Working with Data

MATH 4939 – Winter 2020

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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:

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

```
Loading required package: carData
```

```
class(Davis)
```

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

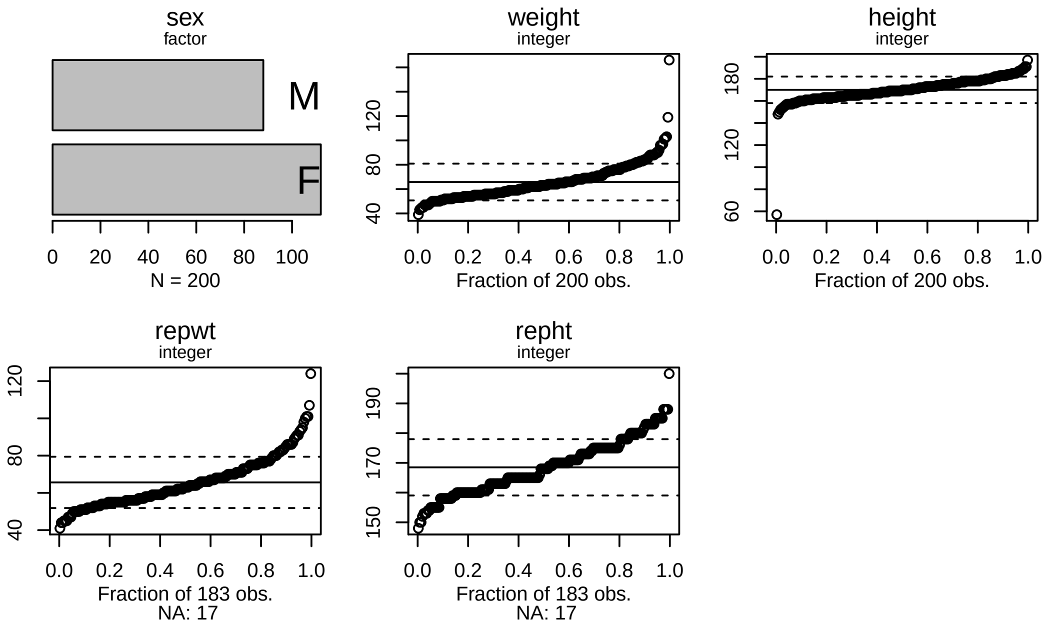
```r
brief(Davis)
```

```
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
```

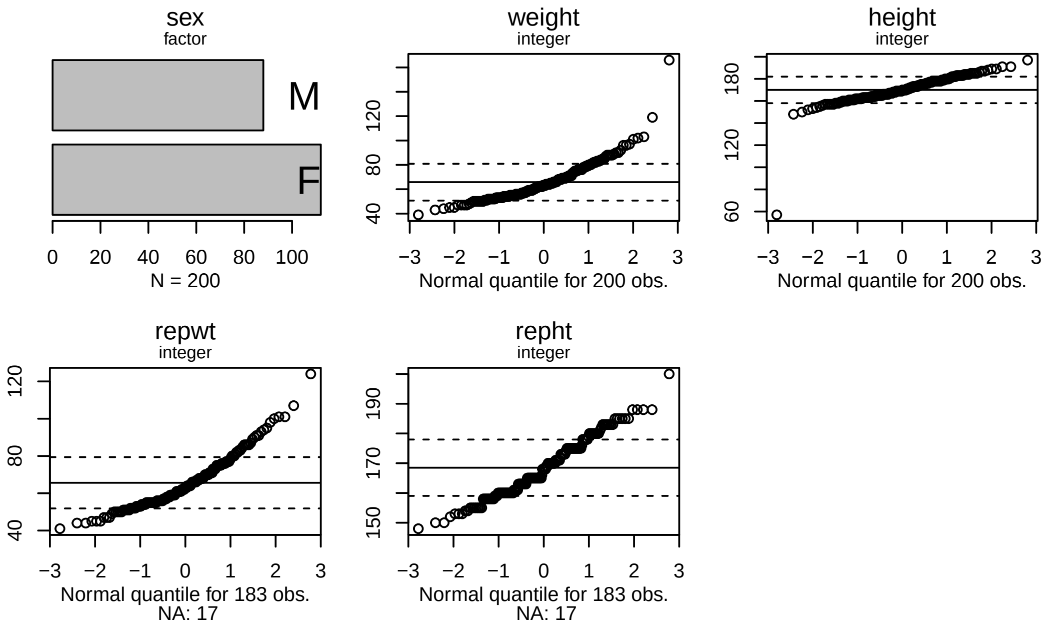
```r
library(spida2)
```

```
spida2: development branch 0.2.0.9000.
```

```r
xqplot(Davis) # uniform quantiles
```




```
xqplot(Davis, ptype = 'n')   # normal quantiles
```




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

```r
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]       [f]    [f]
 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),
```

```r
  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  : Factor w/ 2 levels "anonymous","public": 2 2 2 2 2
 $ sex        : Factor w/ 2 levels "female","male": 2 2 2 2 2 1 1
```

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="https://socialsciences.mcmaster.ca/jfox/Books/Companion/data
  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
              [f]    [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 —-

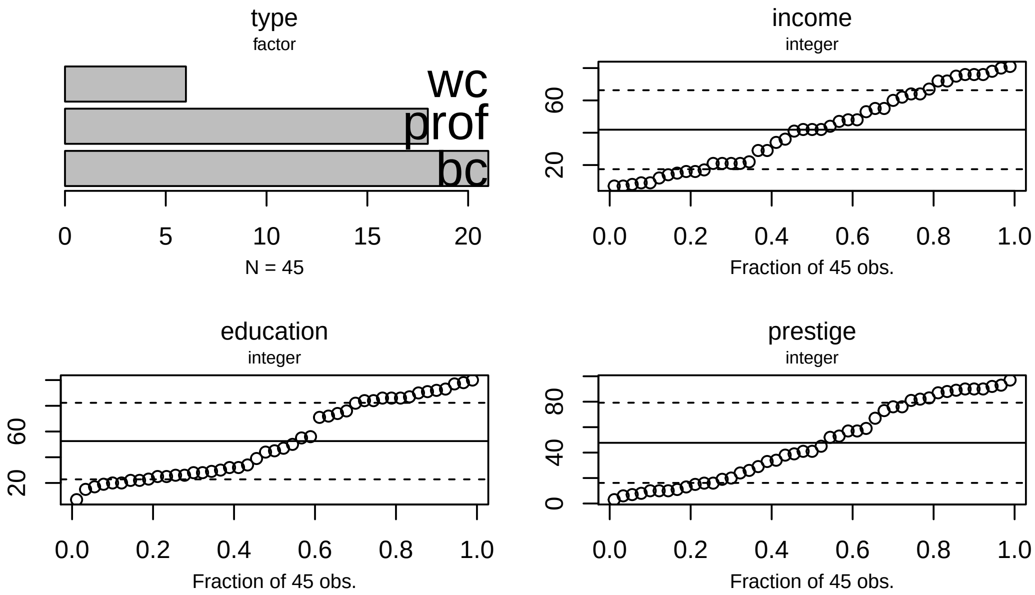
We're going to download this text file from John Fox's website to illustrate what it looks like when reading a local file:

```
download.file(
  "https://socialsciences.mcmaster.ca/jfox/Books/Companion/data/Dunc
  "Duncan.txt")
Duncan <- read.table("Duncan.txt", header = TRUE)
brief(Duncan)
```

```
  45 x 4 data.frame (40 rows omitted)
             type income education prestige
              [f]    [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)
```




```
# 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 packages ----------------------------------

<U+2713> ggplot2 3.2.1     <U+2713> purrr   0.3.3
<U+2713> tibble  2.1.3     <U+2713> dplyr   0.8.3
<U+2713> tidyr   1.0.0     <U+2713> stringr 1.4.0
<U+2713> readr   1.3.1     <U+2713> forcats 0.4.0
```

```
-- 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()
```

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:

```r
search()
```

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

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

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

```
# A tibble: 45 x 4
  type  income education prestige
  <fct>  <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
# ... with 40 more rows
```

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

```
45 x 4 tbl_df (40 rows and 1 columns omitted)

Warning: Setting row names on a tibble is deprecated.

   type . . . education prestige
    [f]             [i]      [i]
1  prof              86       82
2  prof              76       83
3  prof              92       90
. . .
44 bc                47       41
45 bc                32       10
```

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

```
45 x 4 data.frame (40 rows omitted)
   type income education prestige
    [f]     [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/MATH4939/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.

