df
```

```
      city day1 day2 day3
1 Montreal   20   25   30
2  Toronto   23   26   19
3 New York   28   35   32
```

```
sapply(df, class) # returns a vector if it can
```

```
       city        day1        day2        day3
"character"   "integer"   "integer"   "integer"
```

```
lapply(df, class) # always returns a list
```

```
$city
[1] "character"

$day1
[1] "integer"

$day2
```

```
[1] "integer"

$day3
[1] "integer"
```

4.2 Simple function

Simple function for now, later we'll use a generic function and methods

```
to_farenheit <- function(x) {
  if(is.factor(x) || !is.numeric(x) ) x # why 'is.factor'?
  else 32 + (9/5)*x
}
to_farenheit
```

```
function (x)
{
    if (is.factor(x) || !is.numeric(x))
        x
    else 32 + (9/5) * x
}
```

```
lapply(df, to_farenheit) # but this is a list
```

```
$city
[1] "Montreal" "Toronto"  "New York"

$day1
[1] 68.0 73.4 82.4
```

```
$day2
[1] 77.0 78.8 95.0

$day3
[1] 86.0 66.2 89.6
```

```
as.data.frame(lapply(df, to_farenheit))
```

```
      city day1 day2 day3
1 Montreal 68.0 77.0 86.0
2  Toronto 73.4 78.8 66.2
3 New York 82.4 95.0 89.6
```

5 Multilevel data

5.1 Extensions of apply functions

```
library(spida2)
library(lattice)
library(latticeExtra)
```

```

Attaching package: 'latticeExtra'

The following object is masked from 'package:ggplot2':

    layer
```

Data on math achievement tests in high schools in US 1977 students in 40 schools: 21 Catholic and 19 Public variables: - school id - mathach math achievement - ses socioeconomic status - Sex: Female Male - Minority status: Yes or No - Size of the school - Sector: Catholic or Public - PRACAD: priority given to acacemics in school - DISCLIM: disciplinary climate of school

```
head(hs)
```

```
  school mathach    ses    Sex Minority Size   Sector PRACAD
1   1317  12.862  0.882 Female       No  455 Catholic   0.95
2   1317   8.961  0.932 Female      Yes  455 Catholic   0.95
3   1317   4.756 -0.158 Female      Yes  455 Catholic   0.95
4   1317  21.405  0.362 Female      Yes  455 Catholic   0.95
5   1317  20.748  1.372 Female       No  455 Catholic   0.95
6   1317  18.362  0.132 Female      Yes  455 Catholic   0.95
  DISCLIM
1  -1.694
2  -1.694
3  -1.694
4  -1.694
5  -1.694
6  -1.694
```

Note that the first use of 'hs' copies 'hs' from spida2. Changes that you make are only local. If you want to get the original back from spida2, use:

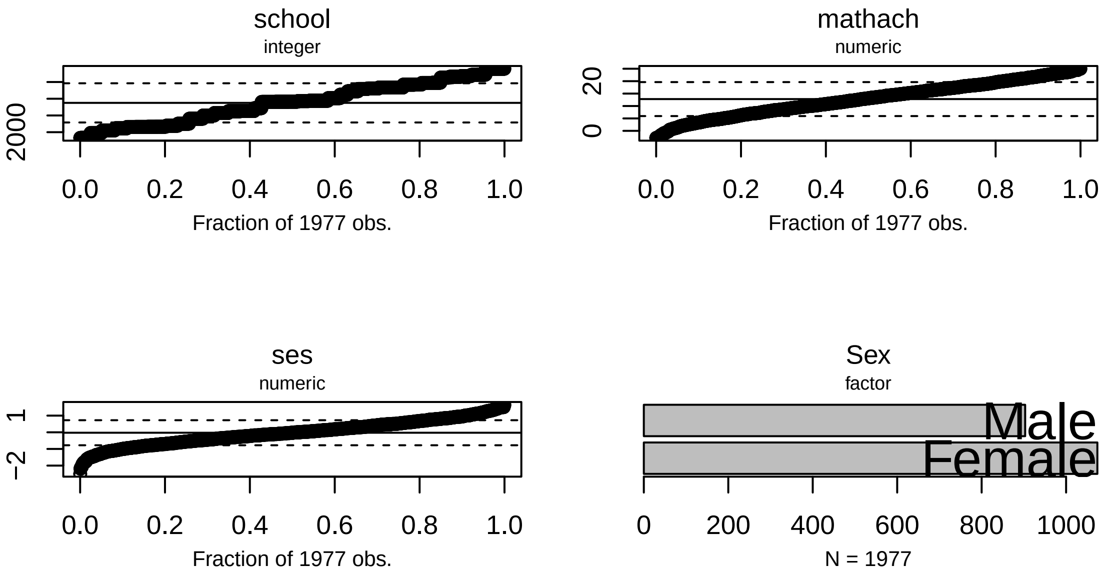
```
data(hs)
```

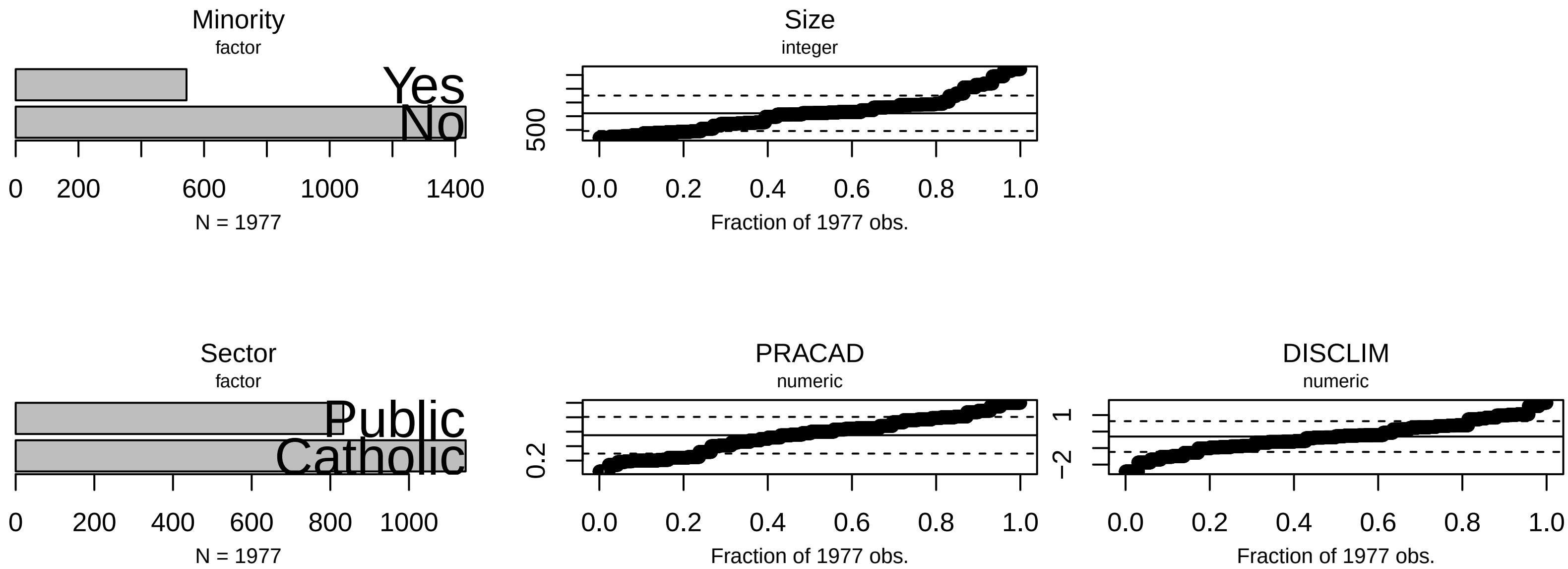
or, if it's necessary to be more specific:

```
data(hs, package = 'spida2')
dim(hs)
```

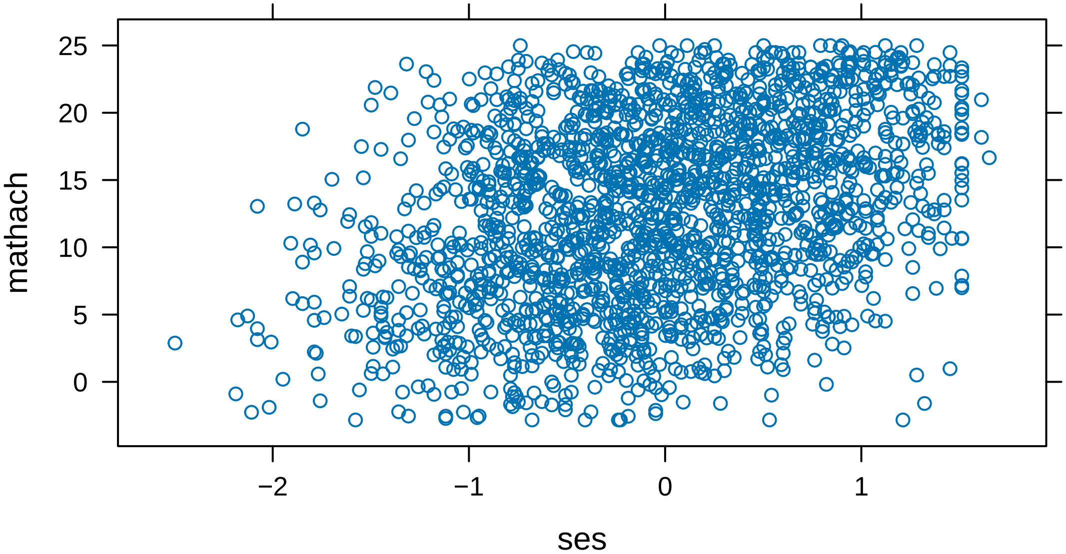
```
[1] 1977    9
```

```
xqplot(hs, mfrow = c(2,2))
```

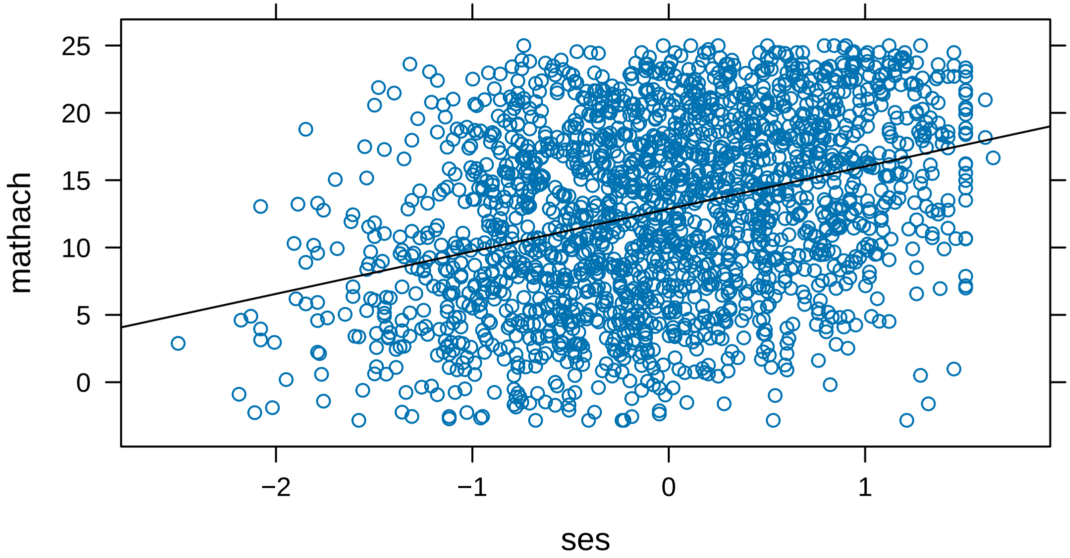




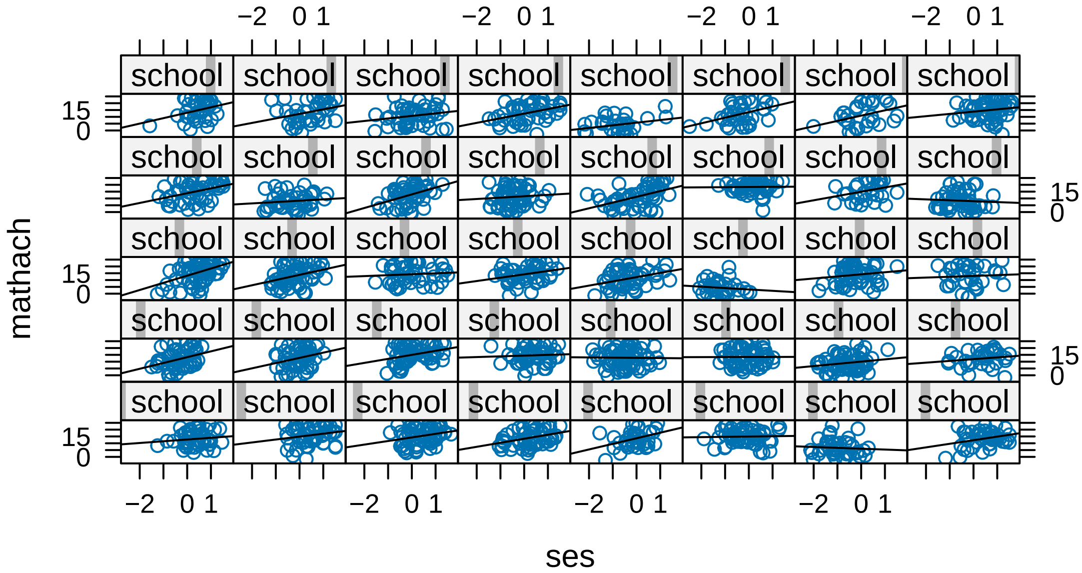

```
xyplot(mathach ~ ses, hs)
```



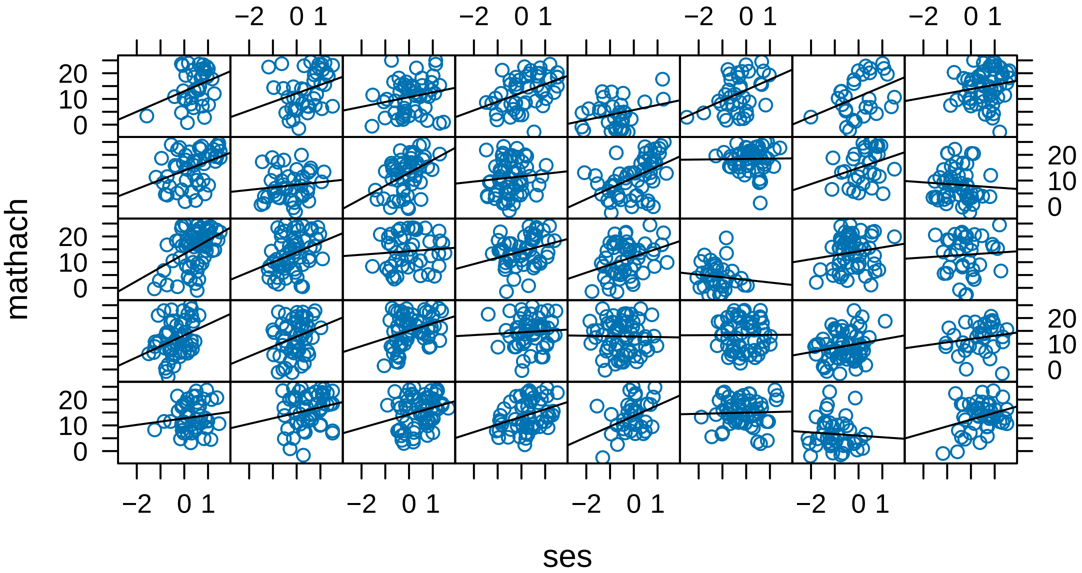

```
xyplot(mathach ~ ses, hs) + layer(panel.lmline(...))
```



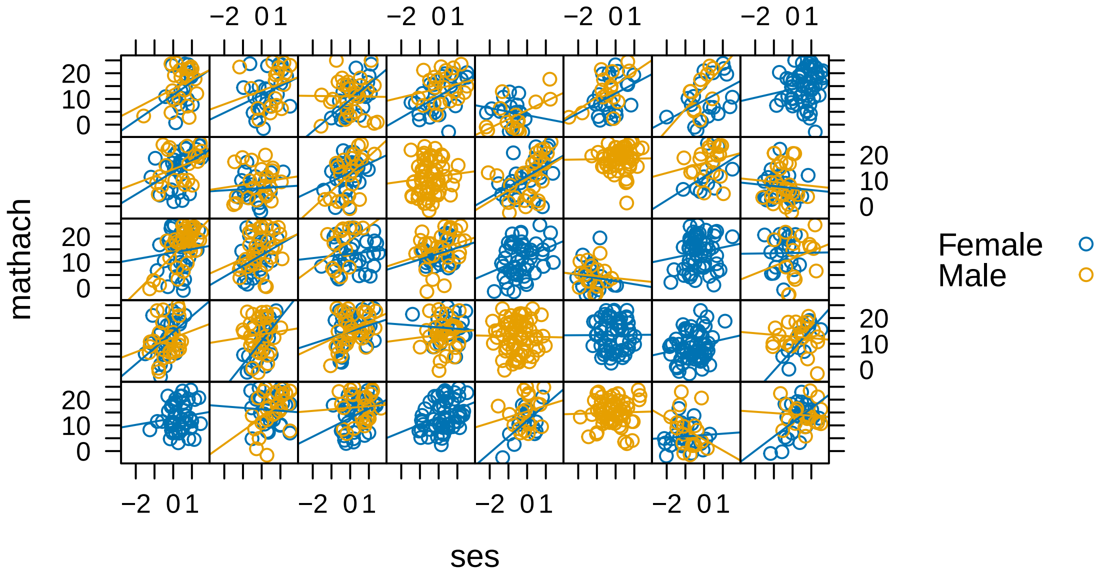

```
xyplot(mathach ~ ses | school, hs) + layer(panel.lmline(...))
```




```r
xyplot(mathach ~ ses | school, hs, strip = FALSE) +
  layer(panel.lmline(...))
```




```r
xyplot(mathach ~ ses | school, hs,
       groups = Sex, strip = FALSE,
       auto.key = T) +
  glayer(panel.lmline(...))
```



Note: Two types of variables:

- student-level variables vary from student to student:
  - Synonyms: micro or level 1 variables
- school-level variables vary from school to school but constant within schools
  - Synonyms: macro or level 2 variables, contextual variable
- could have additional levels: School Board, State, etc.

We can use the tapply function to get information on individual schools

```
tapply(hs$mathach, hs$school, mean)
```

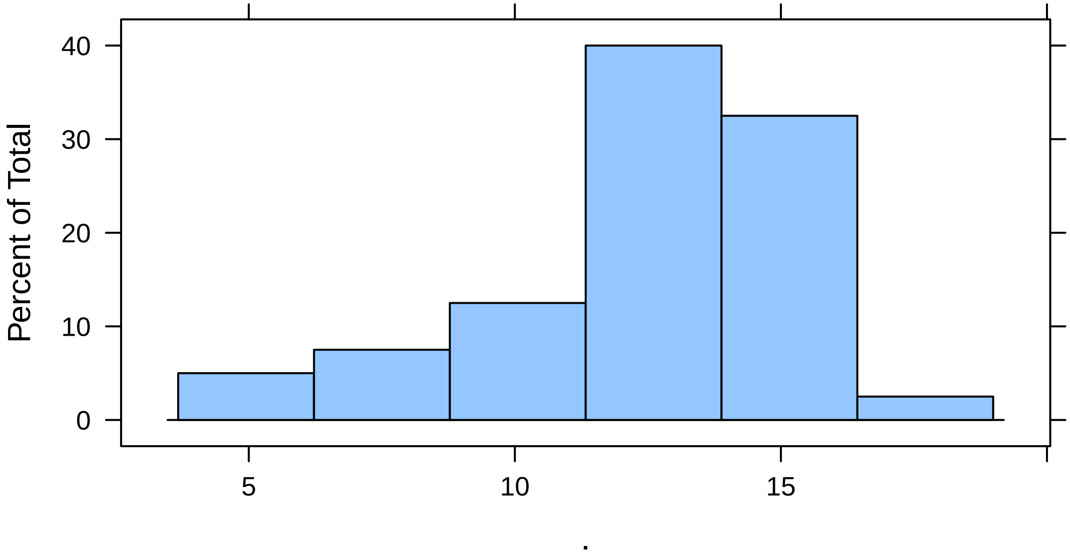
```
     1317      1906      2208      2458      2626      2629 
13.177687 15.983170 15.404667 13.985684 13.396605 14.907772 
     2639      2658      2771      3013      3610      3992 
```