```
class(dt)
```

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

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

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

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

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

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

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

```
       Name       Age  Purchase
   "factor" "numeric" "numeric"
```

```
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 
 "factor" "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:

```
dt2 <- read_excel('_file.xlsx', na = 'NA', col_type = rep('text', nc
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:

```
z <- as.numeric(as.character(dd$x))  # note that 'as.character' is
z # have a look
dd$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
z <- as.character(dd$x)
# Have a look:
z
z <- gsub('[ -]','', z)  # remove all blanks and hyphens.
    # Note that the hyphen must be first or last in the brackets,
    # otherwise it denotes a range, i.e. '[A-Z]' matches any
    # capital letter.
z <- sub('^#','', z)  # remove leading # signs,'^' is an 'anchor' m
z # have another look
table(nchar(z))
# If valid data must have a length of 9:
z9 <- nchar(z) == 9
z <- ifelse(z9, as.numeric(z), NA)
dd$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,
  readxl::read_excel(file, sheet = sheet,
                                    col_types = rep("text", num.col
}
```

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
```

```r
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)
     # 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     : Factor w/ 3 levels "bc","prof","wc": 2 2 2 2 2 2 2 2
 $ 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: `%>%`

```
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
  5 Levels: Andrew Smith Edwards John Smith ... Smith, Mary
```

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
Levels: 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

```r
1:5
```

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

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

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

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

```
  [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
```

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
```

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

```
     city      day1      day2      day3 
 "factor" "integer" "integer" "integer" 
```

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

```
$city
[1] "factor"

$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

```r
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 # why 'is.factor'?
  else 32 + (9/5)*x
}
```

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

```
$city
[1] Montreal Toronto  New York
Levels: Montreal New York Toronto

$day1
[1] 68.0 73.4 82.4

$day2
[1] 77.0 78.8 95.0

$day3
[1] 86.0 66.2 89.6
```

```r
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 —-

```r
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

```r
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:

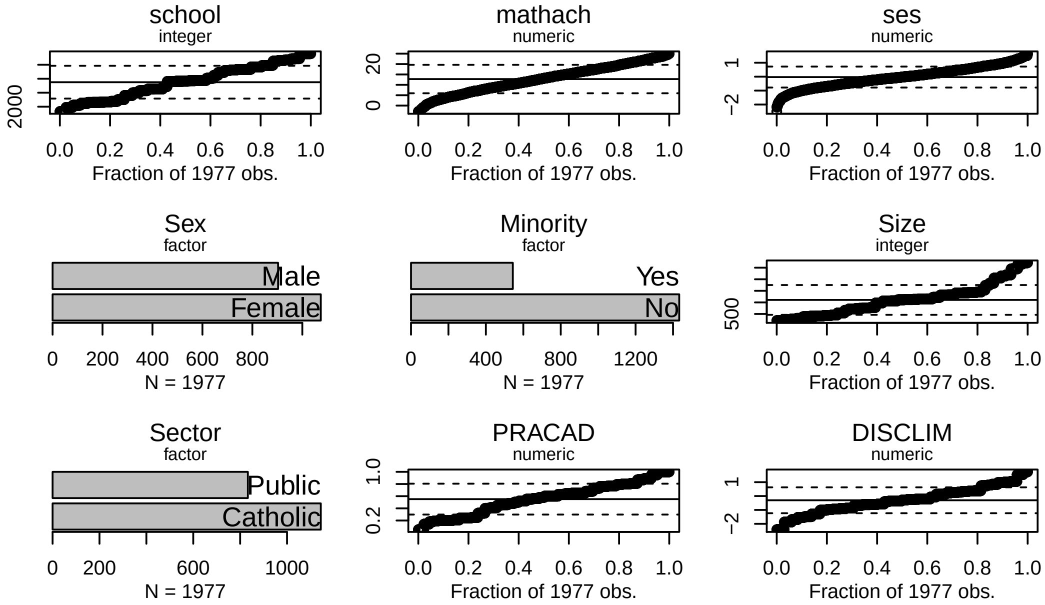
```r
data(hs)
```

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

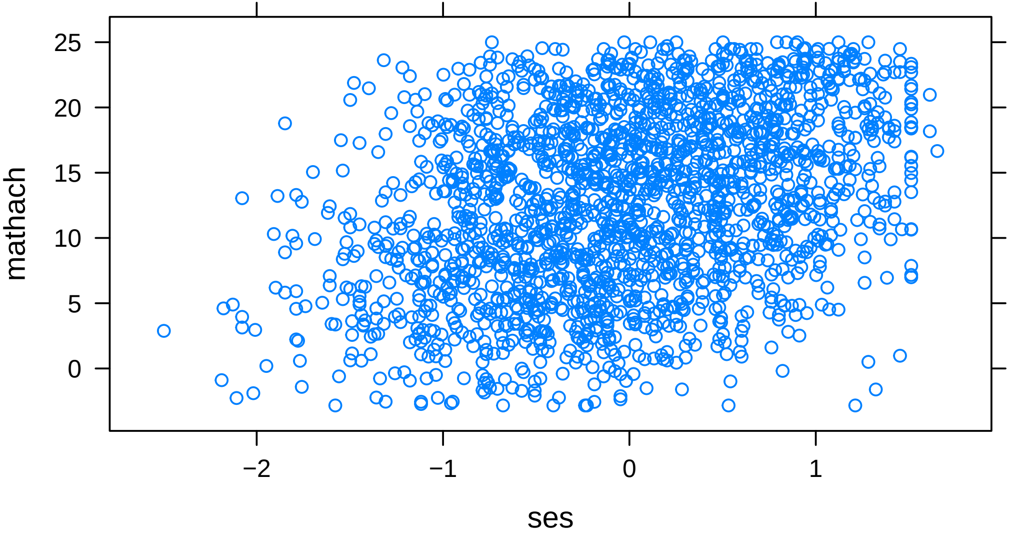
```r
data(hs, package = 'spida2')
dim(hs)
```

```
[1] 1977    9
```

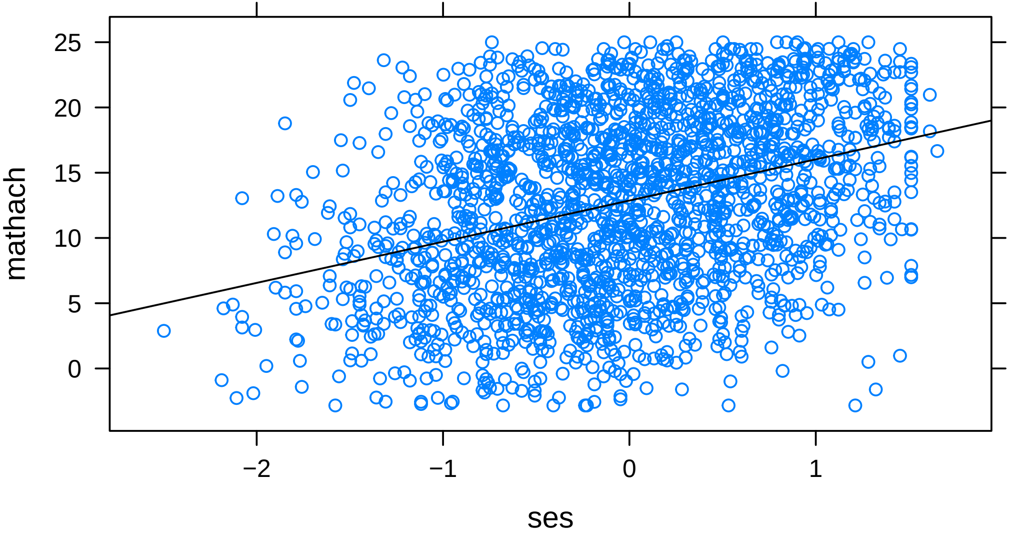
```r
xqplot(hs)
```



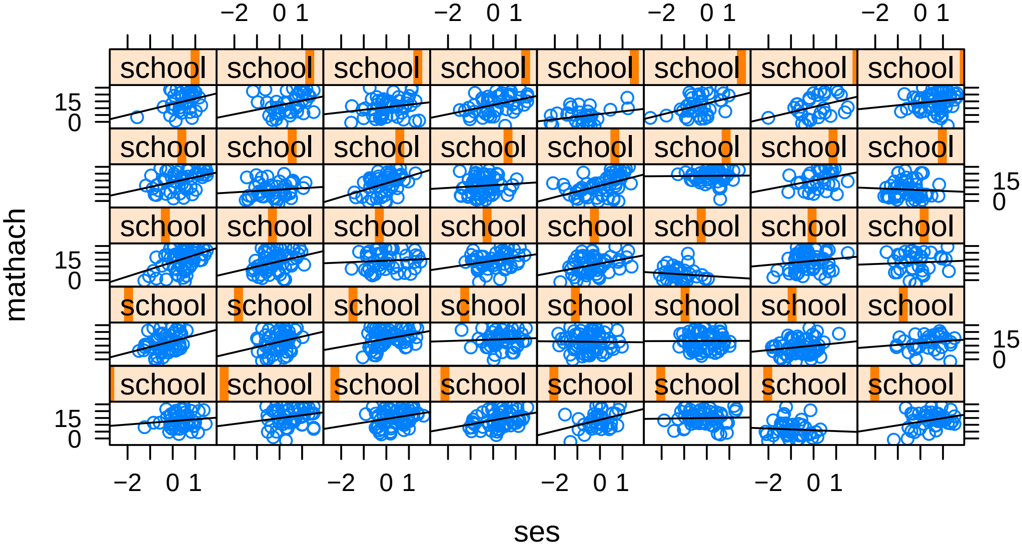

```
xyplot(mathach ~ ses, hs)
```



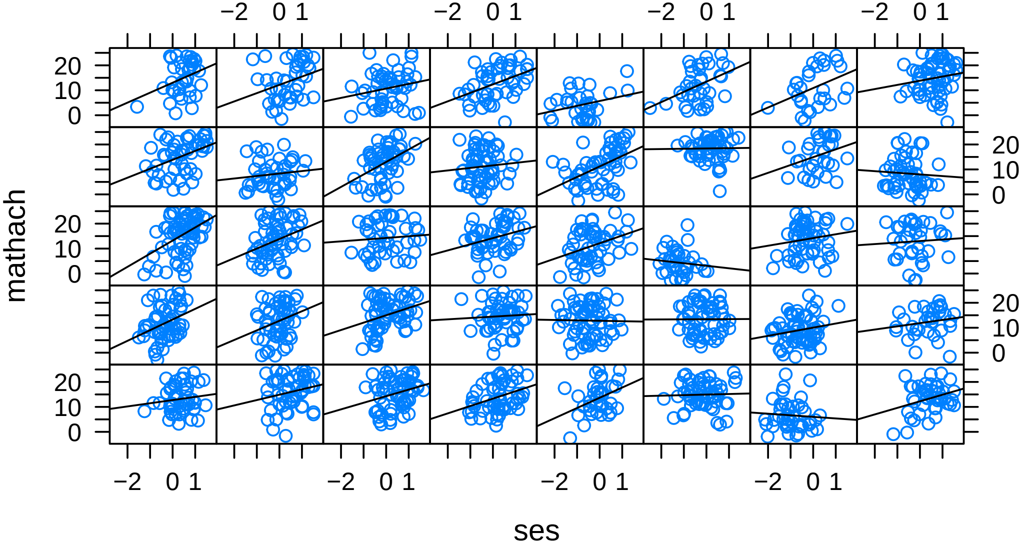

```r
xyplot(mathach ~ ses, hs) + layer(panel.lmline(...))
```




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

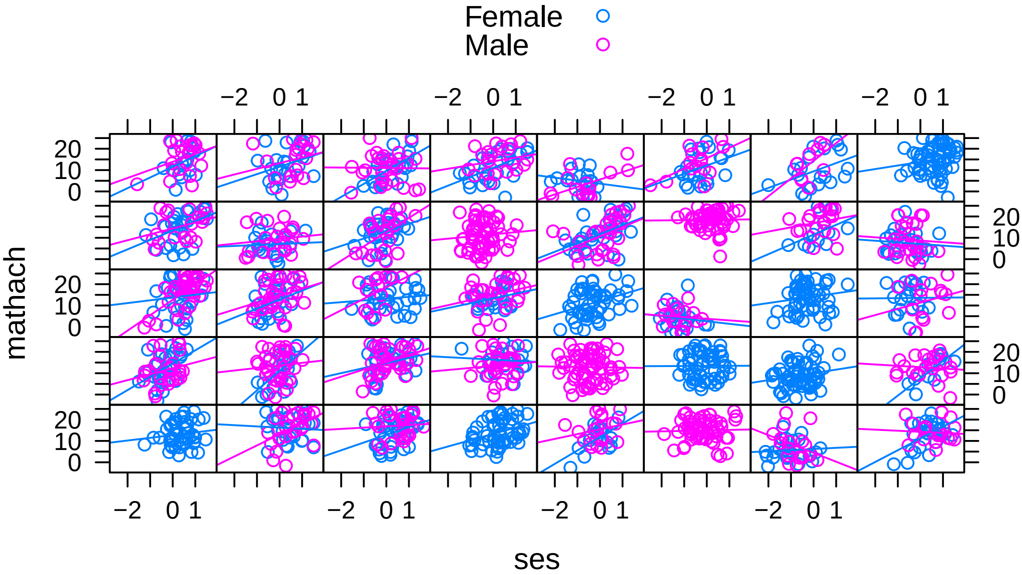



```
xyplot(mathach ~ ses | school, hs, strip = FALSE) +
  layer(panel.lmline(...))
```



mathach
ses
−2
0
1
0
10
20

```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)
```