```
 6.615476 13.396156 11.844109 12.610830 15.354953 14.645208
     4292      4511      4530      4868      5619      5640
12.864354 13.409034  9.055698 12.310176 15.416242 13.160105
     5650      5720      5761      5762      6074      6484
14.273533 14.282302 11.138058  4.324865 13.779089 12.912400
     6897      7172      7232      7342      7345      7688
15.097633  8.066818 12.542635 11.166414 11.338554 18.422315
     7697      7890      7919      8531      8627      8707
15.721781  8.341098 14.849973 13.528683 10.883717 12.883938
     8854      8874      9550      9586
 4.239781 12.055028 11.089138 14.863695
```

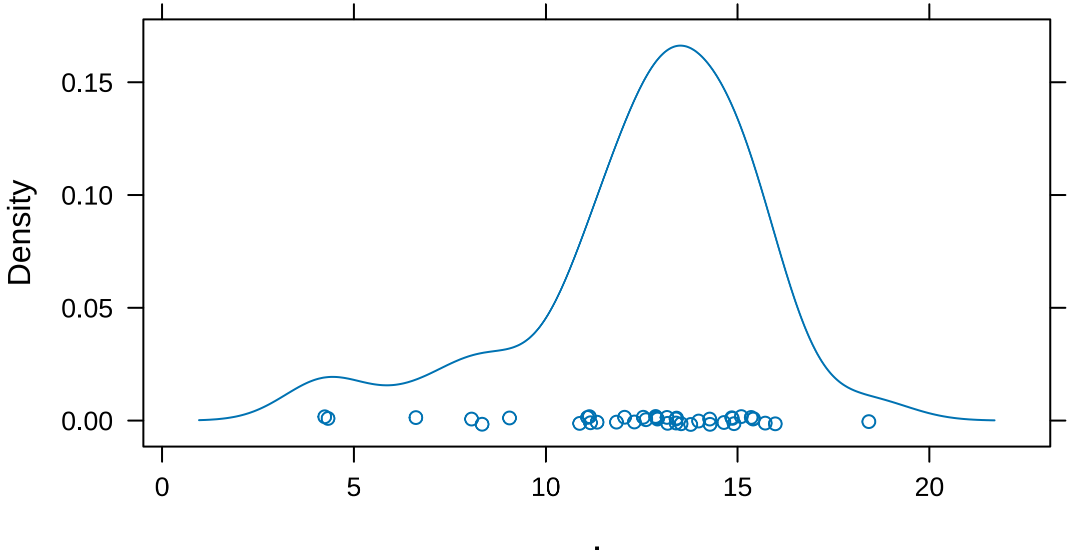
tapply(Y, id, function, extra arguments):

- apply 'function' to each chunk of 'Y' created by levels of 'id',
- use 'id' for names

```
library(latticeExtra)
tapply(hs$mathach, hs$school, mean)  %>% histogram
```




```r
tapply(hs$mathach, hs$school, mean)  %>% densityplot
```



But often it's more useful to have the result incorporated back into the data set. We can use `spida2::capply`

```
hs <-
  within(hs, {
    mathach_mean <- capply(mathach, school, mean)
  }
  )
head(hs)
```

```
    school mathach    ses    Sex Minority Size   Sector PRACAD
  1   1317  12.862  0.882 Female       No  455 Catholic   0.95
  2   1317   8.961  0.932 Female      Yes  455 Catholic   0.95
  3   1317   4.756 -0.158 Female      Yes  455 Catholic   0.95
  4   1317  21.405  0.362 Female      Yes  455 Catholic   0.95
```

```
5   1317  20.748  1.372 Female        No  455 Catholic   0.95
6   1317  18.362  0.132 Female       Yes  455 Catholic   0.95
  DISCLIM mathach_mean
1  -1.694     13.17769
2  -1.694     13.17769
3  -1.694     13.17769
4  -1.694     13.17769
5  -1.694     13.17769
6  -1.694     13.17769
```

```r
some(hs)  # random selection of rows (from car)
```

```
     school mathach    ses    Sex Minority Size   Sector PRACAD
160    2208  14.845  0.242 Female       No 1061 Catholic   0.68
238    2626  10.530  0.122   Male       No 2142   Public   0.40
349    2639   3.089 -1.138   Male      Yes 2713   Public   0.14
369    2658  22.388 -0.648   Male       No  780 Catholic   0.79
384    2658  16.172  0.652 Female       No  780 Catholic   0.79
577    3992   5.092  0.392   Male       No 1114 Catholic   0.73
905    5619  23.062  0.932   Male       No 1118 Catholic   0.77
1100   5761   3.422 -0.598 Female       No  215 Catholic   0.63
1692   8531  22.401 -1.178   Male       No 2190   Public   0.58
1852   8854   6.306 -1.438   Male       No  745   Public   0.18
     DISCLIM mathach_mean
160   -0.864    15.404667
238    0.142    13.396605
349   -0.282     6.615476
369   -0.961    13.396156
384   -0.961    13.396156
```

```
  577   -1.534    14.645208
  905   -1.286    15.416242
  1100  -0.892    11.138058
  1692   0.132    13.528683
  1852  -0.228     4.239781
```

Like tapply but return a vector that has the same shape as Y

Creative use of functions gives broad possibilities

How variable is mathach in each school?

```
hs <- within(
  hs,
  {
    mathach_sd <- capply(mathach, school, sd)
    ses_sd <- capply(ses, school, sd)
  }
)
```

These variables can be called 'sample computed contextual' variables because they would be different for a different sample.

`capply` can also be used for within-school transformations that are do not produce contextual variables.

e.g. within-school ranks

```
hs <- within(
  hs,
  {
    mathach_rk <- capply(mathach, school, rank)
  }
)
```

```r
some(hs)
```

```
     school mathach    ses    Sex Minority Size   Sector PRACAD
16     1317  20.039  1.152 Female      Yes  455 Catholic   0.95
256    2626  22.421  0.072   Male       No 2142   Public   0.40
284    2629  19.188  0.422   Male       No 1314 Catholic   0.81
635    4292   5.427 -0.468   Male      Yes 1328 Catholic   0.76
1067   5761   2.076 -1.118 Female       No  215 Catholic   0.63
1216   6484  15.296  1.122   Male       No  726   Public   0.19
1291   6897  19.303  1.312   Male       No 1415   Public   0.55
1356   7232  21.628 -0.368 Female       No 1154   Public   0.20
1410   7342   4.335 -0.048   Male      Yes 1220 Catholic   0.46
1833   8854  -1.714 -0.578   Male      Yes  745   Public   0.18
     DISCLIM mathach_mean    ses_sd mathach_sd mathach_rk
16    -1.694    13.177687 0.5561583   5.462586         40
256    0.142    13.396605 0.5601067   6.242649         35
284   -0.613    14.907772 0.7063209   5.165071         43
635   -0.674    12.864354 0.6511382   6.219492         11
1067  -0.892    11.138058 0.7122389   6.544368          5
1216   0.218    12.912400 0.6958345   7.426520         19
1291  -0.361    15.097633 0.7445231   6.647635         34
1356   0.975    12.542635 0.5743482   6.721008         50
1410   0.380    11.166414 0.5648459   6.393930         10
1833  -0.228     4.239781 0.8036439   5.406482          7
```

within-school deviations

```r
hs <- within(
  hs,
```

```r
  {
    mathach_dev <- mathach - capply(mathach, school, mean)
    ses_dev <- ses - capply(ses, school, mean)
  }
)
some(hs)
```

```
       school mathach    ses    Sex Minority Size   Sector PRACAD
  50     1906  20.455  0.382 Female       No  400 Catholic   0.87
  112    2208  18.460  1.392 Female       No 1061 Catholic   0.68
  227    2626   7.775 -0.128   Male       No 2142   Public   0.40
  368    2658  13.662  0.672 Female       No  780 Catholic   0.79
  505    3013  19.696 -0.168   Male       No  760   Public   0.56
  526    3610  21.034  1.012   Male       No 1431 Catholic   0.80
  759    4530   5.922 -1.788 Female      Yes  435 Catholic   0.60
  869    5619  19.757  0.922   Male       No 1118 Catholic   0.77
  1108   5761  14.730  0.192 Female      Yes  215 Catholic   0.63
  1272   6897  15.885 -0.388   Male      Yes 1415   Public   0.55
       DISCLIM mathach_mean    ses_sd mathach_sd mathach_rk
  50    -0.939    15.983170 0.6135833   6.515435         36
  112   -0.864    15.404667 0.5981188   6.122802         40
  227    0.142    13.396605 0.5601067   6.242649          8
  368   -0.961    13.396156 0.6402846   5.642341         24
  505   -0.213    12.610830 0.4799328   6.985697         42
  526   -0.621    15.354953 0.6316415   5.894163         50
  759   -0.245     9.055698 0.6210062   5.567967         21
  869   -1.286    15.416242 0.5972748   7.280409         47
  1108  -0.892    11.138058 0.7122389   6.544368         34
```

```
1272  -0.361    15.097633 0.7445231   6.647635         22
         ses_dev mathach_dev
50   -0.12962264   4.4718302
112   0.96883333   3.0553333
227  -0.06315789  -5.6216053
368   0.23355556   0.2658444
505  -0.12377358   7.0851698
526   0.89187500   5.6790469
759  -1.19111111  -3.1336984
869   0.50166667   4.3407576
1108  0.51500000   3.5919423
1272 -0.73755102   0.7873673
```

```r
lm(mathach_dev ~ ses_dev, hs)
```

```

Call:
lm(formula = mathach_dev ~ ses_dev, data = hs)

Coefficients:
(Intercept)      ses_dev
  1.612e-16    2.223e+00
```

```r
lm(mathach_dev ~ ses_dev, hs) %>% summary
```

```

Call:
lm(formula = mathach_dev ~ ses_dev, data = hs)

Residuals:
```

```
     Min       1Q   Median       3Q      Max
-19.0093  -4.4831   0.2262   4.7600  17.0043

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) 1.612e-16  1.366e-01    0.00        1
ses_dev     2.223e+00  2.145e-01   10.37   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 6.072 on 1975 degrees of freedom
Multiple R-squared:  0.05159, Adjusted R-squared:  0.05111
F-statistic: 107.4 on 1 and 1975 DF,  p-value: < 2.2e-16
```

```r
lm(mathach ~ ses + factor(school), hs) %>% summary
```

```
Call:
lm(formula = mathach ~ ses + factor(school), data = hs)

Residuals:
     Min       1Q   Median       3Q      Max
-19.0093  -4.4831   0.2262   4.7600  17.0043

Coefficients:
                   Estimate Std. Error t value Pr(>|t|)
(Intercept)        12.40995    0.88839  13.969  < 2e-16 ***
ses                 2.22319    0.21664  10.262  < 2e-16 ***
factor(school)1906  2.43579    1.22255   1.992  0.04647 *
```

```
factor(school)2208  2.05394    1.18778   1.729  0.08393 .
factor(school)2458  1.06932    1.20174   0.890  0.37368
factor(school)2626  1.13081    1.33469   0.847  0.39696
factor(school)2629  2.80384    1.20602   2.325  0.02018 *
factor(school)2639 -3.65037    1.32655  -2.752  0.00598 **
factor(school)2658  0.01146    1.27276   0.009  0.99281
factor(school)2771  0.18883    1.22047   0.155  0.87706
factor(school)3013  0.29921    1.22493   0.244  0.80705
factor(school)3610  2.67795    1.17207   2.285  0.02243 *
factor(school)3992  1.42292    1.22203   1.164  0.24441
factor(school)4292  1.53522    1.18100   1.300  0.19378
factor(school)4511  1.23727    1.20074   1.030  0.30294
factor(school)4530 -2.02725    1.19262  -1.700  0.08932 .
factor(school)4868 -0.90260    1.37476  -0.657  0.51155
factor(school)5619  2.07182    1.16354   1.781  0.07513 .
factor(school)5640  1.14276    1.20678   0.947  0.34378
factor(school)5650  1.81369    1.27452   1.423  0.15489
factor(school)5720  1.79995    1.22390   1.471  0.14154
factor(school)5761 -0.55380    1.23610  -0.448  0.65419
factor(school)5762 -5.43072    1.38255  -3.928 8.86e-05 ***
factor(school)6074  1.98441    1.21387   1.635  0.10226
factor(school)6484  0.91406    1.36804   0.668  0.50412
factor(school)6897  1.91057    1.24550   1.534  0.12520
factor(school)7172 -3.69881    1.28742  -2.873  0.00411 **
factor(school)7232  0.33303    1.23121   0.270  0.78681
factor(school)7342 -0.24793    1.20900  -0.205  0.83754
factor(school)7345 -1.14531    1.20826  -0.948  0.34330
factor(school)7688  5.59910    1.21712   4.600 4.49e-06 ***
factor(school)7697  2.73770    1.39980   1.956  0.05064 .
```

```
factor(school)7890 -2.90678    1.24761  -2.330  0.01992 *
factor(school)7919  1.42253    1.34195   1.060  0.28926
factor(school)8531  0.21146    1.30432   0.162  0.87123
factor(school)8627 -1.75929    1.22313  -1.438  0.15050
factor(school)8707  0.12912    1.25258   0.103  0.91791
factor(school)8854 -6.48777    1.41989  -4.569 5.20e-06 ***
factor(school)8874  0.40269    1.36036   0.296  0.76725
factor(school)9550 -1.43872    1.44385  -0.996  0.31916
factor(school)9586  1.07281    1.19362   0.899  0.36888
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 6.133 on 1936 degrees of freedom
Multiple R-squared:  0.2118,  Adjusted R-squared:  0.1955
F-statistic:    13 on 40 and 1936 DF,  p-value: < 2.2e-16
```

Other contextual variables:

Proportion of women in each school

```r
hs <- within(
  hs,
  {
    female_prop <- capply(Sex == 'Female', school, mean)
  }
)
some(hs)
```

```
     school mathach    ses    Sex Minority Size   Sector PRACAD
5      1317  20.748  1.372 Female       No  455 Catholic   0.95
```

```
24     1317  13.373  0.082 Female      Yes  455 Catholic   0.95
187    2458  20.210  0.842 Female      Yes  545 Catholic   0.89
390    2658  18.037  0.712 Female       No  780 Catholic   0.79
473    3013   3.180 -0.278 Female       No  760   Public   0.56
872    5619  17.193  0.772   Male       No 1118 Catholic   0.77
940    5640  16.197  0.752   Male       No 1152   Public   0.41
1442   7342  10.033 -0.018   Male       No 1220 Catholic   0.46
1788   8707  12.843  0.852   Male      Yes 1133   Public   0.48
1879   8874  11.694 -0.878 Female      Yes 2650   Public   0.20
     DISCLIM mathach_mean    ses_sd mathach_sd mathach_rk
5     -1.694     13.17769 0.5561583   5.462586         43
24    -1.694     13.17769 0.5561583   5.462586         29
187   -1.484     13.98568 0.6584097   5.848459         45
390   -0.961     13.39616 0.6402846   5.642341         35
473   -0.213     12.61083 0.4799328   6.985697          7
872   -1.286     15.41624 0.5972748   7.280409         33
940    0.256     13.16011 0.5830261   7.102322         36
1442   0.380     11.16641 0.5648459   6.393930         27
1788   1.542     12.88394 0.8042577   6.435737         23
1879   1.742     12.05503 0.7137251   6.931169         19
        ses_dev mathach_dev female_prop
5     1.0266667   7.5703125   1.0000000
24   -0.2633333   0.1953125   1.0000000
187   0.6142105   6.2243158   1.0000000
390   0.2735556   4.6408444   0.6000000
473  -0.2337736  -9.4308302   0.3584906
872   0.3516667   1.7767576   0.4545455
940   0.9285965   3.0368947   0.4210526
1442  0.4298276  -1.1334138   0.0000000
```

```
1788  0.6968750  -0.0409375   0.5416667
1879 -0.5372222  -0.3610278   0.5833333
```

School-level data set:

Normally, the data set will be at the 'finest' level of the data, here students.

If each student had been measured on more than one occasion then the finest level would be the 'occasion'

But many analyses and graphic displays use the data at a higher level

```
up(hs, ~ school)  # one row per school with level 2 (and higher) variables
```

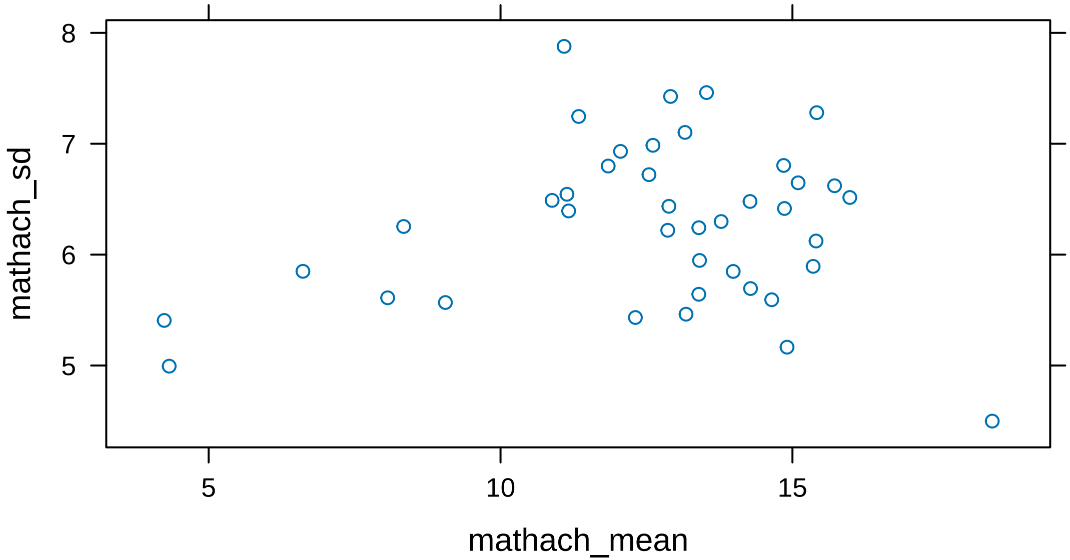
```
     school Size   Sector PRACAD DISCLIM mathach_mean    ses_sd
1317   1317  455 Catholic   0.95  -1.694    13.177687 0.5561583
1906   1906  400 Catholic   0.87  -0.939    15.983170 0.6135833
2208   2208 1061 Catholic   0.68  -0.864    15.404667 0.5981188
2458   2458  545 Catholic   0.89  -1.484    13.985684 0.6584097
2626   2626 2142   Public   0.40   0.142    13.396605 0.5601067
2629   2629 1314 Catholic   0.81  -0.613    14.907772 0.7063209
2639   2639 2713   Public   0.14  -0.282     6.615476 0.6186603
2658   2658  780 Catholic   0.79  -0.961    13.396156 0.6402846
2771   2771  415   Public   0.24   1.048    11.844109 0.5136955
3013   3013  760   Public   0.56  -0.213    12.610830 0.4799328
3610   3610 1431 Catholic   0.80  -0.621    15.354953 0.6316415
3992   3992 1114 Catholic   0.73  -1.534    14.645208 0.6054177
4292   4292 1328 Catholic   0.76  -0.674    12.864354 0.6511382
4511   4511 1068 Catholic   0.52  -1.872    13.409034 0.5813363
4530   4530  435 Catholic   0.60  -0.245     9.055698 0.6210062
4868   4868  657 Catholic   1.00  -0.219    12.310176 0.7100080
5619   5619 1118 Catholic   0.77  -1.286    15.416242 0.5972748
```