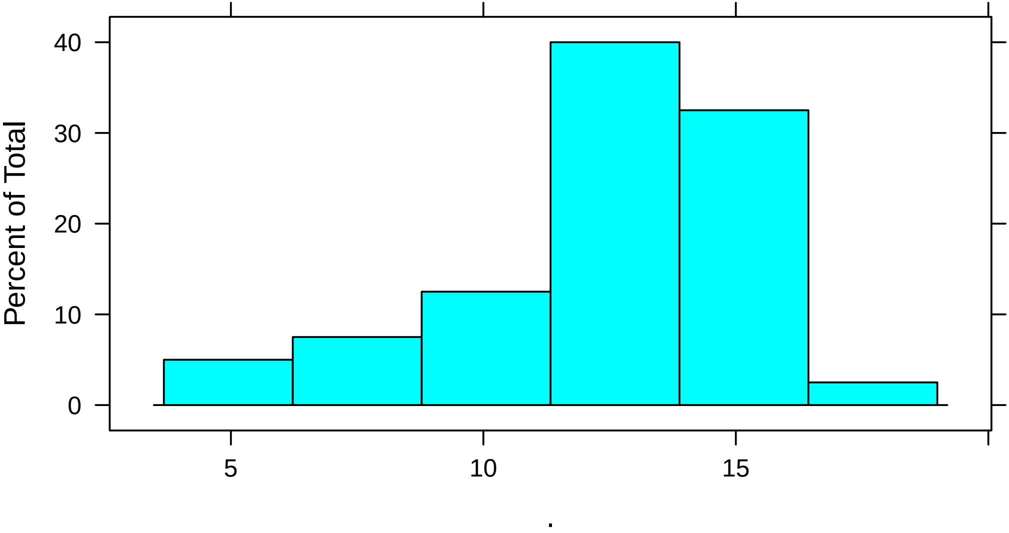
```
     1317      1906      2208      2458      2626      2629 
13.177687 15.983170 15.404667 13.985684 13.396605 14.907772 
     2639      2658      2771      3013      3610      3992 
 6.615476 13.396156 11.844109 12.610830 15.354953 14.645208 
     4292      4511      4530      4868      5619      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
```

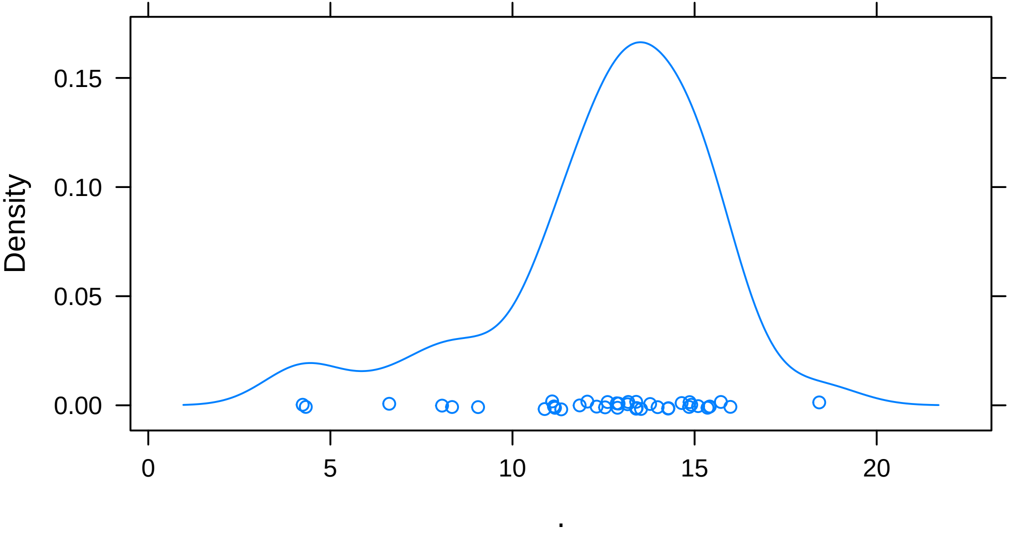
tapply(Y, id, function, extra arguments):

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

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




```
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`

```r
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
61     1906  22.107  0.592   Male       No  400 Catholic   0.87
165    2458   7.814 -1.058 Female      Yes  545 Catholic   0.89
351    2639   8.978 -1.458   Male      Yes 2713   Public   0.14
421    2771  22.896 -0.048 Female       No  415   Public   0.24
786    4530   6.276  0.042 Female       No  435 Catholic   0.60
1213   6484  21.653 -0.378   Male       No  726   Public   0.19
1273   6897  19.830  1.012 Female       No 1415   Public   0.55
1289   6897  23.584  1.372 Female      Yes 1415   Public   0.55
1492   7345   8.157 -0.798 Female      Yes  978   Public   0.64
1634   7890   3.414 -1.598   Male       No  311   Public   0.21
     DISCLIM mathach_mean
61    -0.939    15.983170
165   -1.484    13.985684
```

```
351   -0.282     6.615476
421    1.048    11.844109
786   -0.245     9.055698
1213   0.218    12.912400
1273  -0.361    15.097633
1289  -0.361    15.097633
1492   0.336    11.338554
1634   0.845     8.341098
```

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)
  }
)
some(hs)
```

```
      school mathach    ses    Sex Minority Size   Sector PRACAD
19      1317  11.027  0.722 Female      Yes  455 Catholic   0.95
```

```
95      1906  -1.603  0.282   Male       Yes  400 Catholic   0.87
111     2208   7.847 -0.478 Female        No 1061 Catholic   0.68
145     2208  18.196 -0.468   Male        No 1061 Catholic   0.68
814     4868  19.078  0.902 Female        No  657 Catholic   1.00
905     5619  23.062  0.932   Male        No 1118 Catholic   0.77
1014    5720  19.196  0.432 Female        No  381 Catholic   0.65
1147    5762  -2.832 -1.578 Female       Yes 1826   Public   0.24
1813    8707  15.624 -0.238 Female        No 1133   Public   0.48
1901    9550   5.282 -0.538   Male        No 1532   Public   0.45
     DISCLIM mathach_mean    ses_sd mathach_sd mathach_rk
19    -1.694    13.177687 0.5561583   5.462586         20
95    -0.939    15.983170 0.6135833   6.515435          1
111   -0.864    15.404667 0.5981188   6.122802         10
145   -0.864    15.404667 0.5981188   6.122802         39
814   -0.219    12.310176 0.7100080   5.432838         33
905   -1.286    15.416242 0.5972748   7.280409         57
1014  -0.352    14.282302 0.6641693   5.694073         43
1147   0.364     4.324865 0.5154149   4.993969          1
1813   1.542    12.883938 0.8042577   6.435737         30
```

```
1901    0.791    11.089138 0.7847035   7.877998            8
```

within-school deviations

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

```
     school mathach    ses    Sex Minority Size   Sector PRACAD
150    2208  21.890  0.142   Male       No 1061 Catholic   0.68
550    3610  15.896  0.792   Male      Yes 1431 Catholic   0.80
587    3992   9.989  0.072 Female      Yes 1114 Catholic   0.73
918    5640   7.582 -0.518 Female       No 1152   Public   0.41
1015   5720  13.754 -0.838 Female       No  381 Catholic   0.65
1322   7172   5.788 -0.958 Female      Yes  280 Catholic   0.05
```

```
1478   7345  24.993  1.282   Male        No  978   Public   0.64
1674   7919  19.043  0.762 Female        No 1451   Public   0.50
1762   8627   3.442  0.002   Male       Yes 2452   Public   0.25
1782   8707   1.850 -1.028 Female        No 1133   Public   0.48
     DISCLIM mathach_mean    ses_sd mathach_sd mathach_rk
150   -0.864    15.404667 0.5981188   6.122802         50
550   -0.621    15.354953 0.6316415   5.894163         33
587   -1.534    14.645208 0.6054177   5.592953         12
918    0.256    13.160105 0.5830261   7.102322         14
1015  -0.352    14.282302 0.6641693   5.694073         27
1322   1.013     8.066818 0.6764417   5.610555         18
1478   0.336    11.338554 0.8257296   7.246025         56
1674  -0.402    14.849973 0.5367005   6.804286         25
1762   0.742    10.883717 0.7077276   6.489265          9
1782   1.542    12.883938 0.8042577   6.435737          2
        ses_dev mathach_dev
150  -0.2811667   6.4853333
550   0.6718750   0.5410469
587  -0.2933962  -4.6562075
```

```
918  -0.3414035  -5.5781053
1015 -0.8705660  -0.5283019
1322 -0.6681818  -2.2788182
1478  1.2487500  13.6544464
1674  0.3043243   4.1930270
1762 -0.1028302  -7.4417170
1782 -1.1831250 -11.0339375
```