```
5640   5640 1152   Public   0.41   0.256    13.160105 0.5830261
5650   5650  720 Catholic   0.60  -0.070    14.273533 0.7777414
5720   5720  381 Catholic   0.65  -0.352    14.282302 0.6641693
5761   5761  215 Catholic   0.63  -0.892    11.138058 0.7122389
5762   5762 1826   Public   0.24   0.364     4.324865 0.5154149
6074   6074 2051 Catholic   0.32  -1.018    13.779089 0.6271235
6484   6484  726   Public   0.19   0.218    12.912400 0.6958345
6897   6897 1415   Public   0.55  -0.361    15.097633 0.7445231
7172   7172  280 Catholic   0.05   1.013     8.066818 0.6764417
7232   7232 1154   Public   0.20   0.975    12.542635 0.5743482
7342   7342 1220 Catholic   0.46   0.380    11.166414 0.5648459
7345   7345  978   Public   0.64   0.336    11.338554 0.8257296
7688   7688 1410 Catholic   0.65  -0.575    18.422315 0.5644347
7697   7697 1734   Public   0.20   0.279    15.721781 0.6133712
7890   7890  311   Public   0.21   0.845     8.341098 0.5932263
7919   7919 1451   Public   0.50  -0.402    14.849973 0.5367005
8531   8531 2190   Public   0.58   0.132    13.528683 0.6829747
8627   8627 2452   Public   0.25   0.742    10.883717 0.7077276
8707   8707 1133   Public   0.48   1.542    12.883938 0.8042577
8854   8854  745   Public   0.18  -0.228     4.239781 0.8036439
8874   8874 2650   Public   0.20   1.742    12.055028 0.7137251
9550   9550 1532   Public   0.45   0.791    11.089138 0.7847035
9586   9586  262 Catholic   1.00  -2.416    14.863695 0.5949914
     mathach_sd female_prop Freq
1317   5.462586   1.0000000   48
1906   6.515435   0.5094340   53
2208   6.122802   0.5833333   60
2458   5.848459   1.0000000   57
2626   6.242649   0.4736842   38
```

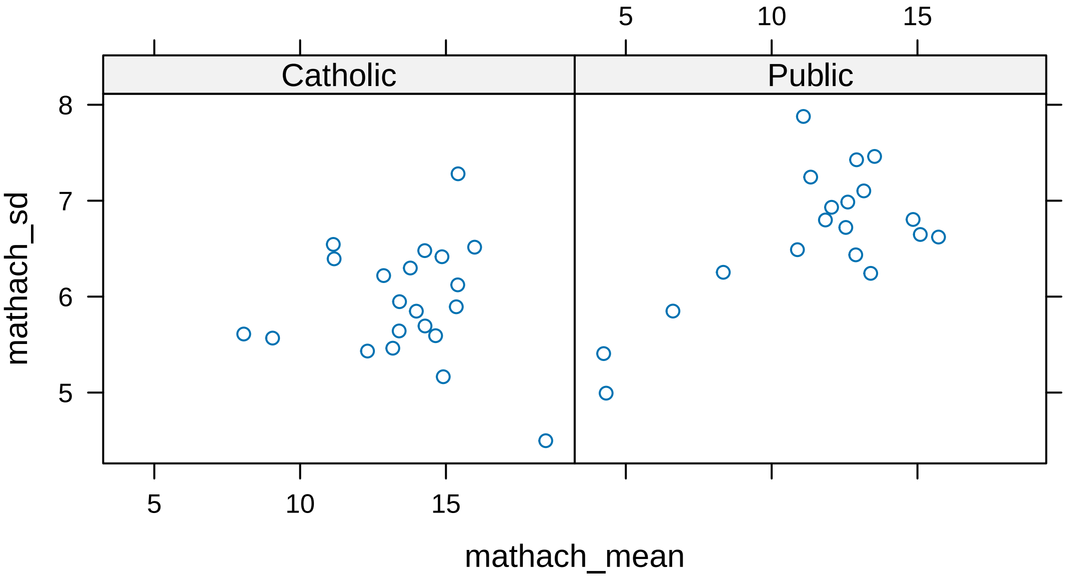
2629	5.165071	0.0000000	57
2639	5.849492	0.5714286	42
2658	5.642341	0.6000000	45
2771	6.798981	0.5090909	55
3013	6.985697	0.3584906	53
3610	5.894163	0.4531250	64
3992	5.592953	0.3962264	53
4292	6.219492	0.0000000	65
4511	5.947499	1.0000000	58
4530	5.567967	1.0000000	63
4868	5.432838	0.3235294	34
5619	7.280409	0.4545455	66
5640	7.102322	0.4210526	57
5650	6.479535	0.7111111	45
5720	5.694073	0.4528302	53
5761	6.544368	1.0000000	52
5762	4.993969	0.5675676	37
6074	6.298483	1.0000000	56
6484	7.426520	0.5714286	35
6897	6.647635	0.5918367	49
7172	5.610555	0.5000000	44
7232	6.721008	0.5769231	52
7342	6.393930	0.0000000	58
7345	7.246025	0.5178571	56
7688	4.498507	0.0000000	54
7697	6.621170	0.3437500	32
7890	6.253697	0.4705882	51
7919	6.804286	0.4324324	37
8531	7.461228	0.5609756	41

```
8627    6.489265    0.4528302    53
8707    6.435737    0.5416667    48
8854    5.406482    0.5312500    32
8874    6.931169    0.5833333    36
9550    7.877998    0.6551724    29
9586    6.416000    1.0000000    59
```

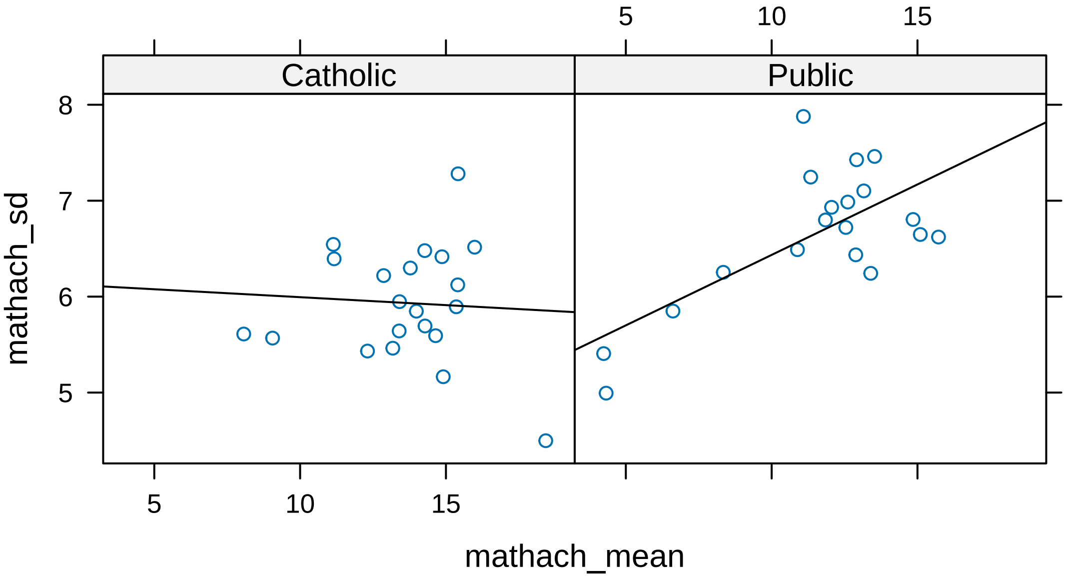
```r
up(hs, ~ school) %>%
  xyplot(mathach_sd ~ mathach_mean, .)
```




```r
up(hs, ~ school) %>%
  xyplot(mathach_sd ~ mathach_mean | Sector, .)
```




```r
up(hs, ~ school) %>%
  xyplot(mathach_sd ~ mathach_mean | Sector, .) +
  layer(panel.lmline(...))
```



Aggregating some variables that vary within schools

```
up(hs, ~school, ~Sex )
```

```
     school Size   Sector PRACAD DISCLIM mathach_mean    ses_sd
1317   1317  455 Catholic   0.95  -1.694    13.177687 0.5561583
1906   1906  400 Catholic   0.87  -0.939    15.983170 0.6135833
2208   2208 1061 Catholic   0.68  -0.864    15.404667 0.5981188
2458   2458  545 Catholic   0.89  -1.484    13.985684 0.6584097
2626   2626 2142   Public   0.40   0.142    13.396605 0.5601067
2629   2629 1314 Catholic   0.81  -0.613    14.907772 0.7063209
2639   2639 2713   Public   0.14  -0.282     6.615476 0.6186603
2658   2658  780 Catholic   0.79  -0.961    13.396156 0.6402846
2771   2771  415   Public   0.24   1.048    11.844109 0.5136955
```

3013	3013	760	Public	0.56	-0.213	12.610830	0.4799328
3610	3610	1431	Catholic	0.80	-0.621	15.354953	0.6316415
3992	3992	1114	Catholic	0.73	-1.534	14.645208	0.6054177
4292	4292	1328	Catholic	0.76	-0.674	12.864354	0.6511382
4511	4511	1068	Catholic	0.52	-1.872	13.409034	0.5813363
4530	4530	435	Catholic	0.60	-0.245	9.055698	0.6210062
4868	4868	657	Catholic	1.00	-0.219	12.310176	0.7100080
5619	5619	1118	Catholic	0.77	-1.286	15.416242	0.5972748
5640	5640	1152	Public	0.41	0.256	13.160105	0.5830261
5650	5650	720	Catholic	0.60	-0.070	14.273533	0.7777414
5720	5720	381	Catholic	0.65	-0.352	14.282302	0.6641693
5761	5761	215	Catholic	0.63	-0.892	11.138058	0.7122389
5762	5762	1826	Public	0.24	0.364	4.324865	0.5154149
6074	6074	2051	Catholic	0.32	-1.018	13.779089	0.6271235
6484	6484	726	Public	0.19	0.218	12.912400	0.6958345
6897	6897	1415	Public	0.55	-0.361	15.097633	0.7445231
7172	7172	280	Catholic	0.05	1.013	8.066818	0.6764417
7232	7232	1154	Public	0.20	0.975	12.542635	0.5743482
7342	7342	1220	Catholic	0.46	0.380	11.166414	0.5648459
7345	7345	978	Public	0.64	0.336	11.338554	0.8257296
7688	7688	1410	Catholic	0.65	-0.575	18.422315	0.5644347
7697	7697	1734	Public	0.20	0.279	15.721781	0.6133712
7890	7890	311	Public	0.21	0.845	8.341098	0.5932263
7919	7919	1451	Public	0.50	-0.402	14.849973	0.5367005
8531	8531	2190	Public	0.58	0.132	13.528683	0.6829747
8627	8627	2452	Public	0.25	0.742	10.883717	0.7077276
8707	8707	1133	Public	0.48	1.542	12.883938	0.8042577
8854	8854	745	Public	0.18	-0.228	4.239781	0.8036439
8874	8874	2650	Public	0.20	1.742	12.055028	0.7137251

```
9550   9550 1532   Public   0.45   0.791    11.089138 0.7847035
9586   9586  262 Catholic   1.00  -2.416    14.863695 0.5949914
     mathach_sd female_prop Freq Sex_Female  Sex_Male
1317   5.462586   1.0000000   48  1.0000000 0.0000000
1906   6.515435   0.5094340   53  0.5094340 0.4905660
2208   6.122802   0.5833333   60  0.5833333 0.4166667
2458   5.848459   1.0000000   57  1.0000000 0.0000000
2626   6.242649   0.4736842   38  0.4736842 0.5263158
2629   5.165071   0.0000000   57  0.0000000 1.0000000
2639   5.849492   0.5714286   42  0.5714286 0.4285714
2658   5.642341   0.6000000   45  0.6000000 0.4000000
2771   6.798981   0.5090909   55  0.5090909 0.4909091
3013   6.985697   0.3584906   53  0.3584906 0.6415094
3610   5.894163   0.4531250   64  0.4531250 0.5468750
3992   5.592953   0.3962264   53  0.3962264 0.6037736
4292   6.219492   0.0000000   65  0.0000000 1.0000000
4511   5.947499   1.0000000   58  1.0000000 0.0000000
4530   5.567967   1.0000000   63  1.0000000 0.0000000
4868   5.432838   0.3235294   34  0.3235294 0.6764706
5619   7.280409   0.4545455   66  0.4545455 0.5454545
5640   7.102322   0.4210526   57  0.4210526 0.5789474
5650   6.479535   0.7111111   45  0.7111111 0.2888889
5720   5.694073   0.4528302   53  0.4528302 0.5471698
5761   6.544368   1.0000000   52  1.0000000 0.0000000
5762   4.993969   0.5675676   37  0.5675676 0.4324324
6074   6.298483   1.0000000   56  1.0000000 0.0000000
6484   7.426520   0.5714286   35  0.5714286 0.4285714
6897   6.647635   0.5918367   49  0.5918367 0.4081633
7172   5.610555   0.5000000   44  0.5000000 0.5000000
```

```
  7232   6.721008   0.5769231   52  0.5769231 0.4230769
  7342   6.393930   0.0000000   58  0.0000000 1.0000000
  7345   7.246025   0.5178571   56  0.5178571 0.4821429
  7688   4.498507   0.0000000   54  0.0000000 1.0000000
  7697   6.621170   0.3437500   32  0.3437500 0.6562500
  7890   6.253697   0.4705882   51  0.4705882 0.5294118
  7919   6.804286   0.4324324   37  0.4324324 0.5675676
  8531   7.461228   0.5609756   41  0.5609756 0.4390244
  8627   6.489265   0.4528302   53  0.4528302 0.5471698
  8707   6.435737   0.5416667   48  0.5416667 0.4583333
  8854   5.406482   0.5312500   32  0.5312500 0.4687500
  8874   6.931169   0.5833333   36  0.5833333 0.4166667
  9550   7.877998   0.6551724   29  0.6551724 0.3448276
  9586   6.416000   1.0000000   59  1.0000000 0.0000000
```

So far, recap:

hs: level 1 data set, 'long' data set up(hs, ~ school): level 2 data set, 'short' data set

What if you want to add new level 2 data to the level 1 data set

```r
states <- read.csv(text=
'
school,state
1317,New York
1906,New York
2208,New York
2458,New York
2626,New York
2629,New York
2639,New York
```

```
2658,New York
2771,New York
3013,New York
3610,Oregon
3992,Oregon
4292,Oregon
4511,Oregon
4530,Oregon
4868,Oregon
5619,Oregon
5640,Oregon
5650,Oregon
5720,West Virginia
5761,West Virginia
5762,West Virginia
6074,West Virginia
6484,West Virginia
6897,West Virginia
7172,West Virginia
7232,West Virginia
7342,West Virginia
7345,West Virginia
7688,South Dakota
7697,South Dakota
7890,South Dakota
7919,South Dakota
8531,South Dakota
8627,South Dakota
```

```
8707,South Dakota
8854,Vermont
8874,Vermont
9550,Vermont
9586,Vermont
')
states  # note that this is fictional
```

```
   school        state
1    1317     New York
2    1906     New York
3    2208     New York
4    2458     New York
5    2626     New York
6    2629     New York
7    2639     New York
8    2658     New York
9    2771     New York
10   3013     New York
11   3610       Oregon
12   3992       Oregon
13   4292       Oregon
14   4511       Oregon
15   4530       Oregon
16   4868       Oregon
17   5619       Oregon
18   5640       Oregon
19   5650       Oregon
```

```
20   5720 West Virginia
21   5761 West Virginia
22   5762 West Virginia
23   6074 West Virginia
24   6484 West Virginia
25   6897 West Virginia
26   7172 West Virginia
27   7232 West Virginia
28   7342 West Virginia
29   7345 West Virginia
30   7688  South Dakota
31   7697  South Dakota
32   7890  South Dakota
33   7919  South Dakota
34   8531  South Dakota
35   8627  South Dakota
36   8707  South Dakota
37   8854       Vermont
38   8874       Vermont
39   9550       Vermont
40   9586       Vermont
```

Merging states into hs

```r
dm <- merge(hs, states, by = 'school', all.x = T)  # left outer join ??
dim(dm)
```

```
[1] 1977   17
```

```r
some(dm)
```

```
     school mathach    ses    Sex Minority Size   Sector PRACAD
298    2629  18.323 -0.078   Male       No 1314 Catholic   0.81
513    3610  22.713  1.372   Male       No 1431 Catholic   0.80
694    4511   9.783  1.012 Female       No 1068 Catholic   0.52
1085   5761  17.042 -0.858 Female      Yes  215 Catholic   0.63
1193   6074  12.511 -0.158 Female       No 2051 Catholic   0.32
1213   6484  21.653 -0.378   Male       No  726   Public   0.19
1342   7232  10.348  0.232 Female       No 1154   Public   0.20
1451   7345  13.085  0.002 Female      Yes  978   Public   0.64
1845   8854  -1.094 -0.758   Male      Yes  745   Public   0.18
1897   9550   5.871 -0.538   Male       No 1532   Public   0.45
     DISCLIM mathach_mean    ses_sd mathach_sd mathach_rk
298   -0.613    14.907772 0.7063209   5.165071         41
513   -0.621    15.354953 0.6316415   5.894163         58
694   -1.872    13.409034 0.5813363   5.947499         22
1085  -0.892    11.138058 0.7122389   6.544368         42
1193  -1.018    13.779089 0.6271235   6.298483         22
1213   0.218    12.912400 0.6958345   7.426520         34
1342   0.975    12.542635 0.5743482   6.721008         17
1451   0.336    11.338554 0.8257296   7.246025         37
1845  -0.228     4.239781 0.8036439   5.406482          8
1897   0.791    11.089138 0.7847035   7.877998          9
         ses_dev mathach_dev female_prop         state
298   0.05964912    3.415228   0.0000000      New York
513   1.25187500    7.358047   0.4531250        Oregon
694   1.11913793   -3.626034   1.0000000        Oregon
```

```
1085 -0.53500000    5.903942   1.0000000 West Virginia
1193  0.11875000   -1.268089   1.0000000 West Virginia
1213 -0.19285714    8.740600   0.5714286 West Virginia
1342  0.32211538   -2.194635   0.5769231 West Virginia
1451 -0.03125000    1.746446   0.5178571 West Virginia
1845 -0.00125000   -5.333781   0.5312500       Vermont
1897 -0.59103448   -5.218138   0.6551724       Vermont
```

5.2 Merge examples

```
grades <- read.table(header = TRUE, text =
'
student course     gp
John    Calculus   3.5
Mary    Algebra    3.9
Paul    Calculus   3.2
John    Statistics 3.9
John    Algebra    3.9
Mary    Statistics 4.0
')
grades
```

```
  student     course  gp
1    John   Calculus 3.5
2    Mary    Algebra 3.9
3    Paul   Calculus 3.2
4    John Statistics 3.9
5    John    Algebra 3.9
```

```
  6    Mary Statistics 4.0
```

```r
courses <- read.table(header = TRUE, text =
'
course   credits
Calculus       6
Algebra        3
Statistics     3
')
courses
```

```
        course credits
  1   Calculus       6
  2    Algebra       3
  3 Statistics       3
```

```r
email <- read.table(header = T, text =
'
student email
John    john123
Paul    paul456
Walter  wally6
')
email
```

```
    student   email
  1    John john123
  2    Paul paul456
  3  Walter  wally6
```

5.2.1 Calculate GPA

1. need weights

```
grades <- merge(grades, courses, by = 'course', all = T)
grades
```

```
      course student  gp credits
  1    Algebra    Mary 3.9       3
  2    Algebra    John 3.9       3
  3   Calculus    John 3.5       6
  4   Calculus    Paul 3.2       6
  5 Statistics    John 3.9       3
  6 Statistics    Mary 4.0       3
```

```
grades$gp_tot <- with(
  grades,
  capply(gp * credits, student, sum)
)
grades$credit_tot <- with(
  grades,
  capply(credits, student, sum)
)
```

2. weighted average

```
grades$gpa <- with(grades, gp_tot / credit_tot)

up(grades, ~ student)
```

```
       student gp_tot credit_tot  gpa Freq
```

```
John     John   44.4          12 3.70    3
Mary     Mary   23.7           6 3.95    2
Paul     Paul   19.2           6 3.20    1
```

```r
grade_report <- up(grades, ~ student)
grade_report
```

```
       student gp_tot credit_tot  gpa Freq
John     John   44.4          12 3.70    3
Mary     Mary   23.7           6 3.95    2
Paul     Paul   19.2           6 3.20    1
```

3. merge with email

```r
merge(grade_report, email, by = 'student')
```

```
  student gp_tot credit_tot gpa Freq   email
1    John   44.4         12 3.7    3 john123
2    Paul   19.2          6 3.2    1 paul456
```

```r
          # inner join, only students in BOTH files
merge(grade_report, email, by = 'student', all = T)
```

```
  student gp_tot credit_tot  gpa Freq   email
1    John   44.4         12 3.70    3 john123
2    Mary   23.7          6 3.95    2    <NA>
3    Paul   19.2          6 3.20    1 paul456
4  Walter     NA         NA   NA   NA  wally6
```

```r
          # outer join, students in EITHER files
merge(grade_report, email, by = 'student', all.x = T)
```

```
  student gp_tot credit_tot  gpa Freq   email
1    John   44.4         12 3.70    3 john123
2    Mary   23.7          6 3.95    2    <NA>
3    Paul   19.2          6 3.20    1 paul456
```

```
          # all rows in first file
```

Other way of using capply on data frames but not efficient with very large files

```
grades$gpa2 <- capply(grades, grades$student, with,
                      sum(gp*credits)/sum(credits))
up(grades, ~ student)
```

```
     student gp_tot credit_tot  gpa gpa2 Freq
John    John   44.4         12 3.70 3.70    3
Mary    Mary   23.7          6 3.95 3.95    2
Paul    Paul   19.2          6 3.20 3.20    1
```

Create transcripts

Add course average to student file

```
grades$course_average <-
  with(grades, capply(gp, course, mean)) # no weights! why?
```

List of transcripts

```
split(grades, grades$student)
```

```
$John
    course student  gp credits gp_tot credit_tot gpa gpa2
2  Algebra    John 3.9       3   44.4         12 3.7  3.7
3 Calculus    John 3.5       6   44.4         12 3.7  3.7
```

```
5 Statistics    John 3.9       3   44.4         12 3.7  3.7
  course_average
2           3.90
3           3.35
5           3.95

$Mary
      course student  gp credits gp_tot credit_tot  gpa gpa2
1    Algebra    Mary 3.9       3   23.7          6 3.95 3.95
6 Statistics    Mary 4.0       3   23.7          6 3.95 3.95
  course_average
1           3.90
6           3.95

$Paul
    course student  gp credits gp_tot credit_tot gpa gpa2
4 Calculus    Paul 3.2       6   19.2          6 3.2  3.2
  course_average
4           3.35
```

6 The many ways of referring to variables

A confusing aspect of R is that there are many ways to refer to an object

- name: if an object is in the current environment

```
grades
```

```
        course student  gp credits gp_tot credit_tot  gpa gpa2
```

```
1    Algebra    Mary 3.9       3   23.7          6 3.95 3.95
2    Algebra    John 3.9       3   44.4         12 3.70 3.70
3   Calculus    John 3.5       6   44.4         12 3.70 3.70
4   Calculus    Paul 3.2       6   19.2          6 3.20 3.20
5 Statistics    John 3.9       3   44.4         12 3.70 3.70
6 Statistics    Mary 4.0       3   23.7          6 3.95 3.95
  course_average
1           3.90
2           3.90
3           3.35
4           3.35
5           3.95
6           3.95
```

- selecting from a data frame (FQN: fully qualified name)

```r
grades$student
```

```
[1] "Mary" "John" "John" "Paul" "John" "Mary"
```

```r
grades[['student']]
```

```
[1] "Mary" "John" "John" "Paul" "John" "Mary"
```

```r
grades['student'] # but this is the data frame with the variable
```

```
  student
1    Mary
2    John
3    John
4    Paul
```

```
5     John
6     Mary
```

- by name using with or within

```r
with(grades, student)
```

```
[1] "Mary" "John" "John" "Paul" "John" "Mary"
```

```r
grades <- within(grades, {
  gpa3 <- capply(
    gp * credits,
    student, sum) / capply(credits, student, sum)
})
grades
```

```
      course student  gp credits gp_tot credit_tot  gpa gpa2
1    Algebra    Mary 3.9       3   23.7          6 3.95 3.95
2    Algebra    John 3.9       3   44.4         12 3.70 3.70
3   Calculus    John 3.5       6   44.4         12 3.70 3.70
4   Calculus    Paul 3.2       6   19.2          6 3.20 3.20
5 Statistics    John 3.9       3   44.4         12 3.70 3.70
6 Statistics    Mary 4.0       3   23.7          6 3.95 3.95
  course_average gpa3
1           3.90 3.95
2           3.90 3.70
3           3.35 3.70
4           3.35 3.20
5           3.95 3.70
6           3.95 3.95
```

- as argument to a function

```r
sum(grades$credits)
```

```
[1] 24
```

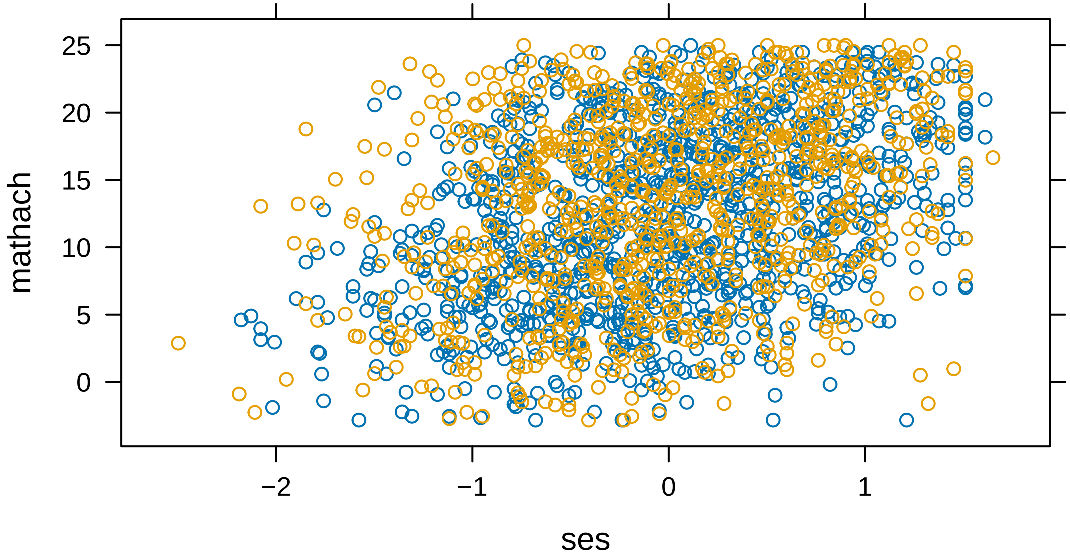
- formula

```r
tab(grades, ~ student)
```

```
student
 John  Mary  Paul Total
    3     2     1     6
```

- name in a data frame that is another argument

```r
xyplot(mathach ~ ses, hs, group = Sex)
```



Note: in this example mathach and ses are referrenced by a formula interpreted in hs but 'Sex' is interpreted by name interpreted with `hs`

- by name in a character string

```
merge(grades, courses, by = 'course')  # can't just use: by = course
```

```
      course student  gp credits.x gp_tot credit_tot  gpa gpa2
1    Algebra    Mary 3.9         3   23.7          6 3.95 3.95
2    Algebra    John 3.9         3   44.4         12 3.70 3.70
3   Calculus    John 3.5         6   44.4         12 3.70 3.70
4   Calculus    Paul 3.2         6   19.2          6 3.20 3.20
5 Statistics    John 3.9         3   44.4         12 3.70 3.70
6 Statistics    Mary 4.0         3   23.7          6 3.95 3.95
  course_average gpa3 credits.y
```

```
1              3.90 3.95         3
2              3.90 3.70         3
3              3.35 3.70         6
4              3.35 3.20         6
5              3.95 3.70         3
6              3.95 3.95         3
```

Why so many ways that seem – and are – completely inconsistent

Because R is an evolving language that tries to be backward compatible.

In the early days (of S) data frames didn't even exist. To run a regression you needed the X matrix and the y vector and use 'lsfit(X,y)'.

Formulas, environments, etc. were all added gradually. When a new idea, formulas for example, is added to R, many people writing packages think it's cool and start using it. So a lot of packages written since 2000 make heavy use of formulas to refer to variables. But the old original functions often don't.

Some additions really catch on, e.g. pipes: `%>%`, which are just a few years old.

7 OOP: Object-oriented programming

- 'generic function': a function that selects another function to perform a task. The selection is based ont the 'class' of the object that is the lifirst argument of the generic function.
- 'method': a function called by a generic function depending on the class of the object.

Example:

```
to_farenheit
```

```
function (x)
{
```

```
    if (is.factor(x) || !is.numeric(x))
        x
    else 32 + (9/5) * x
}
<bytecode: 0x5f5d99291558>
```

Omesh (a student in 2018) asked 'why can't we write it to use it on a data frame?' But we would also like to use it on variables because sometimes it won't be every numeric variable that's a temperature in C.

First: note that the objects we work on have 'classes'

```r
class(2.3)
```

```
[1] "numeric"
```

```r
class(1:2)
```

```
[1] "integer"
```

```r
class(factor('a'))
```

```
[1] "factor"
```

```r
class('ab')
```

```
[1] "character"
```

```r
class(df)
```

```
[1] "data.frame"
```

Note that, in contrast with 'is.numeric', classes distinguish between numeric and factor.

Generic function:

```r
to_farenheit <- function(x,...) {
  UseMethod('to_farenheit')
}
```

'to_farenheit' will look at the class of X and use one of the following methods.

Methods:

```r
to_farenheit.numeric <- function(x,...) {
  32 + (9/5)*x
}

to_farenheit.default <- function(x,...) {
  x  # for any other class
}
```

But what about data frames??

```r
to_farenheit.data.frame <- function(x,...) {
  as.data.frame(lapply(x, to_farenheit))
}
```

Let's try this out

```r
to_farenheit(0)
```

```
[1] 32
```

```r
to_farenheit(37)
```

```
[1] 98.6
```

```r
to_farenheit(-273.15)
```

```
[1] -459.67
```

```r
to_farenheit(100)
```

```
[1] 212
```

```r
to_farenheit(factor(0))
```

```
[1] 0
Levels: 0
```

```r
to_farenheit(c('absolute zero','boiling point'))
```

```
[1] "absolute zero" "boiling point"
```

```r
df
```

```
      city day1 day2 day3
1 Montreal   20   25   30
2  Toronto   23   26   19
3 New York   28   35   32
```

```r
class(df)
```

```
[1] "data.frame"
```

```r
to_farenheit.data.frame(df)
```

```
      city day1 day2 day3
1 Montreal 68.0 77.0 86.0
2  Toronto 73.4 78.8 66.2
```

```
  3 New York 82.4 95.0 89.6
```

```r
to_farenheit(df)
```

```
        city day1 day2 day3
  1 Montreal 68.0 77.0 86.0
  2  Toronto 73.4 78.8 66.2
  3 New York 82.4 95.0 89.6
```

I can use 'to_farenheit' to do 'anything'!!

```r
methods(to_farenheit)
```

```
  [1] to_farenheit.data.frame to_farenheit.default
  [3] to_farenheit.numeric
  see '?methods' for accessing help and source code
```

The above illustrate creating a 'generic function' and 'methods' for existing classes: here 'numeric', 'integer', 'default' and 'data.frame'

If an object has a class attribute, e.g. data.frames, then the value of the attribute is its class.

If it doesn't have a class attribute then it has an implicit class depending on its type and structure. For example, matrices has the class "matrix" whether their content is numeric or character. However, for a vector, class is 'integer' for an integer, 'numeric' for a double, 'character' for a character.

Is there an underlying logic to it all?

7.1 Creating a new class

I can define new methods for other classes

7.1.1 Creating a class and methods for existing generics

Many functions are 'generic', e.g. print, summary

So when you create a new statistical methods you can write a function that creates a new class

then you can write methods for your new class

e.g. lm

```
fit <- lm(day1 ~ day2, df)
class(fit)
```

```
[1] "lm"
```

```
print(fit)
```

```

Call:
lm(formula = day1 ~ day2, data = df)

Coefficients:
(Intercept)         day2
     3.5055       0.7033
```

```
summary(fit)
```

```

Call:
lm(formula = day1 ~ day2, data = df)

Residuals:
      1       2       3
```

```
-1.0879  1.2088 -0.1209

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   3.5055     6.0753   0.577    0.667
day2          0.7033     0.2094   3.359    0.184

Residual standard error: 1.631 on 1 degrees of freedom
Multiple R-squared:  0.9186,	Adjusted R-squared:  0.8372 
F-statistic: 11.28 on 1 and 1 DF,  p-value: 0.1842
```

what function is actually used?

```r
methods(class = 'lm')
```

```
 [1] add1                 alias                anova               
 [4] Anova                avPlot               avPlot3d            
 [7] Boot                 bootCase             boxCox              
[10] brief                case.names           ceresPlot           
[13] coerce               confidenceEllipse    confint             
[16] Confint              cooks.distance       crPlot              
[19] crPlot3d             deltaMethod          deviance            
[22] dfbeta               dfbetaPlots          dfbetas             
[25] dfbetasPlots         drop1                dummy.coef          
[28] durbinWatsonTest     effects              extractAIC          
[31] family               formula              fortify             
[34] getData              getFix               hatvalues           
[37] hccm                 infIndexPlot         influence           
[40] influencePlot        initialize           inverseResponsePlot 
[43] kappa                labels               leveneTest          
```

```
[46] leveragePlot        linearHypothesis    logLik
[49] mcPlot              mmp                 model.frame
[52] model.matrix        ncvTest             nextBoot
[55] nobs                outlierTest         plot
[58] powerTransform      predict             Predict
[61] print               proj                qqPlot
[64] qr                  residualPlot        residualPlots
[67] residuals           rstandard           rstudent
[70] S                   show                sigmaHat
[73] simulate            slotsFromS3         spreadLevelPlot
[76] summary             symbox              variable.names
[79] vcov                vif
see '?methods' for accessing help and source code
```

great way to get ideas about what to do with an object!

```
getS3method('print','lm') # most methods are 'S3', a few are 'S4'
```

```
function (x, digits = max(3L, getOption("digits") - 3L), ...)
{
    cat("\nCall:\n", paste(deparse(x$call), sep = "\n", collapse = "\n"),
        "\n\n", sep = "")
    if (length(coef(x))) {
        cat("Coefficients:\n")
        print.default(format(coef(x), digits = digits), print.gap = 2L,
            quote = FALSE)
    }
    else cat("No coefficients\n")
    cat("\n")
    invisible(x)
```

```
}
<bytecode: 0x5f5d9e898240>
<environment: namespace:stats>
```

```r
getS3method('summary','lm')
```

```
function (object, correlation = FALSE, symbolic.cor = FALSE,
    ...)
{
    z <- object
    p <- z$rank
    rdf <- z$df.residual
    if (p == 0) {
        r <- z$residuals
        n <- length(r)
        w <- z$weights
        if (is.null(w)) {
            rss <- sum(r^2)
        }
        else {
            rss <- sum(w * r^2)
            r <- sqrt(w) * r
        }
        resvar <- rss/rdf
        ans <- z[c("call", "terms", if (!is.null(z$weights)) "weights")]
        class(ans) <- "summary.lm"
        ans$aliased <- is.na(coef(object))
        ans$residuals <- r
        ans$df <- c(0L, n, length(ans$aliased))
```

```
        ans$coefficients <- matrix(NA_real_, 0L, 4L, dimnames = list(NULL,
            c("Estimate", "Std. Error", "t value", "Pr(>|t|)")))
        ans$sigma <- sqrt(resvar)
        ans$r.squared <- ans$adj.r.squared <- 0
        ans$cov.unscaled <- matrix(NA_real_, 0L, 0L)
        if (correlation)
            ans$correlation <- ans$cov.unscaled
        return(ans)
    }
    if (is.null(z$terms))
        stop("invalid 'lm' object:  no 'terms' component")
    if (!inherits(object, "lm"))
        warning("calling summary.lm(<fake-lm-object>) ...")
    Qr <- qr.lm(object)
    n <- NROW(Qr$qr)
    if (is.na(z$df.residual) || n - p != z$df.residual)
        warning("residual degrees of freedom in object suggest this is not an \"lm\" fit")
    r <- z$residuals
    f <- z$fitted.values
    if (!is.null(z$offset)) {
        f <- f - z$offset
    }
    w <- z$weights
    if (is.null(w)) {
        mss <- if (attr(z$terms, "intercept"))
            sum((f - mean(f))^2)
        else sum(f^2)
        rss <- sum(r^2)
    }
```

```
else {
    mss <- if (attr(z$terms, "intercept")) {
        m <- sum(w * f/sum(w))
        sum(w * (f - m)^2)
    }
    else sum(w * f^2)
    rss <- sum(w * r^2)
    r <- sqrt(w) * r
}
resvar <- rss/rdf
if (is.finite(resvar) && resvar < (mean(f)^2 + var(c(f))) *
    1e-30)
    warning("essentially perfect fit: summary may be unreliable")
p1 <- 1L:p
R <- chol2inv(Qr$qr[p1, p1, drop = FALSE])
se <- sqrt(diag(R) * resvar)
est <- z$coefficients[Qr$pivot[p1]]
tval <- est/se
ans <- z[c("call", "terms", if (!is.null(z$weights)) "weights")]
ans$residuals <- r
ans$coefficients <- cbind(Estimate = est, `Std. Error` = se,
    `t value` = tval, `Pr(>|t|)` = 2 * pt(abs(tval), rdf,
        lower.tail = FALSE))
ans$aliased <- is.na(z$coefficients)
ans$sigma <- sqrt(resvar)
ans$df <- c(p, rdf, NCOL(Qr$qr))
if (p != attr(z$terms, "intercept")) {
    df.int <- if (attr(z$terms, "intercept"))
        1L
```

```
        else 0L
        ans$r.squared <- mss/(mss + rss)
        ans$adj.r.squared <- 1 - (1 - ans$r.squared) * ((n -
            df.int)/rdf)
        ans$fstatistic <- c(value = (mss/(p - df.int))/resvar,
            numdf = p - df.int, dendf = rdf)
    }
    else ans$r.squared <- ans$adj.r.squared <- 0
    ans$cov.unscaled <- R
    dimnames(ans$cov.unscaled) <- dimnames(ans$coefficients)[c(1,
        1)]
    if (correlation) {
        ans$correlation <- (R * resvar)/outer(se, se)
        dimnames(ans$correlation) <- dimnames(ans$cov.unscaled)
        ans$symbolic.cor <- symbolic.cor
    }
    if (!is.null(z$na.action))
        ans$na.action <- z$na.action
    class(ans) <- "summary.lm"
    ans
}
<bytecode: 0x5f5d9e96d398>
<environment: namespace:stats>
```

Suppose you create a new kind of object, e.g. 'wald'

```r
w <- wald(fit)
class(w)
```

```
[1] "wald"
```

Usually created by a ‘contructor’ function of the same name Note the last thing the function does:

```
wald
```

```
function (fit, Llist = "", clevel = 0.95, pred = NULL, data = NULL,
    debug = FALSE, maxrows = 25, full = FALSE, fixed = FALSE,
    invert = FALSE, method = "svd", overdispersion = FALSE, df = NULL,
    pars = NULL, ...)
{
    if (full)
        return(wald(fit, getX(fit)))
    if (!is.null(pred))
        return(wald(fit, getX(fit, pred)))
    dataf <- function(x, ...) {
        x <- cbind(x)
        rn <- rownames(x)
        if (length(unique(rn)) < length(rn))
            rownames(x) <- NULL
        data.frame(x, ...)
    }
    as.dataf <- function(x, ...) {
        x <- cbind(x)
        rn <- rownames(x)
        if (length(unique(rn)) < length(rn))
            rownames(x) <- NULL
        as.data.frame(x, ...)
    }
    unique.rownames <- function(x) {
        ret <- c(tapply(1:length(x), x, function(xx) {
            if (length(xx) == 1) "" else 1:length(xx)
```

```
    }))[tapply(1:length(x), x)]
    ret <- paste(x, ret, sep = "")
    ret
}
if (inherits(fit, "stanfit")) {
    fix <- if (is.null(pars))
        getFix(fit)
    else getFix(fit, pars = pars, ...)
    if (!is.matrix(Llist))
        stop(paste("Sorry: wald needs Llist to be a n x",
            length(fix$fixed), "matrix for this stanfit object"))
}
else {
    fix <- getFix(fit)
}
beta <- fix$fixed
vc <- if (isTRUE(overdispersion))
    overdisp_fun(fit)["ratio"] * fix$vcov
else if (isFALSE(overdispersion))
    fix$vcov
else fix$vcov
dfs <- if (is.null(df))
    fix$df
else df + 0 * fix$df
if (is.character(Llist))
    Llist <- structure(list(Llist), names = Llist)
if (!is.list(Llist))
    Llist <- list(Llist)
ret <- list()
```

```
for (ii in 1:length(Llist)) {
    ret[[ii]] <- list()
    Larg <- Llist[[ii]]
    L <- NULL
    if (is.character(Larg)) {
        L <- Lmat(fit, Larg, fixed = fixed, invert = invert)
    }
    else {
        if (is.numeric(Larg)) {
            if (is.null(dim(Larg))) {
              if (debug)
                disp(dim(Larg))
              if ((length(Larg) < length(beta)) && (all(Larg >
                0) || all(Larg < 0))) {
                L <- diag(length(beta))[Larg, ]
                dimnames(L) <- list(names(beta)[Larg], names(beta))
              }
              else L <- rbind(Larg)
            }
            else L <- Larg
        }
    }
    if (debug) {
        disp(Larg)
        disp(L)
    }
    Ldata <- attr(L, "data")
    Lna <- L[, is.na(beta), drop = FALSE]
    narows <- apply(Lna, 1, function(x) sum(abs(x))) > 0
```

```
L <- L[, !is.na(beta), drop = FALSE]
attr(L, "data") <- Ldata
beta <- beta[!is.na(beta)]
if (method == "qr") {
    qqr <- qr(t(na.omit(L)))
    L.rank <- qqr$rank
    if (debug)
        disp(t(qr.Q(qqr)))
    L.full <- t(qr.Q(qqr))[1:L.rank, , drop = FALSE]
}
else if (method == "svd") {
    if (debug)
        disp(L)
    sv <- svd(na.omit(L), nu = 0)
    if (debug)
        disp(sv)
    tol.fac <- max(dim(L)) * max(sv$d)
    if (debug)
        disp(tol.fac)
    if (tol.fac > 1e+06)
        warning("Poorly conditioned L matrix, calculated numDF may be incorrect")
    tol <- tol.fac * .Machine$double.eps
    if (debug)
        disp(tol)
    L.rank <- sum(sv$d > tol)
    if (debug)
        disp(L.rank)
    if (debug)
        disp(t(sv$v))
```