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

```

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

Coefficients:
(Intercept)      ses_dev
  1.149e-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) 1.149e-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
190   2458  15.496 1.342 Female       No  545 Catholic   0.89
```

```
475    3013  16.722 -0.428 Female        No  760   Public  0.56
491    3013  13.009  0.232   Male        No  760   Public  0.56
582    3992   8.693 -0.988   Male        No 1114 Catholic  0.73
917    5640   1.427 -0.768 Female        No 1152   Public  0.41
995    5650   8.526 -0.288 Female       Yes  720 Catholic  0.60
1457   7345   8.788 -1.528 Female       Yes  978   Public  0.64
1542   7688  12.146 -0.068   Male        No 1410 Catholic  0.65
1567   7697   7.015  0.562 Female        No 1734   Public  0.20
1758   8627  18.999  1.012 Female        No 2452   Public  0.25
     DISCLIM mathach_mean    ses_sd mathach_sd mathach_rk
190   -1.484     13.98568 0.6584097   5.848459         36
475   -0.213     12.61083 0.4799328   6.985697         36
491   -0.213     12.61083 0.4799328   6.985697         26
582   -1.534     14.64521 0.6054177   5.592953          7
917    0.256     13.16011 0.5830261   7.102322          4
995   -0.070     14.27353 0.7777414   6.479535         13
1457   0.336     11.33855 0.8257296   7.246025         21
1542  -0.575     18.42231 0.5644347   4.498507          5
1567   0.279     15.72178 0.6133712   6.621170          6
```

```
1758   0.742      10.88372 0.7077276   6.489265            49
        ses_dev mathach_dev female_prop
190   1.1142105   1.5103158   1.0000000
475  -0.3837736   4.1111698   0.3584906
491   0.2762264   0.3981698   0.3584906
582  -1.3533962  -5.9522075   0.3962264
917  -0.5914035 -11.7331053   0.4210526
995  -0.3104444  -5.7475333   0.7111111
1457 -1.5612500  -2.5505536   0.5178571
1542 -0.2538889  -6.2763148   0.0000000
1567  0.3037500  -8.7067812   0.3437500
1758  0.9071698   8.1152830   0.4528302
```

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

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

```
      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
```

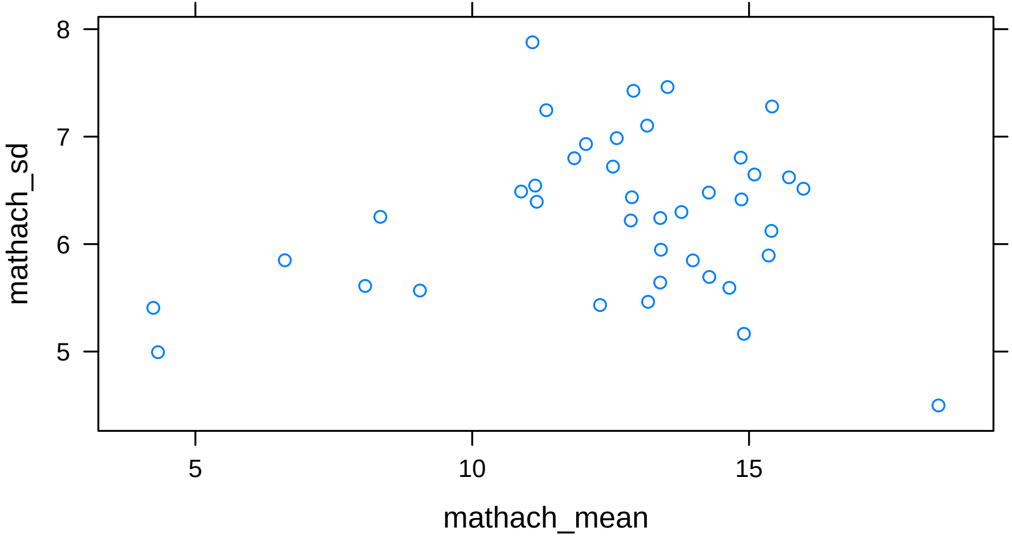
4868	4868	657	Catholic	1.00	-0.219	12.310176	0.7100080
5619	5619	1118	Catholic	0.77	-1.286	15.416242	0.5972748
5640	5640	1152	Public	0.41	0.256	13.160105	0.5830261
5650	5650	720	Catholic	0.60	-0.070	14.273533	0.7777414
5720	5720	381	Catholic	0.65	-0.352	14.282302	0.6641693
5761	5761	215	Catholic	0.63	-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
1317   5.462586   1.0000000
1906   6.515435   0.5094340
2208   6.122802   0.5833333
2458   5.848459   1.0000000
2626   6.242649   0.4736842
2629   5.165071   0.0000000
2639   5.849492   0.5714286
2658   5.642341   0.6000000
2771   6.798981   0.5090909
3013   6.985697   0.3584906
3610   5.894163   0.4531250
3992   5.592953   0.3962264
```

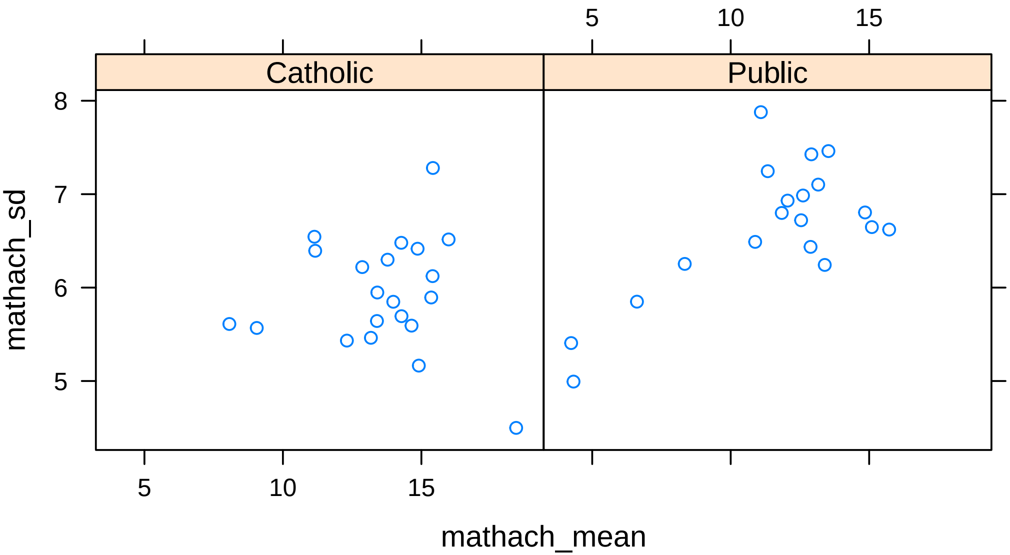
4292	6.219492	0.0000000
4511	5.947499	1.0000000
4530	5.567967	1.0000000
4868	5.432838	0.3235294
5619	7.280409	0.4545455
5640	7.102322	0.4210526
5650	6.479535	0.7111111
5720	5.694073	0.4528302
5761	6.544368	1.0000000
5762	4.993969	0.5675676
6074	6.298483	1.0000000
6484	7.426520	0.5714286
6897	6.647635	0.5918367
7172	5.610555	0.5000000
7232	6.721008	0.5769231
7342	6.393930	0.0000000
7345	7.246025	0.5178571
7688	4.498507	0.0000000
7697	6.621170	0.3437500

```
 7890  6.253697  0.4705882
 7919  6.804286  0.4324324
 8531  7.461228  0.5609756
 8627  6.489265  0.4528302
 8707  6.435737  0.5416667
 8854  5.406482  0.5312500
 8874  6.931169  0.5833333
 9550  7.877998  0.6551724
 9586  6.416000  1.0000000
```

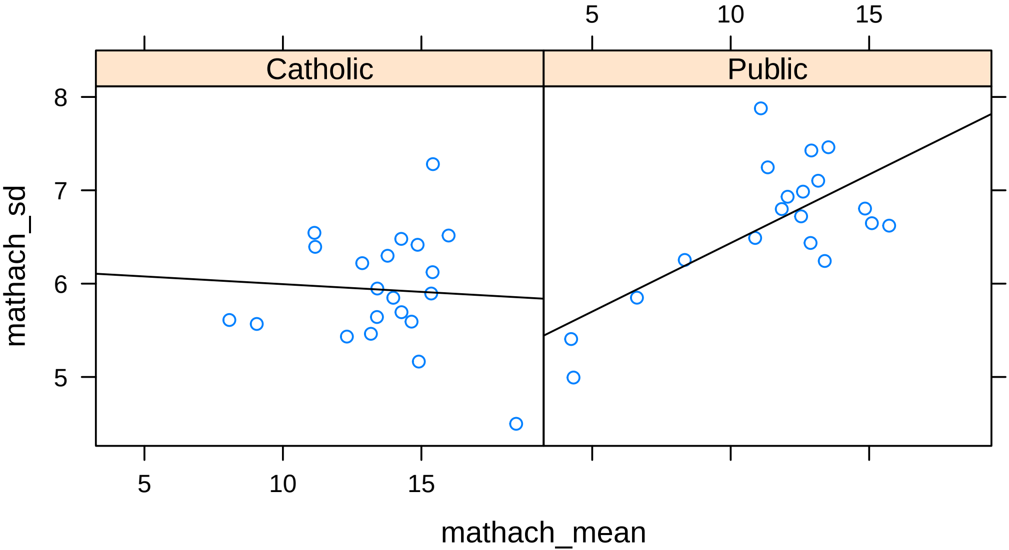
```
up(hs, ~ school) %>% xyplot(mathach_sd ~ mathach_mean, .)
```




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




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


Catholic
Public
mathach_sd
mathach_mean
5
10
15
8
7
6
5

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 Sex_Female  Sex_Male
1317   5.462586   1.0000000  1.0000000 0.0000000
1906   6.515435   0.5094340  0.5094340 0.4905660
2208   6.122802   0.5833333  0.5833333 0.4166667
2458   5.848459   1.0000000  1.0000000 0.0000000
2626   6.242649   0.4736842  0.4736842 0.5263158
2629   5.165071   0.0000000  0.0000000 1.0000000
2639   5.849492   0.5714286  0.5714286 0.4285714
2658   5.642341   0.6000000  0.6000000 0.4000000
2771   6.798981   0.5090909  0.5090909 0.4909091
3013   6.985697   0.3584906  0.3584906 0.6415094
3610   5.894163   0.4531250  0.4531250 0.5468750
```

3992	5.592953	0.3962264	0.3962264	0.6037736
4292	6.219492	0.0000000	0.0000000	1.0000000
4511	5.947499	1.0000000	1.0000000	0.0000000
4530	5.567967	1.0000000	1.0000000	0.0000000
4868	5.432838	0.3235294	0.3235294	0.6764706
5619	7.280409	0.4545455	0.4545455	0.5454545
5640	7.102322	0.4210526	0.4210526	0.5789474
5650	6.479535	0.7111111	0.7111111	0.2888889
5720	5.694073	0.4528302	0.4528302	0.5471698
5761	6.544368	1.0000000	1.0000000	0.0000000
5762	4.993969	0.5675676	0.5675676	0.4324324
6074	6.298483	1.0000000	1.0000000	0.0000000
6484	7.426520	0.5714286	0.5714286	0.4285714
6897	6.647635	0.5918367	0.5918367	0.4081633
7172	5.610555	0.5000000	0.5000000	0.5000000
7232	6.721008	0.5769231	0.5769231	0.4230769
7342	6.393930	0.0000000	0.0000000	1.0000000
7345	7.246025	0.5178571	0.5178571	0.4821429
7688	4.498507	0.0000000	0.0000000	1.0000000

```
7697    6.621170   0.3437500  0.3437500 0.6562500
7890    6.253697   0.4705882  0.4705882 0.5294118
7919    6.804286   0.4324324  0.4324324 0.5675676
8531    7.461228   0.5609756  0.5609756 0.4390244
8627    6.489265   0.4528302  0.4528302 0.5471698
8707    6.435737   0.5416667  0.5416667 0.4583333
8854    5.406482   0.5312500  0.5312500 0.4687500
8874    6.931169   0.5833333  0.5833333 0.4166667
9550    7.877998   0.6551724  0.6551724 0.3448276
9586    6.416000   1.0000000  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

```
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 joi
dim(dm)
```

```
## [1] 1977   17
```

```r
some(dm)
```

```
     school mathach    ses    Sex Minority Size   Sector PRACAD
144    2208  23.529  0.932 Female       No 1061 Catholic   0.68
170    2458  17.205  0.262 Female      Yes  545 Catholic   0.89
592    3992  14.913  0.192   Male      Yes 1114 Catholic   0.73
605    3992   8.531  0.912   Male      Yes 1114 Catholic   0.73
972    5650   4.682  0.482 Female      Yes  720 Catholic   0.60
1290   6897  11.309 -1.188 Female      Yes 1415   Public   0.55
1556   7688  19.567 -1.278   Male       No 1410 Catholic   0.65
1566   7697  13.179 -0.718   Male       No 1734   Public   0.20
1615   7890   9.680 -1.518 Female       No  311   Public   0.21
1872   8874   7.779 -0.568 Female       No 2650   Public   0.20
     DISCLIM mathach_mean    ses_sd mathach_sd mathach_rk
144   -0.864    15.404667 0.5981188   6.122802       57.0
170   -1.484    13.985684 0.6584097   5.848459       39.0
592   -1.534    14.645208 0.6054177   5.592953       25.0
605   -1.534    14.645208 0.6054177   5.592953        6.0
```

```
972   -0.070    14.273533 0.7777414   6.479535         5.0
1290  -0.361    15.097633 0.7445231   6.647635        16.0
1556  -0.575    18.422315 0.5644347   4.498507        29.0
1566   0.279    15.721781 0.6133712   6.621170        12.5
1615   0.845     8.341098 0.5932263   6.253697        34.0
1872   1.742    12.055028 0.7137251   6.931169        11.0
         ses_dev mathach_dev female_prop         state
144   0.50883333   8.1243333   0.5833333      New York
170   0.03421053   3.2193158   1.0000000      New York
592  -0.17339623   0.2677925   0.3962264        Oregon
605   0.54660377  -6.1142075   0.3962264        Oregon
972   0.45955556  -9.5915333   0.7111111        Oregon
1290 -1.53755102  -3.7886327   0.5918367 West Virginia
1556 -1.46388889   1.1446852   0.0000000  South Dakota
1566 -0.97625000  -2.5427812   0.3437500  South Dakota
1615 -0.99529412   1.3389020   0.4705882  South Dakota
1872 -0.22722222  -4.2760278   0.5833333       Vermont
```

5.2 Merge examples —-