```
    L.full <- t(sv$v)[seq_len(L.rank), , drop = FALSE]
}
else stop("method not implemented: choose 'svd' or 'qr'")
if (debug && method == "qr") {
    disp(qqr)
    disp(dim(L.full))
    disp(dim(vc))
    disp(vc)
}
if (debug)
    disp(L.full)
if (debug)
    disp(vc)
vv <- L.full %*% vc %*% t(L.full)
eta.hat <- L.full %*% beta
Fstat <- (t(eta.hat) %*% qr.solve(vv, eta.hat, tol = 1e-10))/L.rank
included.effects <- apply(L, 2, function(x) sum(abs(x),
    na.rm = TRUE)) != 0
denDF <- min(dfs[included.effects])
numDF <- L.rank
ret[[ii]]$anova <- list(numDF = numDF, denDF = denDF,
    `F-value` = Fstat, `p-value` = pf(Fstat, numDF, denDF,
        lower.tail = FALSE))
if (!isFALSE(overdispersion)) {
    ret[[ii]]$anova <- c(ret[[ii]]$anova, `overdispersion variance factor` = if (isTRUE(overd
}
if (isTRUE(overdispersion)) {
    ret[[ii]]$anova <- c(ret[[ii]]$anova, overdisp_fun(fit)[c(1,
        3, 4)])
```

```
}
etahat <- L %*% beta
etahat[narows] <- NA
if (nrow(L) <= maxrows) {
    etavar <- L %*% vc %*% t(L)
    etasd <- sqrt(diag(etavar))
}
else {
    etavar <- NULL
    etasd <- sqrt(apply(L * (L %*% vc), 1, sum))
}
denDF <- apply(L, 1, function(x, dfs) min(dfs[x != 0]),
    dfs = dfs)
aod <- cbind(Estimate = c(etahat), Std.Error = etasd,
    DF = denDF, `t-value` = c(etahat/etasd), `p-value` = 2 *
        pt(abs(etahat/etasd), denDF, lower.tail = FALSE))
colnames(aod)[ncol(aod)] <- "p-value"
if (debug)
    disp(aod)
if (!is.null(clevel)) {
    hw <- qt(1 - (1 - clevel)/2, aod[, "DF"]) * aod[,
        "Std.Error"]
    aod <- cbind(aod, LL = aod[, "Estimate"] - hw, UL = aod[,
        "Estimate"] + hw)
    if (debug)
        disp(colnames(aod))
    labs <- paste(c("Lower", "Upper"), format(clevel))
    colnames(aod)[ncol(aod) + c(-1, 0)] <- labs
}
```

```
        if (debug)
            disp(rownames(aod))
        aod <- as.dataf(aod)
        rownames(aod) <- rownames(as.dataf(L))
        labs(aod) <- names(dimnames(L))[1]
        ret[[ii]]$estimate <- aod
        ret[[ii]]$coef <- c(etahat)
        ret[[ii]]$vcov <- etavar
        ret[[ii]]$L <- L
        ret[[ii]]$se <- etasd
        ret[[ii]]$L.full <- L.full
        ret[[ii]]$L.rank <- L.rank
        if (debug)
            disp(attr(Larg, "data"))
        data.attr <- attr(Larg, "data")
        if (is.null(data.attr) && !(is.null(data)))
            data.attr <- data
        ret[[ii]]$data <- data.attr
    }
    names(ret) <- names(Llist)
    attr(ret, "class") <- "wald"
    ret
}
<bytecode: 0x5f5d9de56cc0>
<environment: namespace:spida2>
```

What can we do with a ‘wald’ object?

```r
methods(class='wald')
```

```
 [1] as.data.frame cell          coef          print
 [5] rpfmt
 see '?methods' for accessing help and source code
```

```r
coef(w)
```

```
 [1] 3.5054945 0.7032967
```

```r
as.data.frame(w)
```

```
                  coef        se        U2         L2   p-value
 (Intercept) 3.5054945 6.0753033 15.656101 -8.6451121 0.6668304
 day2        0.7032967 0.2093688  1.122034  0.2845591 0.1842008
               t-value DF L.1 L.2
 (Intercept) 0.5770073  1   1   0
 day2        3.3591288  1   0   1
```

```r
w  # prints
```

```
  numDF denDF  F-value p-value
      2     1 321.5723  0.0394
             Estimate Std.Error DF  t-value  p-value Lower 0.95
 (Intercept) 3.505495 6.075303  1  0.577007 0.66683 -73.688553
 day2        0.703297 0.209369  1  3.359129 0.18420  -1.956986
             Upper 0.95
 (Intercept) 80.699542
 day2         3.363579
```

```r
rpfmt(w)
```

```
            Estimate
(Intercept) "3.505 (0.66683)"
day2        "0.703 (0.18420)"
```

```r
cell(w) # ???
```

```
      coefficient  coefficient
 [1,] -117.848592   4.83502624
 [2,] -117.607744   4.86752202
 [3,] -116.888917   4.88358349
 [4,] -115.694948   4.88314729
 [5,] -114.030549   4.86621513
 [6,] -111.902290   4.83285383
 [7,] -109.318568   4.78319505
 [8,] -106.289582   4.71743478
 [9,] -102.827284   4.63583254
[10,]  -98.945340   4.53871037
[11,]  -94.659069   4.42645158
[12,]  -89.985387   4.29949920
[13,]  -84.942740   4.15835426
[14,]  -79.551027   4.00357377
[15,]  -73.831529   3.83576861
[16,]  -67.806817   3.65560100
[17,]  -61.500667   3.46378200
[18,]  -54.937968   3.26106863
[19,]  -48.144619   3.04826090
[20,]  -41.147431   2.82619867
```

```
[21,]  -33.974018  2.59575831
[22,]  -26.652691  2.35784927
[23,]  -19.212343  2.11341047
[24,]  -11.682338  1.86340659
[25,]   -4.092394  1.60882429
[26,]    3.527535  1.35066828
[27,]   11.147378  1.08995740
[28,]   18.737062  0.82772054
[29,]   26.266633  0.56499264
[30,]   33.706377  0.30281056
[31,]   41.026932  0.04220902
[32,]   48.199407 -0.21578351
[33,]   55.195495 -0.47014885
[34,]   61.987586 -0.71988314
[35,]   68.548876 -0.96400079
[36,]   74.853469 -1.20153838
[37,]   80.876484 -1.43155845
[38,]   86.594151 -1.65315322
[39,]   91.983905 -1.86544817
[40,]   97.024475 -2.06760545
[41,]  101.695968 -2.25882724
[42,]  105.979949 -2.43835889
[43,]  109.859510 -2.60549185
[44,]  113.319340 -2.75956654
[45,]  116.345785 -2.89997490
[46,]  118.926901 -3.02616278
[47,]  121.052501 -3.13763219
[48,]  122.714197 -3.23394321
[49,]  123.905431 -3.31471574
```

```
[50,]   124.621501  -3.37963101
[51,]   124.859581  -3.42843284
[52,]   124.618733  -3.46092861
[53,]   123.899906  -3.47699009
[54,]   122.705937  -3.47655388
[55,]   121.041538  -3.45962172
[56,]   118.913279  -3.42626042
[57,]   116.329557  -3.37660164
[58,]   113.300571  -3.31084137
[59,]   109.838273  -3.22923913
[60,]   105.956329  -3.13211697
[61,]   101.670058  -3.01985818
[62,]    96.996376  -2.89290580
[63,]    91.953729  -2.75176085
[64,]    86.562016  -2.59698037
[65,]    80.842518  -2.42917520
[66,]    74.817806  -2.24900760
[67,]    68.511656  -2.05718860
[68,]    61.948957  -1.85447522
[69,]    55.155608  -1.64166749
[70,]    48.158420  -1.41960526
[71,]    40.985007  -1.18916490
[72,]    33.663680  -0.95125586
[73,]    26.223332  -0.70681706
[74,]    18.693327  -0.45681318
[75,]    11.103383  -0.20223088
[76,]     3.483454   0.05592512
[77,]    -4.136389   0.31663601
[78,]   -11.726073   0.57887286
```

```
 [79,]   -19.255644   0.84160077
 [80,]   -26.695388   1.10378284
 [81,]   -34.015943   1.36438439
 [82,]   -41.188418   1.62237692
 [83,]   -48.184506   1.87674226
 [84,]   -54.976597   2.12647655
 [85,]   -61.537887   2.37059420
 [86,]   -67.842480   2.60813178
 [87,]   -73.865495   2.83815186
 [88,]   -79.583162   3.05974663
 [89,]   -84.972916   3.27204157
 [90,]   -90.013486   3.47419885
 [91,]   -94.684979   3.66542065
 [92,]   -98.968960   3.84495230
 [93,]  -102.848521   4.01208526
 [94,]  -106.308351   4.16615995
 [95,]  -109.334796   4.30656830
 [96,]  -111.915912   4.43275619
 [97,]  -114.041512   4.54422560
 [98,]  -115.703208   4.64053662
 [99,]  -116.894442   4.72130915
[100,]  -117.610512   4.78622442
[101,]  -117.848592   4.83502624
attr(,"parms")
attr(,"parms")$center
           [,1]      [,2]
center 3.505495 0.7032967

attr(,"parms")$shape
```

```
                Coefficients
Coefficients  (Intercept)        day2
  (Intercept)   36.909310 -1.25661152
  day2          -1.256612  0.04383529

attr(,"parms")$radius
[1] 19.97498

attr(,"class")
[1] "ell"
```

if you want to see the method:

```
spida2:::coef.wald  # if you know where it is
```

```
function (obj, se = FALSE)
{
    if (length(obj) == 1) {
        ret <- ret <- obj[[1]]$coef
        if (is.logical(se) && (se == TRUE)) {
            ret <- cbind(coef = ret, se = obj[[1]]$se)
        }
        else if (se > 0) {
            ret <- cbind(coef = ret, coefp = ret + se * obj[[1]]$se,
                coefm = ret - se * obj[[1]]$se)
            attr(ret, "factor") <- se
        }
    }
    else ret <- sapply(obj, coef.wald)
    ret
```

```
}
<bytecode: 0x5f5d9e79aa00>
<environment: namespace:spida2>
```

```r
getAnywhere(coef.wald)
```

```
A single object matching 'coef.wald' was found
It was found in the following places
  registered S3 method for coef from namespace spida2
  namespace:spida2
with value

function (obj, se = FALSE)
{
    if (length(obj) == 1) {
        ret <- ret <- obj[[1]]$coef
        if (is.logical(se) && (se == TRUE)) {
            ret <- cbind(coef = ret, se = obj[[1]]$se)
        }
        else if (se > 0) {
            ret <- cbind(coef = ret, coefp = ret + se * obj[[1]]$se,
                coefm = ret - se * obj[[1]]$se)
            attr(ret, "factor") <- se
        }
    }
    else ret <- sapply(obj, coef.wald)
    ret
}
<bytecode: 0x5f5d9e79aa00>
```

```
<environment: namespace:spida2>
```

```r
getS3method('coef','wald')
```

```
function (obj, se = FALSE)
{
    if (length(obj) == 1) {
        ret <- ret <- obj[[1]]$coef
        if (is.logical(se) && (se == TRUE)) {
            ret <- cbind(coef = ret, se = obj[[1]]$se)
        }
        else if (se > 0) {
            ret <- cbind(coef = ret, coefp = ret + se * obj[[1]]$se,
                coefm = ret - se * obj[[1]]$se)
            attr(ret, "factor") <- se
        }
    }
    else ret <- sapply(obj, coef.wald)
    ret
}
<bytecode: 0x5f5d9e79aa00>
<environment: namespace:spida2>
```

8 Data wrangling

8.1 Regular Expressions to replace strings within string variables

Expertise with regular expressions is one of the most valuable skills you can learn for data manipulation.

Here's a site you can use to experiment with regular expressions. Add it to your R editing bookmarks.

Contribute questions, links and comments to Piazza.

Here's a useful summary prepared by Jeff Lee in the Winter 2016 class. Most descriptions of regular expressions make them look extremely complicated. You can get along with a few basic ideas that are very flexible and that have sufficed for 99.9% of my problems.

8.1.1 Basic Regular Expressions

Using regular expressions is a way to alter, search, count, adjust texts or strings of characters.

There are 3 main groups of R functions that use regular expressions that we will look at.

First look at the function grep

```r
x <- c("Hello", "He", "Hel", "hello", "hel1")
grep("hel", x)
```

```
[1] 4 5
```

As you can see, grep returns the index of all elements of x that contain "hel". It does not return the index of "Hello" because grep is case sensitive.

We say the *pattern* "hel" *matches* substrings in the target. To ignore the case, we can use:

```r
grep("hel", x, ignore.case = T)
```

```
[1] 1 3 4 5
```

A similar effect is achieved by using square brackets: [], which signify 'match any one character in the list'.

```r
grep("[Hh]el", x)
```

```
[1] 1 3 4 5
```

Suppose you want to know how many of these elements of x contain "hel" or "Hel"

```r
length(grep("[hH]el", x))
```

```
[1] 4
```

If you want to see the actual strings matched instead of their indices, use

```r
grep("[Hh]el", x, value = TRUE)
```

```
[1] "Hello" "Hel"   "hello" "hel1"
```

or, with spida2:

```r
library(spida2)
grepv("[Hh]el", x)
```

```
[1] "Hello" "Hel"   "hello" "hel1"
```

Finally if you want a logical index vector:

```r
grepl("[Hh]el", x)
```

```
[1]  TRUE FALSE  TRUE  TRUE  TRUE
```

8.1.2 Taking a closer look at gsub

gsub and sub are great ways to modify substrings in a reproducible way. For example, you can use them to modify variable names in a way that will work when you receive an updated version of a data set. In most data sets, you will have variables names that are acronyms or short forms and you may want to replace those variable names with something that people will understand.

The difference between sub and gsub is that sub will replace only the first match in each string, gsub (g stands for global) will replace all matches. Compare:

```r
sub("l","WWW", x)
```

```
 [1] "HeWWWlo" "He"      "HeWWW"   "heWWWlo" "heWWW1"
```

```r
gsub("l","WWW", x)
```

```
 [1] "HeWWWWWWo" "He"        "HeWWW"     "heWWWWWWo" "heWWW1"
```

The most difficult part about regular expressions is the syntax. These are helpful websites with information on syntax.

- Quick-Start: Regex Cheat Sheet
- Regular Expressions in R by Albert Y. Kim
- RegExr to interactively try out regular expressions

There's a thorough treatment at Microsoft's Regular Expression Language – Quick Reference

Also you can get help in R:

```r
?regex
?gsub
```

There are many special characters that let you do almost anything you want with regular expressions. Here are the most important ones:

- Special characters: All characters match themselves except the special characters: . $ ^ { [(|) * + ? \. Also }] are special characters when they close a matching brace and - is a special character when it appears within square brackets.
- Special matching characters:
  - .: a period matches any single character
  - [abc]: matches any single character in the list
  - [A-Z]: matches a single character in the range A to Z. If you want to include a hyphen as matching character, it must come first, e.g. `[-a-z]`.

- [A-Za-z0-9]: matches any single alphanumeric character
- [^a-z]: matches any single character that is NOT a lower case letter. The caret ^ at the beginning of the bracketed list negates the rest of the list. A caret anywhere else is just a caret.
- `(` and `)` can be used to form sub groups. `(` are not `)` matched. To match a parenthesis you need to 'escape' it: "'\(a\)" in a string in R.
- `|` means "or": `(a|b)c` is the same as `[ab]c`

• Anchors:
  - `^` matches the beginning and `$` matches the end of a string. Thus `"^and"` matches only strings that start with "and", while `"and$"` matches only strings that end with "and". To only get exact matches, i.e. strings that are exactly equal to "and", use both `"^and$"`, e.g. `"^match this exactly$"`.

• Quantifiers: how many repeats of the previous match:
  - `*` matches the previous match 0 or more times
  - `+` matches the previous match one or more times
  - `?` matches the previous match zero or one time
  - `{n}` matches the previous match exactly n times
  - `{n,m}` matches the previous match n to m times
  - `{n,}` matches the previous match at least n times
  - `{,m}` matches the previous match at most m times Quantifiers are 'greedy' in the sense that they will match as much of the string as they can. Adding `?` to a quantifier makes it 'lazy'. It will match as few occurences as possible.

8.1.3 Common Regular Expressions

"."*: the '.' means any single character and *" means zero or more of the previous match. So this is the 'universal' match. It matches anything?

```
some_names <- c('Mary Jones', 'Bush, George H. W.', 'George W. Bush', "Capote,Truman")
sub(".*", "OhOh", some_names)
```

```
[1] "OhOh" "OhOh" "OhOh" "OhOh"
```

A powerful tool for substitution is the 'backreference' `\\N` where `N` is a single digit from 1 to 9. In a replacement string `\\N` refers to the Nth parenthesized expression in the pattern. For example:

```
x <- c('Wong, Rodney','Smith,   John', 'Robert Jones')
sub("^([^, ]+), +([^ ]*)$", "\\2 \\1", x)
```

```
 [1] "Rodney Wong"  "John Smith"   "Robert Jones"
```

Parsing Using parentheses to match substrings to change their order in the replacement string.

```
sub(
  "^([^,]*), ?(.*)$",
  "\\2 \\1",
  some_names)
```

```
 [1] "Mary Jones"         "George H. W. Bush" "George W. Bush"
 [4] "Truman Capote"
```

8.1.4 Quiz question

- What is the purpose of `' ?'` in the regular expression above?
- What would happen if we used `' *'` instead?

Important application: Changing the form of variable names in preparation for restructuring from wide to long format

```
var_names <- c('id','Gender','Age',
               'T1_data', 't2_date', 'T3_date',
               'T1_pulse', 'T2_pulse', 'T3_pulse')
var_names
```

```
 [1] "id"       "Gender"   "Age"      "T1_data"  "t2_date"
 [6] "T3_date"  "T1_pulse" "T2_pulse" "T3_pulse"
```

fix ‘data’:

```
modified_names <- sub('data$','date', var_names)
modified_names
```

```
 [1] "id"        "Gender"    "Age"       "T1_date"   "t2_date"
 [6] "T3_date"   "T1_pulse"  "T2_pulse"  "T3_pulse"
```

reorder variable name and time:

```
modified_names <- sub(
  "^([tT])([0-9])_(.*)$",
  "\\3__\\2",
  modified_names
)
modified_names # note that names that don't match the pattern are left unchanged
```

```
 [1] "id"        "Gender"    "Age"       "date__1"   "date__2"
 [6] "date__3"   "pulse__1"  "pulse__2"  "pulse__3"
```

In order to match a special character it needs to be escaped with a backslash ‘\’ before the character.

```
s <- ("HEL$LO")
s
```

```
 [1] "HEL$LO"
```

```
gsub("$", replacement = ".", s) # $ matches the end of the string
```

```
 [1] "HEL$LO."
```

```
gsub("\\$", replacement = ".", s) # \\$ matches the actual $
```

```
 [1] "HEL.LO"
```

As you can see, using two back slashes will actually replace \$ with a period In a string in R you need to use two backslashes to produce one backslash, i.e. you need to escape the escape.

```r
y <- c("hello123","hello213","hel2222lo","llo he123" )
gsub(".*2", "--", y)
```

```
[1] "--3"  "--13" "--lo" "--3"
```

```r
gsub(".*2", "", y) # Note that "" will delete the match
```

```
[1] "3"  "13" "lo" "3"
```

This will remove everything up to and including a 2 in each string. As you can see in hel2222lo, it removes the last 2.

```r
gsub("^hel2","4939", y)
```

```
[1] "hello123"  "hello213"  "4939222lo" "llo he123"
```

The ^ will replace everything that starts with hel2. In this case only the 3rd word started with hel2 so it replaces it with 4939.

```r
gsub("213$","4939", y)
```

```
[1] "hello123"  "hello4939" "hel2222lo" "llo he123"
```

The \$ will replace everything that ends with 213. In this case only the 2nd word ended with 213 so it replaces it with 4939.

```r
gsub("\\bhe","4939", y)
```

```
[1] "4939llo123"  "4939llo213"  "4939l2222lo" "llo 4939123"
```

The double backslash b will replace everything that starts at with 'he' on words instead of strings. In this case, every word had a 'he' in this case.

```r
gsub("hel*1", "4939", y)
```

```
[1] "hello123"   "hello213"   "hel2222lo"  "llo 493923"
```

The * will replace anything that matches at least 0 times. In this case, the last word matches hel and 1 matches 0 times.

The special character | allows alternative choices. It matches either what comes before the | or what comes after it.