```r
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
 John     John   44.4         12 3.70
 Mary     Mary   23.7          6 3.95
 Paul     Paul   19.2          6 3.20
```

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

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

3. merge with email

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

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

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

```
  student gp_tot credit_tot  gpa   email
```

```
1     John    44.4          12 3.70 john123
2     Mary    23.7           6 3.95    <NA>
3     Paul    19.2           6 3.20 paul456
4   Walter      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   email
1     John    44.4          12 3.70 john123
2     Mary    23.7           6 3.95    <NA>
3     Paul    19.2           6 3.20 paul456
```

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

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

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

```
      student gp_tot credit_tot  gpa gpa2
```

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

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
Levels: John Mary Paul
```

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

```
 [1] Mary John John Paul John Mary
Levels: John Mary Paul
```

```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
Levels: John Mary Paul
```

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

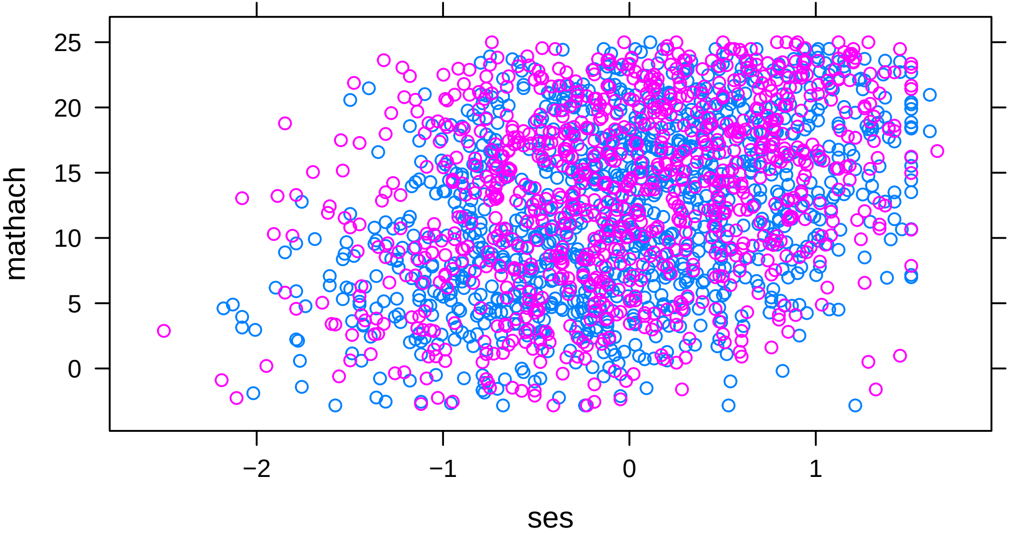
```r
tab(grades, ~ student)
```

```
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 = cours
```

```
       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 # why 'is.factor'?
  else 32 + (9/5)*x
}
<bytecode: 0x0000000018f98058>
```

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'

```
class(2.3)
```

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

```
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:

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

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

But what about data frames??

```
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

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

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

```r
print(fit)
```

```

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

Coefficients:
(Intercept)         day2
     3.5055       0.7033
```

```r
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                Boot                 
```

```
 [7] bootCase              boxCox              brief
[10] case.names            ceresPlot           coerce
[13] confidenceEllipse     confint             Confint
[16] cooks.distance        crPlot              deltaMethod
[19] deviance              dfbeta              dfbetaPlots
[22] dfbetas               dfbetasPlots        drop1
[25] dummy.coef            durbinWatsonTest    effects
[28] extractAIC            family              formula
[31] fortify               getData             getFix
[34] hatvalues             hccm                infIndexPlot
[37] influence             influencePlot       initialize
[40] inverseResponsePlot kappa                 labels
[43] leveneTest            leveragePlot        linearHypothesis
[46] logLik                mcPlot              mmp
[49] model.frame           model.matrix        ncvTest
[52] nextBoot              nobs                outlierTest
[55] plot                  powerTransform      predict
[58] Predict               print               proj
[61] qqnorm                qqPlot              qr
```

```
[64] residualPlot        residualPlots       residuals
[67] rstandard           rstudent            S
[70] show                sigmaHat            simulate
[73] slotsFromS3         spreadLevelPlot     summary
[76] variable.names      vcov
see '?methods' for accessing help and source code
```

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

```r
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", sep = "")
    if (length(coef(x))) {
        cat("Coefficients:\n")
        print.default(format(coef(x), digits = digits), print.gap
            quote = FALSE)
    }
```

```
    else cat("No coefficients\n")
    cat("\n")
    invisible(x)
}
<bytecode: 0x00000000354b70b8>
<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$weights)) "weig
class(ans) <- "summary.lm"
ans$aliased <- is.na(coef(object))
ans$residuals <- r
ans$df <- c(0L, n, length(ans$aliased))
ans$coefficients <- matrix(NA_real_, 0L, 4L, dimnames = li
    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 thi
r <- z$residuals
f <- z$fitted.values
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$terms, "intercept")) {
            m <- sum(w * f/sum(w))
            sum(w * (f - m)^2)
        }
        else sum(w * f^2)
        rss <- sum(w * r^2)
        r <- sqrt(w) * r
    }
    resvar <- rss/rdf
    if (is.finite(resvar) && resvar < (mean(f)^2 + var(c(f))) *
        1e-30)
        warning("essentially perfect fit: summary may be unreliabl
    p1 <- 1L:p
    R <- chol2inv(Qr$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: 0x00000000355a2cc8>
<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", 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 <- 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(b
                  }
                  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$d)
        if (debug)
            disp(tol.fac)
        if (tol.fac > 1e+06)
            warning("Poorly conditioned L matrix, calculated n
        tol <- tol.fac * .Machine$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
    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))
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 = ao
            "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: 0x0000000032542d50>
```

```
<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
(Intercept) 3.5054945 6.0753033 15.656101 -8.6451121
day2        0.7032967 0.2093688  1.122034  0.2845591
```

```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]]$s
                coefm = ret - se * obj[[1]]$se)
            attr(ret, "factor") <- se
        }
    }
    else ret <- sapply(obj, coef.wald)
    ret
```

```
}
<bytecode: 0x0000000031816098>
<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]]$s
                coefm = ret - se * obj[[1]]$se)
            attr(ret, "factor") <- se
        }
    }
    else ret <- sapply(obj, coef.wald)
    ret
}
<bytecode: 0x0000000031816098>
<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]]$se)
        }
        else if (se > 0) {
            ret <- cbind(coef = ret, coefp = ret + se * obj[[1]]$s
                coefm = ret - se * obj[[1]]$se)
            attr(ret, "factor") <- se
        }
    }
    else ret <- sapply(obj, coef.wald)
    ret
}
<bytecode: 0x0000000031816098>
<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

```
x <- c("Hello", "He", "Hel", "hello", "hell")
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:

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

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

```
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:

```
?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')
sub('.*', "OhOh", some_names)
```

"^John(.*)Brown$

```
[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 prog

"0SC/MATH_HON 4 ACT ..."

```r
var_names <- c('id','Gender','Age', 'T1_data', 't2_date', 'T3_date',
var_names
```

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

fix 'data':

```r
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:

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

```
 [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.

```
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"  "49391222lo" "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 —-

```
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.

```
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.

```
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.

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

9.3 Relational data base form — SQL

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'

```
library(spida2)
```

The time-invariant variable relation contains the following.