```r
gsub("hel|213", "4939", y)
```

```
[1] "4939lo123"  "4939lo4939" "49392222lo" "llo he123"
```

The | is an 'or' feature. This pattern will replace anything with a hel or 213. If it can match either hel and 213 it will replace both.

Note that you can use and mix quantifiers and operators together. Perhaps the most common combination is .* which matches anything

8.1.5 Taking a look at regexpr

```r
y <- c("hello123","hello213","hel2222lo","llo he123","zork")
regexpr("he(.*)", y)
```

```
[1]  1  1  1  5 -1
attr(,"match.length")
[1]  8  8  9  5 -1
attr(,"index.type")
[1] "chars"
attr(,"useBytes")
[1] TRUE
```

regexpr returns the position of the first character matched.

attr(,“match.length”) is the number of characters matched in each string, -1 if no match.

```r
regexpr("hel(.*)", y)
```

```
[1]  1  1  1 -1 -1
attr(,"match.length")
[1]  8  8  9 -1 -1
attr(,"index.type")
[1] "chars"
attr(,"useBytes")
[1] TRUE
```

As you can see, the 4th word does not have hel in it.

```r
gregexpr("he(.*)", y)
```

```
[[1]]
[1] 1
attr(,"match.length")
[1] 8
attr(,"index.type")
[1] "chars"
attr(,"useBytes")
[1] TRUE

[[2]]
[1] 1
attr(,"match.length")
[1] 8
attr(,"index.type")
[1] "chars"
```

```
attr(,"useBytes")
[1] TRUE

[[3]]
[1] 1
attr(,"match.length")
[1] 9
attr(,"index.type")
[1] "chars"
attr(,"useBytes")
[1] TRUE

[[4]]
[1] 5
attr(,"match.length")
[1] 5
attr(,"index.type")
[1] "chars"
attr(,"useBytes")
[1] TRUE

[[5]]
[1] -1
attr(,"match.length")
[1] -1
attr(,"index.type")
[1] "chars"
attr(,"useBytes")
[1] TRUE
```

gregexpr will return a list of all the matches.

9 Reshaping Data

I have to reshape data almost every time I see a client. In fact some clients come to see me just to have their data reshaped. I need to keep it fast and simple.

Most serious data errors I encounter come from mishaps in attempting to reshape data by hand, for example, by cutting and pasting portions of worksheets in Excel.

I encounter two major reasons for reshaping data:

1. Longitudinal data and hierarchical data (where each subject may be seen and measured more than once) needs to be in different shapes (long or wide) for different methods of analysis. Traditional multivariate methods expect wide data and newer mixed model approaches require long data.
2. Categorical data needs to be in different forms; long (one row per observation), aggregated, or tabular for different analyses (logistic regression, binomial regression or log-linear modeling).

The shape in which you get the data must not determine your method of analysis. You need to be able to go back and forth easily among data shapes to use the analyses you wish to apply.

A longitudinal example: This is a simple example from a pretend medical study in which each subject is seen on a varying number of visits. This is the data set in **long** form.

9.1 Long form

```
dlong <- read.table(strip.white = T, header = TRUE, text =
"
sid  name   visit date         sex      sysbp temp
1    Sam    1     2019-01-21   male     124   36.5
```

```
1    Sam    2     2019-03-15   male     129   36.8
2    Joan   1     2019-02-10   female   115   37.1
3    Kate   1     2018-06-16   female   132   37.3
3    Kate   2     2018-09-03   female   139   36.7
3    Kate   3     2019-04-20   female   138   36.9
")
```

```
dlong
```

```
  sid name visit       date    sex sysbp temp
1   1  Sam     1 2019-01-21   male   124 36.5
2   1  Sam     2 2019-03-15   male   129 36.8
3   2 Joan     1 2019-02-10 female   115 37.1
4   3 Kate     1 2018-06-16 female   132 37.3
5   3 Kate     2 2018-09-03 female   139 36.7
6   3 Kate     3 2019-04-20 female   138 36.9
```

We can identify four types of variables:

1. a **subject id** variable that uniquely identifies each subject. Names are not usually adequate for this purpose since two subjects could share the same name. A good example in a university setting is the student number.
2. a **time index** variable consisting of small integers that, for each subject, identifies the *visit* or *occasion*.
3. **Value** variables that are measurements or characteristics of subjects or of visits. They fall into two classes:
    a. **Time-varying** (or **visit-level**) variables that can vary from visit to visit. In this example, these are: *date, sysbp* and *temp*.
    b. **Time-invariant** (or _subject-level___) variables that remain the same within each subject from visit to visit. In this example these are: *name* and *sex*. Sometimes, a variable may appear to be time-invariant in the observed data but would be time-varying if one had observed more data.

Note:

1. The **subject id** by **time index** combinations should be unique although it is possible to have deeper indexing. For example, if each visit has two phases: *am* and *pm*, then there could be a deeper indexing variable, *phase* with values *am* and *pm*. Then the combinations of the **subject id** by **time index** by **phase index** would need to be unique.
2. It is not necessary to have all possible combinations in the data.
3. The groups of rows belonging to the same subject are often called **clusters**.

9.2 Wide form

Here's the same data in **wide** form with one row per subject. Sorry the input is too wide for the screen, but you can infer what it is from the display of `dwide` below.

```r
dwide <- read.table(strip.white = T, header = TRUE, text =
"
sid name sex    date_1     date_2     date_3     sysbp_1 sysbp_2 sysbp_3 temp_1 temp_2 temp_3
1 Sam  male   2019-01-21 2019-03-15 NA         124 129 NA  36.5 36.8 NA
2 Joan female 2019-02-10 NA         NA         113  NA NA  37.1 NA NA
3 Kate female 2018-06-16 2018-09-03 2018-04-20 132 138 132 37.3 36.7 36.9
")
dwide
```

```
  sid name    sex     date_1     date_2     date_3 sysbp_1
1   1  Sam   male 2019-01-21 2019-03-15       <NA>     124
2   2 Joan female 2019-02-10       <NA>       <NA>     113
3   3 Kate female 2018-06-16 2018-09-03 2018-04-20     132
  sysbp_2 sysbp_3 temp_1 temp_2 temp_3
1     129      NA   36.5   36.8     NA
2      NA      NA   37.1     NA     NA
3     138     132   37.3   36.7   36.9
```

9.3 Relational data base form

In an RDB, this data would be represented by two *relations* (data frames) which can be merged as needed for analyses.

One relation contains time invariant variables and the second contain time-varying variables plus the subject id variable (called a **key**) needed to link the time-varying variables with the time-invariant variables.

Instead of re-entering from scratch, we'll start using the tools in 'spida2'

```r
library(spida2)
```

The time-invariant variable relation contains the following.

```r
dti <- up(dlong, ~sid)
dti
```

```
  sid name    sex Freq
1   1  Sam   male    2
2   2 Joan female    1
3   3 Kate female    3
```

The time-varying relation is:

```r
dtv <- subset(dlong, select = !(names(dlong) %in% names(dti)[-1]))
dtv
```

```
  sid visit       date sysbp temp
1   1     1 2019-01-21   124 36.5
2   1     2 2019-03-15   129 36.8
3   2     1 2019-02-10   115 37.1
4   3     1 2018-06-16   132 37.3
5   3     2 2018-09-03   139 36.7
6   3     3 2019-04-20   138 36.9
```

Note that the 'select' argument of the 'subset' function selects variables.

You can get the long file back with:

```r
merge(dti, dtv, all = T)
```

```
  sid name    sex Freq visit       date sysbp temp
1   1  Sam   male    2     1 2019-01-21   124 36.5
2   1  Sam   male    2     2 2019-03-15   129 36.8
3   2 Joan female    1     1 2019-02-10   115 37.1
4   3 Kate female    3     1 2018-06-16   132 37.3
```

```
5   3 Kate female    3      2 2018-09-03   139 36.7
6   3 Kate female    3      3 2019-04-20   138 36.9
```

I encourage researchers who use Excel for data entry to keep their data in multiple spreadsheets, one for each data level as in a relational data base. This reduces errors in data entry and updating. The principle is that **if you need to correct the value of a variable you should only have to do it in one place**.

Keeping separate spreadsheets for different data levels makes this possible. For example, if you need to correct the spelling of a name, you only need to make the correction in one place. Currently, I find that the best way to read Excel spreadsheets is with the 'read_excel' function in the 'readxl' package.

9.4 From Wide to Long

The **tolong** function in the 'spida2' package relies on the form of the variable names to transform the wide data frame to a long form. The function looks for a *separator* between the name of the value variable and the *time index*. The default is '_' which can be changed with the 'sep' argument. The default name created for the *time index* variable is 'time'.

```r
dwide
```

```
  sid name    sex     date_1     date_2     date_3 sysbp_1
1   1  Sam   male 2019-01-21 2019-03-15       <NA>     124
2   2 Joan female 2019-02-10       <NA>       <NA>     113
3   3 Kate female 2018-06-16 2018-09-03 2018-04-20     132
  sysbp_2 sysbp_3 temp_1 temp_2 temp_3
1     129      NA   36.5   36.8     NA
2      NA      NA   37.1     NA     NA
3     138     132   37.3   36.7   36.9
```

```r
tolong(dwide)
```

```
    sid name    sex time       date sysbp temp id
```

```
  1.1    1  Sam   male    1 2019-01-21   124 36.5  1
  1.2    1  Sam   male    2 2019-03-15   129 36.8  1
  1.3    1  Sam   male    3       <NA>    NA   NA  1
  2.1    2 Joan female    1 2019-02-10   113 37.1  2
  2.2    2 Joan female    2       <NA>    NA   NA  2
  2.3    2 Joan female    3       <NA>    NA   NA  2
  3.1    3 Kate female    1 2018-06-16   132 37.3  3
  3.2    3 Kate female    2 2018-09-03   138 36.7  3
  3.3    3 Kate female    3 2018-04-20   132 36.9  3
```

It's best to specify a name for the *time index*. Otherwise, if a variable named 'time' already exists it will get clobbered by 'tolong'.

Also, the new 'id' variable generated by 'tolong' refers to the row numbers of the input data frame. If a variable named 'id' already exists and has unique values, 'tolong' will use that variable. You can specify a variable name as the id variable

```
dtolong <- tolong(dwide, timevar = 'visit', idvar = 'sid')
dtolong
```

```
    sid name    sex visit       date sysbp temp
  1.1    1  Sam   male     1 2019-01-21   124 36.5
  1.2    1  Sam   male     2 2019-03-15   129 36.8
  1.3    1  Sam   male     3       <NA>    NA   NA
  2.1    2 Joan female     1 2019-02-10   113 37.1
  2.2    2 Joan female     2       <NA>    NA   NA
  2.3    2 Joan female     3       <NA>    NA   NA
  3.1    3 Kate female     1 2018-06-16   132 37.3
  3.2    3 Kate female     2 2018-09-03   138 36.7
  3.3    3 Kate female     3 2018-04-20   132 36.9
```

It's often useful to reorder longitudinal data, e.g. for plotting:

```r
sortdf(dtolong, ~ sid/visit)
```

```
    sid name    sex visit       date sysbp temp
1.1   1  Sam   male     1 2019-01-21   124 36.5
1.2   1  Sam   male     2 2019-03-15   129 36.8
1.3   1  Sam   male     3       <NA>    NA   NA
2.1   2 Joan female     1 2019-02-10   113 37.1
2.2   2 Joan female     2       <NA>    NA   NA
2.3   2 Joan female     3       <NA>    NA   NA
3.1   3 Kate female     1 2018-06-16   132 37.3
3.2   3 Kate female     2 2018-09-03   138 36.7
3.3   3 Kate female     3 2018-04-20   132 36.9
```

When the variables are not conveniently named we can often use regular expressions to transform the names into a form that works with 'tolong'. See the additional material on regular expressions in the extra notes.

9.5 From Long to Wide

This is a bit trickier because there are no clues from the form of the variable names that some are subscripted. We need to specify the **id** variable and the **time index** variable.

Standard reshape functions also expect you to indicate which variables are time-varying so that only those variables get indexed in the wide form. With a large dataset this can be an enormous amount of work, which the 'towide' function gets the computer to do for you. The function identifies which variables are time-varying and which are not and only the time-varying variables get expanded by indexing.

```r
towide(dtolong, idvar = 'sid', timevar = 'visit')
```

```
  sid     date_1 sysbp_1 temp_1     date_2 sysbp_2 temp_2
1   1 2019-01-21     124   36.5 2019-03-15     129   36.8
```

```
  2   2 2019-02-10     113   37.1        <NA>      NA     NA
  3   3 2018-06-16     132   37.3 2018-09-03     138   36.7
        date_3 sysbp_3 temp_3 name    sex
  1       <NA>      NA     NA  Sam   male
  2       <NA>      NA     NA Joan female
  3 2018-04-20     132   36.9 Kate female
```

9.6 Working with Dates

Many longitudinal data sets include a variable for the date on which data were recorded. Sometimes, the earliest date for each subject is the date on which a special event occurred, such as the date of an injury in clinical data. The dates of events can be of interest for more than one reason. For example the elapsed time (in days, months of years) since the data of injury will be a important variable. The calendar date may also be important if there are possible seasonal effects that require adjustment or investigation. We use the small data set `dlong` created earlier to illustrate the manipulation of date variables.

Suppose we don't have the visit variable but need to construct it from the `date` variable

```
dlong <- read.table(strip.white = T, header = TRUE, text =
"
sid  name   date         sex      sysbp temp
1    Sam    2019-01-21   male     124   36.5
1    Sam    2019-03-15   male     129   36.8
2    Joan   2019-02-10   female   115   37.1
3    Kate   2018-06-16   female   132   37.3
3    Kate   2018-09-03   female   139   36.7
3    Kate   2019-04-20   female   138   36.9
")
```

The first step is to read the `date` as a "Date" object that will allow us to perform date arithmetic.

```r
dlong$date.d <- as.Date(dlong$date)
```

The orginal `date` variable was entered in the format R uses by default. If it were in a different format you might need to tell `as.Date()` about the input format. See the help file for the function `strptime()` for a complete list of conversion specifications. For example, to read dates in a Month Day, Year form you would use

```r
dates <- c("April 5, 2025","January 1, 1970",
           "February 29, 1970", "February 29, 1972",
           "February 28, 2000", "February 29, 2000","March 1, 2000")
date.f <- as.Date(dates, "%B %d, %Y")
class(date.f)
```

```
[1] "Date"
```

```r
date.f
```

```
[1] "2025-04-05" "1970-01-01" NA           "1972-02-29"
[5] "2000-02-28" "2000-02-29" "2000-03-01"
```

```r
unclass(date.f)   # internal representation
```

```
[1] 20183     0    NA   789 11015 11016 11017
```

```r
date.n <- as.numeric(date.f)
date.n            # to do arithmetic on dates
```

```
[1] 20183     0    NA   789 11015 11016 11017
```

This example illustrate a number of features of `Date` objects:

1. Their internal representation is an integer showing the number of days since January 1, 1970.
2. To perform mathematical operations on dates, convert the `Date` object to a numeric object.
3. The conversion to a `Date` object knows about "some" leap years.

We show how to create a sequential `visit` variable for `dlong`, how to create a numerical 'date of injury' corresponding to the first visit and how to create a variable showing the number of elapsed months since injury:

Start by sorting the data frame on `date`, then create new variables:

```
dlong <- dlong[ order(dlong$date), ]
dlong
```

```
  sid name       date    sex sysbp temp     date.d
4   3 Kate 2018-06-16 female   132 37.3 2018-06-16
5   3 Kate 2018-09-03 female   139 36.7 2018-09-03
1   1  Sam 2019-01-21   male   124 36.5 2019-01-21
3   2 Joan 2019-02-10 female   115 37.1 2019-02-10
2   1  Sam 2019-03-15   male   129 36.8 2019-03-15
6   3 Kate 2019-04-20 female   138 36.9 2019-04-20
```

```
dlong <- within(
  dlong,
  {
    date.f <- as.Date(date, format = "%Y-%m-%d")
    # this is the default format so didn't need to be specified
    date.n <- as.numeric(date.f)
    date.first <- capply(date.n, name, min)
    elapsed.days <- date.n - date.first
    elapsed.months <- elapsed.days / (365.25/12)
    elapsed.years <- elapsed.days / 365.25
    visit <- capply(date.n, name, rank)
  }
)
dlong[order(dlong$name, dlong$visit),]
```

```
  sid name       date    sex sysbp temp     date.d visit
3   2 Joan 2019-02-10 female   115 37.1 2019-02-10     1
4   3 Kate 2018-06-16 female   132 37.3 2018-06-16     1
5   3 Kate 2018-09-03 female   139 36.7 2018-09-03     2
6   3 Kate 2019-04-20 female   138 36.9 2019-04-20     3
1   1  Sam 2019-01-21   male   124 36.5 2019-01-21     1
2   1  Sam 2019-03-15   male   129 36.8 2019-03-15     2
  elapsed.years elapsed.months elapsed.days date.first date.n
3     0.0000000       0.000000            0      17937  17937
4     0.0000000       0.000000            0      17698  17698
5     0.2162902       2.595483           79      17698  17777
6     0.8432580      10.119097          308      17698  18006
1     0.0000000       0.000000            0      17917  17917
2     0.1451061       1.741273           53      17917  17970
      date.f
3 2019-02-10
4 2018-06-16
5 2018-09-03
6 2019-04-20
1 2019-01-21
2 2019-03-15
```

9.7 More examples

Many sources of global data let you retrieve data from various countries by variable. After concatenating the raw data for the various variables, you get something that looks like this:

```
dd <- read.table(header=T,text="
country    variable   1990 1991 1992 1993
```

```
Canada     population   20   21   24   26
Mexico     population   50   52   53   54
Canada     income       10   12   12   11
Mexico     income       30   31   33   34
")
dd
```

```
  country   variable X1990 X1991 X1992 X1993
1  Canada population    20    21    24    26
2  Mexico population    50    52    53    54
3  Canada     income    10    12    12    11
4  Mexico     income    30    31    33    34
```

Note how 'read.table' prepended an 'X' to the years since a valid variable names can't start with a number.

We need to get the variable names in the right form for 'tolong'. The 'easy' way is to use regular expressions.

```
names(dd) <- sub('^X', 'value__', names(dd))
dd
```

```
  country   variable value__1990 value__1991 value__1992
1  Canada population          20          21          24
2  Mexico population          50          52          53
3  Canada     income          10          12          12
4  Mexico     income          30          31          33
  value__1993
1          26
2          54
3          11
4          34
```

The regular expression '^X' matches a capital X at the begining of a string. Wherever it is found, it gets replaced by 'year___'. I'm in the habit of using a repeated underscore,'___', as a seperator to avoid conflicts with other underscores in variable names.

Now we're ready for the first step:

```
dl <- tolong(dd, sep = '__', timevar = 'year')
dl
```

```
         country   variable year value id
  1.1990  Canada population 1990    20  1
  1.1991  Canada population 1991    21  1
  1.1992  Canada population 1992    24  1
  1.1993  Canada population 1993    26  1
  2.1990  Mexico population 1990    50  2
  2.1991  Mexico population 1991    52  2
  2.1992  Mexico population 1992    53  2
  2.1993  Mexico population 1993    54  2
  3.1990  Canada     income 1990    10  3
  3.1991  Canada     income 1991    12  3
  3.1992  Canada     income 1992    12  3
  3.1993  Canada     income 1993    11  3
  4.1990  Mexico     income 1990    30  4
  4.1991  Mexico     income 1991    31  4
  4.1992  Mexico     income 1992    33  4
  4.1993  Mexico     income 1993    34  4
```

Now, our 'id' or **key** uses the combination of two variables: *country* and *year* because we want one row for each of those combinations.

Also, our 'timevar' is 'variable':

```r
d2 <- towide(dl, idvar = c('country','year'), timevar = 'variable')
d2
```

```
  country year value_population id_population value_income
1  Canada 1990               20             1           10
2  Canada 1991               21             1           12
3  Canada 1992               24             1           12
4  Canada 1993               26             1           11
5  Mexico 1990               50             2           30
6  Mexico 1991               52             2           31
7  Mexico 1992               53             2           33
8  Mexico 1993               54             2           34
  id_income
1         3
2         3
3         3
4         3
5         4
6         4
7         4
8         4
```

We don't need the 'id_..' variables and we rename the value variables:

```r
d2 <- d2[, - grep('^id_', names(d2))]
d2
```

```
  country year value_population value_income
1  Canada 1990               20           10
2  Canada 1991               21           12
```

```
  3  Canada 1992                24          12
  4  Canada 1993                26          11
  5  Mexico 1990                50          30
  6  Mexico 1991                52          31
  7  Mexico 1992                53          33
  8  Mexico 1993                54          34
```

```
names(d2) <- sub('^value_','', names(d2))
d2
```

```
    country year population income
  1  Canada 1990         20     10
  2  Canada 1991         21     12
  3  Canada 1992         24     12
  4  Canada 1993         26     11
  5  Mexico 1990         50     30
  6  Mexico 1991         52     31
  7  Mexico 1992         53     33
  8  Mexico 1993         54     34
```

. . . and you are ready to do some analyses.

9.8 Variables and years in long form

Another common format for global health has both variables and time in long form.

```
dd <- read.table(header=TRUE, text = "
country   year   variable    value country.code  rownum
Canada     2001    atemp       20   CAN             1
Canada     2002    atemp       23   CAN             2
US         2001    atemp       23   USA             3
```

```r
US          2002    atemp        23   USA            4
Canada      2001    wind        120   CAN            5
Canada      2002    wind        123   CAN            6
US          2001    wind        123   USA            7
US          2002    wind        123   USA            8
Canada      2001    rain        220   CAN            9
Canada      2002    rain        223   CAN            10
US          2001    rain        223   USA            11
US          2002    rain        223   USA            12
")
(dw <- towide(
  dd,
  idvar = c('country','year'),
  timevar = 'variable'))
```

```
    country year value_atemp rownum_atemp value_wind rownum_wind
  1  Canada 2001          20            1        120           5
  2  Canada 2002          23            2        123           6
  3      US 2001          23            3        123           7
  4      US 2002          23            4        123           8
    value_rain rownum_rain country.code
  1        220           9          CAN
  2        223          10          CAN
  3        223          11          USA
  4        223          12          USA
```

```r
#
# to keep only the variable name as a name
#
```

```r
names(dw) <- sub('^value_','', names(dw))
dw
```

```
  country year atemp rownum_atemp wind rownum_wind rain
1  Canada 2001    20            1  120           5  220
2  Canada 2002    23            2  123           6  223
3      US 2001    23            3  123           7  223
4      US 2002    23            4  123           8  223
  rownum_rain country.code
1           9          CAN
2          10          CAN
3          11          USA
4          12          USA
```

```r
#
# to get rid of other time varying variable
#
dw <- dw[, - grep('_', names(dw))]
dw
```

```
  country year atemp wind rain country.code
1  Canada 2001    20  120  220          CAN
2  Canada 2002    23  123  223          CAN
3      US 2001    23  123  223          USA
4      US 2002    23  123  223          USA
```

9.9 Working with long data frames

One advantage of working with long (as opposed to wide) data is the ease with with which you can do calculations using the **clusters** much more easily if you have the right tool.

Using the original long data frame:

```
dlong
```

```
  sid name       date    sex sysbp temp     date.d visit
4   3 Kate 2018-06-16 female   132 37.3 2018-06-16     1
5   3 Kate 2018-09-03 female   139 36.7 2018-09-03     2
1   1  Sam 2019-01-21   male   124 36.5 2019-01-21     1
3   2 Joan 2019-02-10 female   115 37.1 2019-02-10     1
2   1  Sam 2019-03-15   male   129 36.8 2019-03-15     2
6   3 Kate 2019-04-20 female   138 36.9 2019-04-20     3
  elapsed.years elapsed.months elapsed.days date.first date.n
4     0.0000000       0.000000            0      17698  17698
5     0.2162902       2.595483           79      17698  17777
1     0.0000000       0.000000            0      17917  17917
3     0.0000000       0.000000            0      17937  17937
2     0.1451061       1.741273           53      17917  17970
6     0.8432580      10.119097          308      17698  18006
      date.f
4 2018-06-16
5 2018-09-03
1 2019-01-21
3 2019-02-10
2 2019-03-15
6 2019-04-20
```

we would like to have the variables in different columns and the years in different rows.

We create a long data frame with respect to year and then a wide one with respect to variable, suppose we want to create new variables for the mean ‘sysbp’ and ‘temp’ for each subject.

The **capply** function does this. It applies a function to the values of a variable in each cluster and returns a result that has the right form to be added as a variable to the data frame.

```
dlong2 <- within(
  dlong, {
    temp_m <- capply(temp, sid, mean)
  }
)
dlong2
```

```
   sid name       date    sex sysbp temp     date.d visit
 4   3 Kate 2018-06-16 female   132 37.3 2018-06-16     1
 5   3 Kate 2018-09-03 female   139 36.7 2018-09-03     2
 1   1  Sam 2019-01-21   male   124 36.5 2019-01-21     1
 3   2 Joan 2019-02-10 female   115 37.1 2019-02-10     1
 2   1  Sam 2019-03-15   male   129 36.8 2019-03-15     2
 6   3 Kate 2019-04-20 female   138 36.9 2019-04-20     3
   elapsed.years elapsed.months elapsed.days date.first date.n
 4     0.0000000       0.000000            0      17698  17698
 5     0.2162902       2.595483           79      17698  17777
 1     0.0000000       0.000000            0      17917  17917
 3     0.0000000       0.000000            0      17937  17937
 2     0.1451061       1.741273           53      17917  17970
 6     0.8432580      10.119097          308      17698  18006
       date.f   temp_m
 4 2018-06-16 36.96667
 5 2018-09-03 36.96667
 1 2019-01-21 36.65000
 3 2019-02-10 37.10000
```

```
2 2019-03-15 36.65000
6 2019-04-20 36.96667
```

capply applies the function *mean* to each *cluster* of values of *temp* defined by a common value of *sid* and returns a result that has the right shape to be added to the data frame. Note that, in contrast with *SAS*, the order of rows in the data frame doesn't matter. That is, clusters don't have be in contiguous rows. Also, in contrast with *tapply*, the function does not have to return a single value.

```r
dlong2 <- within(
  dlong2,
  {
    sysbp_m <- capply(sysbp, sid, mean)
    sysbp_rank <- capply(sysbp, sid, rank)
    temp_rank <- capply(temp, sid, rank)
    temp_sd <- capply(temp, sid, sd)
  }
)
dlong2
```

```
  sid name       date    sex sysbp temp     date.d visit
4   3 Kate 2018-06-16 female   132 37.3 2018-06-16     1
5   3 Kate 2018-09-03 female   139 36.7 2018-09-03     2
1   1  Sam 2019-01-21   male   124 36.5 2019-01-21     1
3   2 Joan 2019-02-10 female   115 37.1 2019-02-10     1
2   1  Sam 2019-03-15   male   129 36.8 2019-03-15     2
6   3 Kate 2019-04-20 female   138 36.9 2019-04-20     3
  elapsed.years elapsed.months elapsed.days date.first date.n
4     0.0000000       0.000000            0      17698  17698
5     0.2162902       2.595483           79      17698  17777
1     0.0000000       0.000000            0      17917  17917
```

```
3     0.0000000      0.000000             0       17937  17937
2     0.1451061      1.741273            53       17917  17970
6     0.8432580     10.119097           308       17698  18006
      date.f    temp_m   temp_sd temp_rank sysbp_rank  sysbp_m
4 2018-06-16 36.96667 0.305505         3          1 136.3333
5 2018-09-03 36.96667 0.305505         1          3 136.3333
1 2019-01-21 36.65000 0.212132         1          1 126.5000
3 2019-02-10 37.10000       NA         1          1 115.0000
2 2019-03-15 36.65000 0.212132         2          2 126.5000
6 2019-04-20 36.96667 0.305505         2          2 136.3333
```

The variable 'temp_sd' is a measure of the variability in their temperature. This way be a variable of interest. Once it has been computed in the long file, it is available for analysis in models at the subject level, with:

```r
up(dlong2, ~sid)
```

```
  sid name    sex date.first   temp_m  temp_sd  sysbp_m Freq
1   1  Sam   male      17917 36.65000 0.212132 126.5000    2
2   2 Joan female      17937 37.10000       NA 115.0000    1
3   3 Kate female      17698 36.96667 0.305505 136.3333    3
```

The long file often provides a much easier way to create new subject-level variables than working with the original data in wide form.

9.10 Reshaping categorical data

Purely categorical data (in which all variables are treated as categofical) can be represented in many ways.

1. Frequency table well suited for log-linear analysis
2. Subject-level long data frame with one observation per subject for logistic regression
3. Aggregated data frame with a frequency variable for Poisson models

4. Data frame with frequencies wide on one variable for binomial or multinomial analyses

We use the 'Titanic' table in base R. It's an array with class 'table' so functions that have methods for the class 'table' will use those methods. The table cells contain the frequecies for each outcome.

9.10.1 Tabular data

```
Titanic
```

```
, , Age = Child, Survived = No

      Sex
Class  Male Female
  1st     0      0
  2nd     0      0
  3rd    35     17
  Crew    0      0

, , Age = Adult, Survived = No

      Sex
Class  Male Female
  1st   118      4
  2nd   154     13
  3rd   387     89
  Crew  670      3

, , Age = Child, Survived = Yes
```

```
      Sex
Class  Male Female
  1st     5      1
  2nd    11     13
  3rd    13     14
  Crew    0      0

, , Age = Adult, Survived = Yes

      Sex
Class  Male Female
  1st    57    140
  2nd    14     80
  3rd    75     76
  Crew  192     20
```

A different view: a flattened table:

```r
ftable(Titanic)
```

```
                   Survived  No Yes
Class Sex    Age                   
1st   Male   Child            0   5
             Adult          118  57
      Female Child            0   1
             Adult            4 140
2nd   Male   Child            0  11
             Adult          154  14
      Female Child            0  13
             Adult           13  80
```

```
3rd   Male   Child         35  13
             Adult        387  75
      Female Child         17  14
             Adult         89  76
Crew  Male   Child          0   0
             Adult        670 192
      Female Child          0   0
             Adult          3  20
```

```
dimnames(Titanic)
```

```
$Class
[1] "1st"  "2nd"  "3rd"  "Crew"

$Sex
[1] "Male"   "Female"

$Age
[1] "Child" "Adult"

$Survived
[1] "No"  "Yes"
```

Permuting the dimensions of the array:

```
ftable(aperm(Titanic, c('Class','Sex','Survived','Age')))
```

```
                      Age Child Adult
Class Sex    Survived
1st   Male   No               0   118
             Yes              5    57
```

```
       Female No          0   4
              Yes         1 140
  2nd  Male   No          0 154
              Yes        11  14
       Female No          0  13
              Yes        13  80
  3rd  Male   No         35 387
              Yes        13  75
       Female No         17  89
              Yes        14  76
  Crew Male   No          0 670
              Yes         0 192
       Female No          0   3
              Yes         0  20
```

```r
dim(Titanic)  # 4-dimensional array
```

```
[1] 4 2 2 2
```

The ‘tab’ function in ‘spida2’ operates on tables to show marginal distributions.

```r
tab(Titanic, ~ Sex)
```

```
Sex
  Male Female  Total
  1731    470   2201
```

```r
tab(Titanic, ~ Sex + Age) # frequencies
```

```
        Age
Sex       Child Adult Total
```

```
  Male       64  1667  1731
  Female     45   425   470
  Total     109  2092  2201
```

```r
tab(Titanic, ~ Sex + Age, pct = 1) # row percentages
```

```
         Age
Sex             Child      Adult      Total
  Male       3.697285  96.302715 100.000000
  Female     9.574468  90.425532 100.000000
  All        4.952294  95.047706 100.000000
```

```r
tab(Titanic, ~ Sex + Age, pct = 2) # column percentages
```

```
         Age
Sex            Child      Adult        All
  Male      58.71560  79.68451  78.64607
  Female    41.28440  20.31549  21.35393
  Total    100.00000 100.00000 100.00000
```

To suppress margins, use the variants 'tab_' and 'tab___'

```r
tab_(Titanic, ~ Sex)
```

```
Sex
  Male Female
  1731    470
```

```r
tab_(Titanic, ~ Sex + Age) # frequencies
```

```
         Age
Sex       Child Adult
```

```
    Male       64  1667
    Female     45   425
```

```r
tab_(Titanic, ~ Sex + Age, pct = 1) # row percentages
```

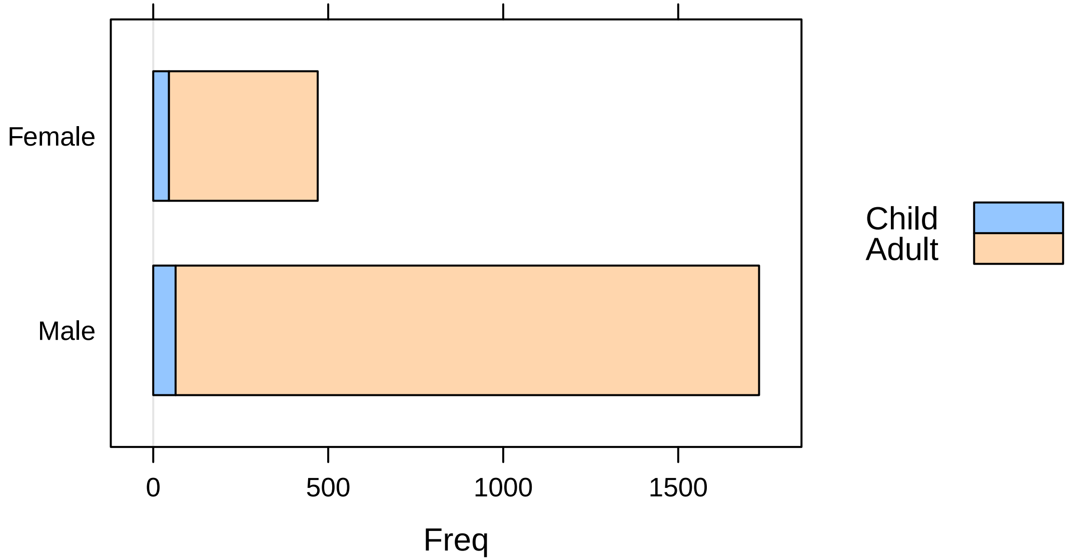
```
            Age
  Sex           Child     Adult
    Male     3.697285 96.302715
    Female   9.574468 90.425532
    All      4.952294 95.047706
```

```r
tab__(Titanic, ~ Sex + Age, pct = 1) # row percentages
```

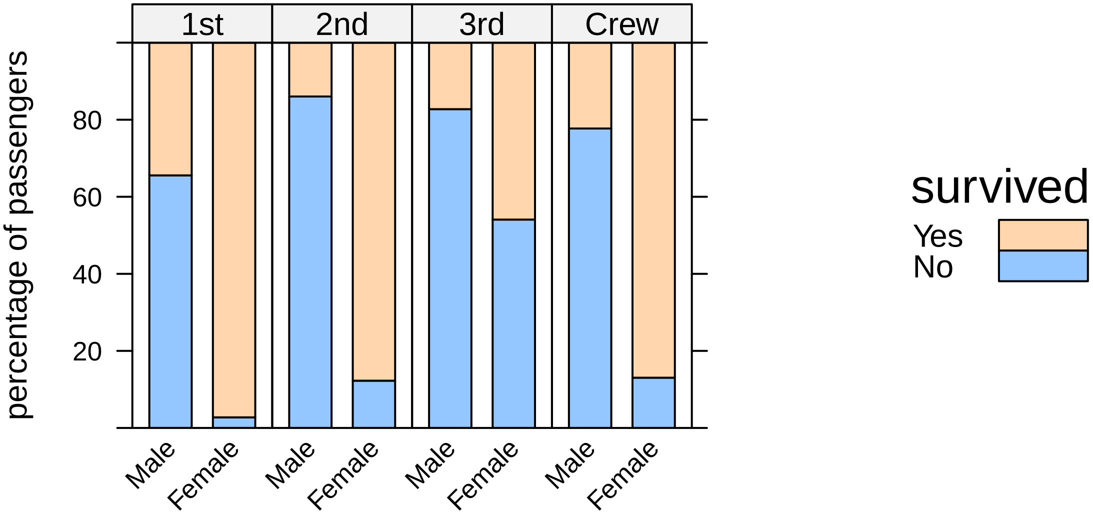
```
            Age
  Sex           Child     Adult
    Male     3.697285 96.302715
    Female   9.574468 90.425532
```

The ouput lends itself well to barcharts

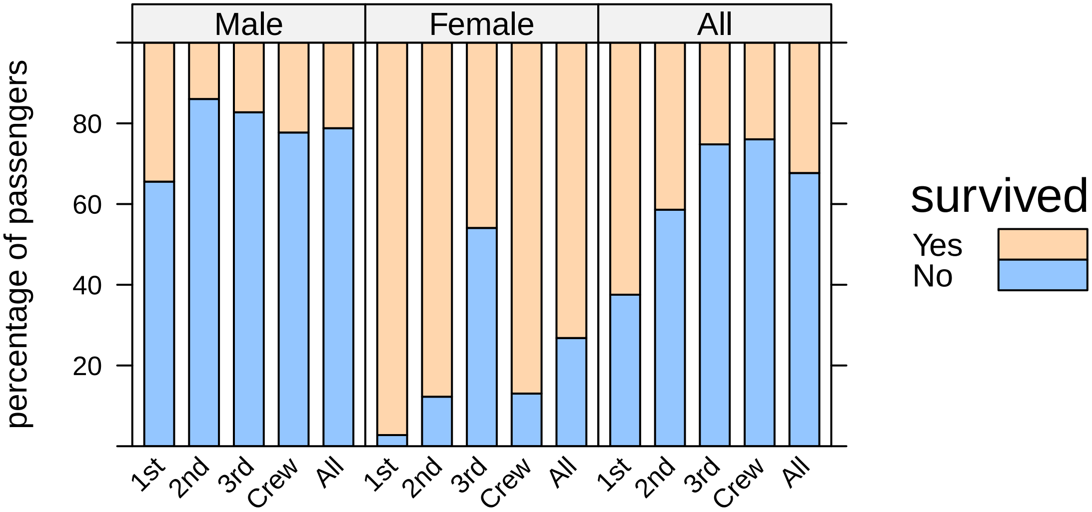
```r
tab_(Titanic, ~ Sex + Age)  %>% barchart(auto.key=T)
```




```
tab__(Titanic, ~  Sex + Class + Survived, pct = c(1,2)) %>%
  barchart(ylab = 'percentage of passengers',
           horizontal = FALSE,
           ylim = c(0,100), layout = c(5,1),
           scales = list(x=list(rot=45)),
           auto.key=list(space='right',title='survived', reverse.rows = T))
```




```
tab_(Titanic, ~  Class + Sex + Survived, pct = c(1,2)) %>%
  barchart(ylab = 'percentage of passengers',
           horizontal = FALSE,
           ylim = c(0,100), layout = c(3,1),
           scales = list(x=list(rot=45)),
           auto.key=list(space='right',title='survived', reverse.rows = T))
```



9.10.2 Making marginal tables

```
tab(Titanic, ~ Sex + Survived)
```

```
          Survived
  Sex          No  Yes Total
    Male     1364  367  1731
    Female    126  344   470
    Total    1490  711  2201
```

```
tab(Titanic, ~ Sex + Survived, pct = 1)
```

```
          Survived
  Sex                No       Yes     Total
    Male       78.79838  21.20162 100.00000
```

```
  Female   26.80851  73.19149 100.00000
  All      67.69650  32.30350 100.00000
```

```r
tab(Titanic, ~ Sex + Survived, pct = 1)  %>%
  round(1)
```

```
         Survived
Sex          No   Yes Total
  Male     78.8  21.2 100.0
  Female   26.8  73.2 100.0
  All      67.7  32.3 100.0
```

```r
tab(Titanic, ~ Sex + Survived + Age, pct = c(1,3)) %>%
  round(1)
```

```
, , Age = Child

         Survived
Sex          No   Yes Total
  Male     54.7  45.3 100.0
  Female   37.8  62.2 100.0
  All      47.7  52.3 100.0

, , Age = Adult

         Survived
Sex          No   Yes Total
  Male     79.7  20.3 100.0
  Female   25.6  74.4 100.0
  All      68.7  31.3 100.0
```

```
, , Age = All

          Survived
Sex            No   Yes Total
  Male      78.8  21.2 100.0
  Female    26.8  73.2 100.0
  All       67.7  32.3 100.0
```

```r
tab(Titanic, ~ Sex + Survived + Age, pct = c(1,3)) %>%
  round(1) %>%
  ftable
```

```
                Age Child Adult   All
Sex    Survived                      
Male   No            54.7  79.7  78.8
       Yes           45.3  20.3  21.2
       Total        100.0 100.0 100.0
Female No            37.8  25.6  26.8
       Yes           62.2  74.4  73.2
       Total        100.0 100.0 100.0
All    No            47.7  68.7  67.7
       Yes           52.3  31.3  32.3
       Total        100.0 100.0 100.0
```

```r
tab(Titanic, ~ Sex + Age + Survived, pct = c(1,2)) %>%
  round(1) %>%
  ftable
```

```
             Survived    No   Yes Total
```

```
Sex    Age
Male   Child          54.7  45.3 100.0
       Adult          79.7  20.3 100.0
       All            78.8  21.2 100.0
Female Child          37.8  62.2 100.0
       Adult          25.6  74.4 100.0
       All            26.8  73.2 100.0
All    Child          47.7  52.3 100.0
       Adult          68.7  31.3 100.0
       All            67.7  32.3 100.0
```

9.11 Frequency data frame

From table to frequency data frame:

```r
Titanic.df <- as.data.frame(Titanic)
brief(Titanic.df)
```

```
32 x 5 data.frame (27 rows omitted)
   Class    Sex   Age Survived Freq
     [f]    [f]   [f]      [f]  [n]
1   1st  Male   Child       No     0
2   2nd  Male   Child       No     0
3   3rd  Male   Child       No    35
. . .
31  3rd  Female Adult       Yes   76
32  Crew Female Adult       Yes   20
```

9.12 Individual data frame

One row per subject (i.e. passenger)

```
indices <- rep(1:nrow(Titanic.df), Titanic.df$Freq)
Titanic.ind <- Titanic.df[indices,]
Titanic.ind$Freq <- NULL
brief(Titanic.ind)
```

```
2201 x 4 data.frame (2196 rows omitted)
       Class    Sex   Age Survived
         [f]    [f]   [f]      [f]
3      3rd  Male   Child       No
3.1    3rd  Male   Child       No
3.2    3rd  Male   Child       No
. . .
32.18  Crew Female Adult       Yes
32.19  Crew Female Adult       Yes
```

```
dd <- droplevels(subset(Titanic.ind, Class != 'Crew'))
(fit <- glm(Survived ~ Class * Sex * Age, Titanic.ind,
           subset = Class != 'Crew', family = binomial))
```

```
Call:  glm(formula = Survived ~ Class * Sex * Age, family = binomial,
    data = Titanic.ind, subset = Class != "Crew")

Coefficients:
                (Intercept)                      Class2nd
                  1.657e+01                    -8.924e-09
                   Class3rd                     SexFemale
```

```
                 -1.756e+01                  -5.115e-08
                   AgeAdult          Class2nd:SexFemale
                 -1.729e+01                   5.093e-08
         Class3rd:SexFemale           Class2nd:AgeAdult
                  7.962e-01                  -1.670e+00
          Class3rd:AgeAdult           SexFemale:AgeAdult
                  1.664e+01                   4.283e+00
Class2nd:SexFemale:AgeAdult  Class3rd:SexFemale:AgeAdult
                 -6.801e-02                  -3.596e+00

Degrees of Freedom: 1315 Total (i.e. Null);  1304 Residual
Null Deviance:       1747
Residual Deviance: 1165   AIC: 1189
```

```r
(fit <- glm(Survived ~ Class * Sex * Age,
           dd, family = binomial))
```

```

Call:  glm(formula = Survived ~ Class * Sex * Age, family = binomial,
    data = dd)

Coefficients:
                (Intercept)                     Class2nd
                  1.657e+01                   -8.924e-09
                   Class3rd                    SexFemale
                 -1.756e+01                   -5.115e-08
                   AgeAdult           Class2nd:SexFemale
                 -1.729e+01                    5.093e-08
         Class3rd:SexFemale            Class2nd:AgeAdult
```

```
               7.962e-01                     -1.670e+00
       Class3rd:AgeAdult            SexFemale:AgeAdult
               1.664e+01                      4.283e+00
Class2nd:SexFemale:AgeAdult  Class3rd:SexFemale:AgeAdult
              -6.801e-02                     -3.596e+00

Degrees of Freedom: 1315 Total (i.e. Null);  1304 Residual
Null Deviance:      1747
Residual Deviance: 1165   AIC: 1189
```

```
fit2 <- glm(Survived ~ (Class + Sex + Age)^2,
           dd, family = binomial)
summary(fit2)
```

```

Call:
glm(formula = Survived ~ (Class + Sex + Age)^2, family = binomial,
    data = dd)

Coefficients:
                    Estimate Std. Error z value Pr(>|z|)
(Intercept)         16.26450  920.38637   0.018    0.986
Class2nd            -0.82145 1005.81946  -0.001    0.999
Class3rd           -17.25489  920.38643  -0.019    0.985
SexFemale            3.59619    0.74781   4.809 1.52e-06 ***
AgeAdult           -16.99213  920.38639  -0.018    0.985
Class2nd:SexFemale  -0.06801    0.67120  -0.101    0.919
Class3rd:SexFemale  -2.79995    0.56875  -4.923 8.52e-07 ***
Class2nd:AgeAdult   -0.84881 1005.81951  -0.001    0.999
```

```
Class3rd:AgeAdult     16.34159  920.38645   0.018    0.986
SexFemale:AgeAdult     0.68679    0.52541   1.307    0.191
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 1746.8  on 1315  degrees of freedom
Residual deviance: 1165.4  on 1306  degrees of freedom
AIC: 1185.4

Number of Fisher Scoring iterations: 15
```

```
summary(fit)  # Why NAs? What next?
```

```

Call:
glm(formula = Survived ~ Class * Sex * Age, family = binomial,
    data = dd)

Coefficients:
                              Estimate Std. Error z value
(Intercept)                  1.657e+01  1.073e+03   0.015
Class2nd                    -8.924e-09  1.294e+03   0.000
Class3rd                    -1.756e+01  1.073e+03  -0.016
SexFemale                   -5.115e-08  2.629e+03   0.000
AgeAdult                    -1.729e+01  1.073e+03  -0.016
Class2nd:SexFemale           5.093e-08  2.806e+03   0.000
Class3rd:SexFemale           7.962e-01  2.629e+03   0.000
```

```
Class2nd:AgeAdult           -1.670e+00  1.294e+03  -0.001
Class3rd:AgeAdult            1.664e+01  1.073e+03   0.016
SexFemale:AgeAdult           4.283e+00  2.629e+03   0.002
Class2nd:SexFemale:AgeAdult -6.801e-02  2.806e+03   0.000
Class3rd:SexFemale:AgeAdult -3.596e+00  2.629e+03  -0.001
                            Pr(>|z|)
(Intercept)                    0.988
Class2nd                       1.000
Class3rd                       0.987
SexFemale                      1.000
AgeAdult                       0.987
Class2nd:SexFemale             1.000
Class3rd:SexFemale             1.000
Class2nd:AgeAdult              0.999
Class3rd:AgeAdult              0.988
SexFemale:AgeAdult             0.999
Class2nd:SexFemale:AgeAdult    1.000
Class3rd:SexFemale:AgeAdult    0.999

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 1746.8  on 1315  degrees of freedom
Residual deviance: 1165.4  on 1304  degrees of freedom
AIC: 1189.4

Number of Fisher Scoring iterations: 15
```

```r
Anova(fit)
```

```
Analysis of Deviance Table (Type II tests)

Response: Survived
              LR Chisq Df Pr(>Chisq)
Class           114.88  2  < 2.2e-16 ***
Sex             318.53  1  < 2.2e-16 ***
Age              20.34  1  6.486e-06 ***
Class:Sex        64.07  2  1.220e-14 ***
Class:Age        37.26  2  8.101e-09 ***
Sex:Age           1.69  1     0.1942
Class:Sex:Age     0.00  2     1.0000
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
anova(fit, fit2)
```

```
Analysis of Deviance Table

Model 1: Survived ~ Class * Sex * Age
Model 2: Survived ~ (Class + Sex + Age)^2
  Resid. Df Resid. Dev Df   Deviance Pr(>Chi)
1      1304     1165.4
2      1306     1165.4 -2 -1.506e-06        1
```

9.13 Frequency data frame with response variable on rows

```r
brief(Titanic.df)
```

```
32 x 5 data.frame (27 rows omitted)
```

```
    Class     Sex    Age Survived Freq
      [f]     [f]    [f]      [f]  [n]
  1    1st   Male    Child       No      0
  2    2nd   Male    Child       No      0
  3    3rd   Male    Child       No     35
  . . .
  31   3rd   Female Adult       Yes    76
  32   Crew Female Adult       Yes    20
```

```
Titanic.wide <-
  towide(Titanic.df,
       idvar = c('Class','Sex','Age'),
       timevar = 'Survived')
fitbin <- glm(
  cbind(Freq_No,Freq_Yes) ~  Class * Sex * Age,
  Titanic.wide, subset = Class != "Crew",
  family = binomial)
Anova(fitbin)
```

```
  Analysis of Deviance Table (Type II tests)

  Response: cbind(Freq_No, Freq_Yes)
                LR Chisq Df Pr(>Chisq)
  Class           114.88  2  < 2.2e-16 ***
  Sex             318.53  1  < 2.2e-16 ***
  Age              20.34  1  6.486e-06 ***
  Class:Sex        64.07  2  1.220e-14 ***
  Class:Age        37.26  2  8.101e-09 ***
  Sex:Age           1.69  1     0.1942
```

```
Class:Sex:Age      0.00  2     1.0000
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
summary(fitbin)
```

```

Call:
glm(formula = cbind(Freq_No, Freq_Yes) ~ Class * Sex * Age, family = binomial,
    data = Titanic.wide, subset = Class != "Crew")

Coefficients:
                            Estimate Std. Error z value
(Intercept)               -2.554e+01  9.518e+04       0
Class2nd                  -6.665e-01  1.307e+05       0
Class3rd                   2.653e+01  9.518e+04       0
SexFemale                  9.704e-01  1.619e+05       0
AgeAdult                   2.626e+01  9.518e+04       0
Class2nd:SexFemale        -1.121e+00  2.053e+05       0
Class3rd:SexFemale        -1.767e+00  1.619e+05       0
Class2nd:AgeAdult          2.337e+00  1.307e+05       0
Class3rd:AgeAdult         -2.561e+01  9.518e+04       0
SexFemale:AgeAdult        -5.253e+00  1.619e+05       0
Class2nd:SexFemale:AgeAdult  1.189e+00  2.053e+05       0
Class3rd:SexFemale:AgeAdult  4.567e+00  1.619e+05       0
                            Pr(>|z|)
(Intercept)                        1
Class2nd                           1
Class3rd                           1
```

```
SexFemale                           1
AgeAdult                            1
Class2nd:SexFemale                  1
Class3rd:SexFemale                  1
Class2nd:AgeAdult                   1
Class3rd:AgeAdult                   1
SexFemale:AgeAdult                  1
Class2nd:SexFemale:AgeAdult         1
Class3rd:SexFemale:AgeAdult         1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 5.8140e+02  on 11  degrees of freedom
Residual deviance: 3.0916e-10  on  0  degrees of freedom
AIC: 60.924

Number of Fisher Scoring iterations: 23
```

Compare with:

```r
Anova(fit)
```

```
Analysis of Deviance Table (Type II tests)

Response: Survived
              LR Chisq Df Pr(>Chisq)
Class           114.88  2  < 2.2e-16 ***
Sex             318.53  1  < 2.2e-16 ***
Age              20.34  1  6.486e-06 ***
Class:Sex        64.07  2  1.220e-14 ***
```

```
Class:Age         37.26  2  8.101e-09 ***
Sex:Age            1.69  1     0.1942
Class:Sex:Age      0.00  2     1.0000
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
summary(fit)
```

```

Call:
glm(formula = Survived ~ Class * Sex * Age, family = binomial,
    data = dd)

Coefficients:
                            Estimate Std. Error z value
(Intercept)                1.657e+01  1.073e+03   0.015
Class2nd                  -8.924e-09  1.294e+03   0.000
Class3rd                  -1.756e+01  1.073e+03  -0.016
SexFemale                 -5.115e-08  2.629e+03   0.000
AgeAdult                  -1.729e+01  1.073e+03  -0.016
Class2nd:SexFemale         5.093e-08  2.806e+03   0.000
Class3rd:SexFemale         7.962e-01  2.629e+03   0.000
Class2nd:AgeAdult         -1.670e+00  1.294e+03  -0.001
Class3rd:AgeAdult          1.664e+01  1.073e+03   0.016
SexFemale:AgeAdult         4.283e+00  2.629e+03   0.002
Class2nd:SexFemale:AgeAdult -6.801e-02  2.806e+03   0.000
Class3rd:SexFemale:AgeAdult -3.596e+00  2.629e+03  -0.001
                          Pr(>|z|)
(Intercept)                  0.988
```

```
Class2nd                        1.000
Class3rd                        0.987
SexFemale                       1.000
AgeAdult                        0.987
Class2nd:SexFemale              1.000
Class3rd:SexFemale              1.000
Class2nd:AgeAdult               0.999
Class3rd:AgeAdult               0.988
SexFemale:AgeAdult              0.999
Class2nd:SexFemale:AgeAdult     1.000
Class3rd:SexFemale:AgeAdult     0.999

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 1746.8  on 1315  degrees of freedom
Residual deviance: 1165.4  on 1304  degrees of freedom
AIC: 1189.4

Number of Fisher Scoring iterations: 15
```

10 Using R Script with Markdown

Here's a posting that describes quite well the difference between an R Markdown script (with extension .Rmd) and a .R script with Markdown. The main advantages of the latter are expressed well:

1) you don't need to transform your original .R script manually into a .Rmd script and
2) the same script can be run interactively in R and be used to generate a clean report.

One problem is that Ctrl-Shift-K produces diagnostics that refer to line numbers in the .Rmd file, whose numbering can be very different from that of the .R file. When this happens you can ‘knit’ the .R file in a way that keeps the intermediate .Rmd file by using the command:

This will leave the intermediate files in your directory so you can interpret error messages.

11 Attributes

The attributes of an object work like Post-it notes on the object. When functions use the object, they can consult the attributes to decide how to use it.

For example, a matrix is stored as a long vector recording the contents of the matrix column by column. The object itself has no information about the dimension of the matrix. The contents of a 3 by 4 matrix could just as easily be a 2 by 6 matrix or a 1 by 12 matrix or, indeed, just a vector of length 12. Functions that use the object as a matrix know what to do with the 12 numbers because of the ‘dim’ attribute.

```
m <- matrix(1:12, 3, 4)
colnames(m) <- letters[1:4]
rownames(m) <- LETTERS[1:3]
attributes(m)
```

```
$dim
[1] 3 4

$dimnames
$dimnames[[1]]
[1] "A" "B" "C"

$dimnames[[2]]
[1] "a" "b" "c" "d"
```

Many attributes are set by the function creating the object. For example the dim attribute is set by the 'matrix' function:

```
m <- matrix(1:12, 3, 4)
attributes(m)
```

```
$dim
[1] 3 4
```

Many attributes can also be set by **replacement** functions and they can be read by the cognate regular function of the corresponding mame. For example, you can read and change the shape of a matrix with the 'dim' functions.

```
dim(m)
```

```
[1] 3 4
```

```
m
```

```
     [,1] [,2] [,3] [,4]
[1,]    1    4    7   10
[2,]    2    5    8   11
[3,]    3    6    9   12
```

```
dim(m) <- c(2,6)
m
```

```
     [,1] [,2] [,3] [,4] [,5] [,6]
[1,]    1    3    5    7    9   11
[2,]    2    4    6    8   10   12
```

11.0.1 Exercises

1. What happens if you try to set a dimension that doesn't doesn't correspond to the size of the matrix?
2. What happens to column and row names if you change the dimension of a matrix?

Other familiar functions that read attributes of a matrix are 'nrow', 'ncol', 'row', 'dimnames'. A very important attribute used for OOP is the 'class' attribute.

See also the 'attr' and its replacement to create and read new attributes.

Here are the attributes of the 'Guyer1' data frame.

```r
attributes(Guyer1)
```

```
$names
[1] "cooperation" "condition"   "sex"

$class
[1] "data.frame"

$row.names
 [1]  1  2  3  4  5  6  7  8  9 10 11 12 13 14 15 16 17 18 19 20
```

```r
dim(Guyer1)
```

```
[1] 20  3
```

12 Traps and Pitfalls

Contribute traps and pitfalls on Piazza

Some of these observations may change as R develops. It would be a good idea to add the version of R in which each behaviour was observed.

12.1 Factors

Many of the tricky silent traps are encountered in the use of factors.

12.1.1 Transformation of factors to characters or codes

In its raw form, a factor is a vector of integers that provides indices into a vector of ‘levels’ for the factor. The levels are attached as an attribute to the factor.

A factor vector can be coerced to its character form or to its numerical indices:

Most functions operating on factors use either the factor’s character form or its numerical form. In most cases, the form used is the only sensible one and there are no surprises. Sometimes the result is not what the user expected and mysterious bugs or outright errors can be produced.

12.1.2 Factors transformed to character

The following functions use the character form of the factor:

12.1.3 Factors transformed to numeric

The following functions use the numeric form. In the first case (indexing) that might seem to be the only sensible interpretation. However, since it is possible to index by name in R, a user could intend to use the character values of a factor to index names but end up with an entirely different result.

In the second case, (‘rbind’), the use of numeric values seems contrary to expectation considering the behaviour of ‘matrix’ above.

Then using ‘rbind’ with a factor and a character, the coercion of the factor to character occurs **after** extracting the numeric codes.

12.1.4 Factors operations that return a factor

Some operators on factors return a factor:

12.1.5 Other special factor pitfalls

Special pitfalls can occur when attempting to transform a factor whose levels are character representations of numbers into a numeric object:

Note in passing that the levels have been ordered numerically instead of lexicographically, as would have been the case if the argument to 'factor' had been c('1','10','2'). Thus the 'factor' function is 'numeric-smart'. facn' almost seems numeric but it is not:

either 'as.character' nor 'as.numeric' returns the original numeric vector:

To get the original numeric vector, one must compose both:

or, one can define a function:

12.1.6 'drop' doesn't work with subset

doesn't drop levels in 'id' (as it should?). Instead, use:

12.2 diag can be tricky

If you use `diag` in a function to get the main diagonal of a matrix (not necessarily square) you might get a bug if you happen to have a 1×1 matrix represented by a scalar (vector of length 1) because:

```
m <- matrix(1:12,3)
m
```

```
     [,1] [,2] [,3] [,4]
[1,]    1    4    7   10
```

```
[2,]    2    5    8   11
[3,]    3    6    9   12
```

```r
diag(m)
```

```
[1] 1 5 9
```

```r
m <- 3.2
diag(m) # Why?
```

```
     [,1] [,2] [,3]
[1,]    1    0    0
[2,]    0    1    0
[3,]    0    0    1
```

If you want to use `diag` in a way that won't give you an identity matrix when the argument happens to be a scalar, the safe way is:

```r
diag(as.matrix(m)) # gives you what you want in any case
```

```
[1] 3.2
```

Here's another example where 'diag' can fail.

Many algorithms using eigenvalue or singular value decompositions (with 'eigen' or 'svd') form a diagonal matrix with the vector of eigen/singular values using the 'diag' function, e.g.

This will fail if the rank of X is equal to 1 since, in that case, `diag(d.inv)` will be an identity matrix of dimension 'floor(d.inv)', while what is needed is a 1 x 1 matrix with a single element 'd.inv'. One solution is to use:

Another is to use the fact that *matrix* premultiplication by a diagonal matrix is the same as *scalar* premultiplication by the vector of diagonal elements. This is so because multiplying the vector by the matrix causes the vector to be recycled to the length of the matrix and pairwise scalar multiplication takes place column by column for the matrix.

Note that extra parentheses are needed because these multiplications are not associative.

12.3 Reading and Writing Data Files

12.3.1 NA as a valid value (the Namibia problem)

Many commands that read data files, e.g. read.csv and read.xls in the package gdata, will, by default, treat the string 'NA' as a missing value whether it occurs in a character or a numeric variable. In numeric variables, blanks are also turned into missing values. If 'NA' occurs as a valid value, for example the two-character ISO country code for Namibia, then you may use the argument 'na.strings = NULL' to ensure that 'NA' is not turned into a missing value. However, NA's used to indicate missing numeric values will now be interpreted as valid character values and numeric variables with NA's will be read as factors.

12.4 Prediction

12.4.1 Prediction with nlme

To get

to produce pp of length equal to 'nrow(dd)', you can use the following combination of 'na.action's:

12.4.2 Exercises

1. What is the difference between the result of: `fac <- factor(letters) levels(fac) <- rev(letters)` and `fac <- factor(letters, levels = rev(letters))`

13 Useful Techniques and Tricks

Contribute "how to's" and useful tricks on Piazza.

13.1 Changing all variables to characters in a data frame

When data frames are being manipulated only as data sets, not for immediate statistical analyses, it is often convenient to have all variables as characters to avoid problems due to the inconsistent behaviour of factors. A very easy way to do this, if dd is a data frame:

```
dd[] <- lapply(dd, as.character)
```

Any side effects?

- Some variable attributes may be lost with as.character.

References

Fox, John, and Sanford Weisberg. 2019. *An R and S-Plus Companion to Applied Regression*. 3rd ed. Sage Publications.