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

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

The time-varying relation is:

```
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:

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

```
  sid name    sex visit       date sysbp temp
1   1  Sam   male     1 2019-01-21   124 36.5
```

```
2    1  Sam   male     2 2019-03-15   129 36.8
3    2 Joan female     1 2019-02-10   115 37.1
4    3 Kate female     1 2018-06-16   132 37.3
5    3 Kate female     2 2018-09-03   139 36.7
6    3 Kate female     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'.

```
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      NA     138   37.3   36.7   36.9
```

Include

$$\begin{tikzcd} & C \arrow[dl] \arrow[dr] & \\ X \arrow[rr, "?"] & & Y \end{tikzcd}$$

Exclude

$$\begin{tikzcd} & M \arrow[dr] & \\ X \arrow[ur] \arrow[rr, "?"] & & Y \end{tikzcd}$$

Judea Pearl

Book of Why

$$X \longrightarrow Y$$

Directed Acyclic Graph (DAG)

Confounder

Instrumental

Covariate

mediator

$Y \sim X + C_1 + C_5$ ✓

$Y \sim X + C_1 + C_5 + E$

Smallest $SE(\beta_X)$

Pearl

Back door criterion: Must block each path of confounder

```
tolong(dwide)
```

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

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

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

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

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

```
     name    sex sid visit       date sysbp temp
1.1   Sam   male   1     1 2019-01-21   124 36.5
```

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

```
towide(dlong, 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     115   37.1       <NA>      NA     NA
3   3 2018-06-16     132   37.3 2018-09-03     139   36.7
      date_3 sysbp_3 temp_3 name    sex
1       <NA>      NA     NA  Sam   male
2       <NA>      NA     NA Joan female
3 2019-04-20     138   36.9 Kate female
```

9.6 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:

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

```
       country   variable year value id
1.1990  Canada population 1990    20  1
2.1990  Mexico population 1990    50  2
3.1990  Canada     income 1990    10  3
4.1990  Mexico     income 1990    30  4
1.1991  Canada population 1991    21  1
2.1991  Mexico population 1991    52  2
3.1991  Canada     income 1991    12  3
4.1991  Mexico     income 1991    31  4
1.1992  Canada population 1992    24  1
2.1992  Mexico population 1992    53  2
```

```
3.1992   Canada       income 1992     12   3
4.1992   Mexico       income 1992     33   4
1.1993   Canada   population 1993     26   1
2.1993   Mexico   population 1993     54   2
3.1993   Canada       income 1993     11   3
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':

```
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
```

```r
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.

9.7 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
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
#
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
```

```r
#
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
```

9.8 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:

```r
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 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 visit       date    sex sysbp temp   temp_m
1   1  Sam     1 2019-01-21   male   124 36.5 36.65000
2   1  Sam     2 2019-03-15   male   129 36.8 36.65000
3   2 Joan     1 2019-02-10 female   115 37.1 37.10000
4   3 Kate     1 2018-06-16 female   132 37.3 36.96667
5   3 Kate     2 2018-09-03 female   139 36.7 36.96667
6   3 Kate     3 2019-04-20 female   138 36.9 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 visit       date    sex sysbp temp   temp_m  temp_sd
1   1  Sam     1 2019-01-21   male   124 36.5 36.65000 0.212132
2   1  Sam     2 2019-03-15   male   129 36.8 36.65000 0.212132
3   2 Joan     1 2019-02-10 female   115 37.1 37.10000       NA
4   3 Kate     1 2018-06-16 female   132 37.3 36.96667 0.305505
5   3 Kate     2 2018-09-03 female   139 36.7 36.96667 0.305505
6   3 Kate     3 2019-04-20 female   138 36.9 36.96667 0.305505
```

```
  temp_rank sysbp_rank  sysbp_m
1         1          1 126.5000
2         2          2 126.5000
3         1          1 115.0000
4         3          1 136.3333
5         1          3 136.3333
6         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   temp_m  temp_sd  sysbp_m
1   1  Sam   male 36.65000 0.212132 126.5000
2   2 Joan female 37.10000       NA 115.0000
3   3 Kate female 36.96667 0.305505 136.3333
```

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

9.9 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.

9.9.1 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
```

```r
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:

```r
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
```

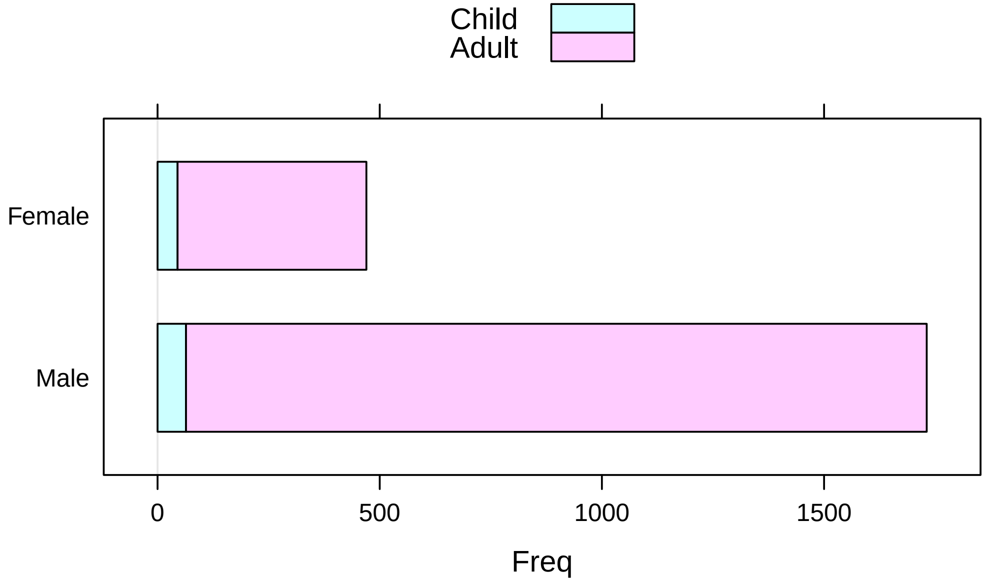
```
        Age
 Sex           Child     Adult
   Male     3.697285 96.302715
   Female   9.574468 90.425532
   All      4.952294 95.047706
```

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

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

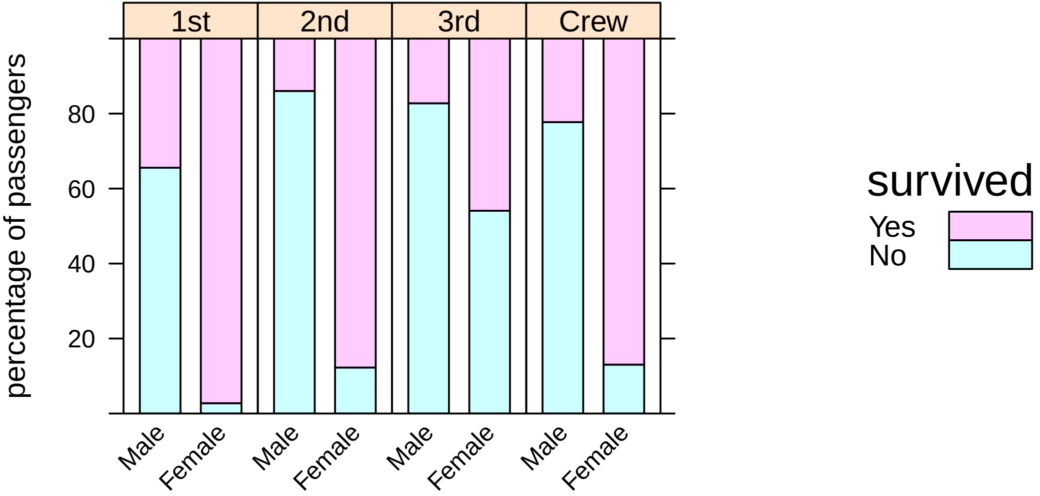
The ouput lends itself well to barcharts

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



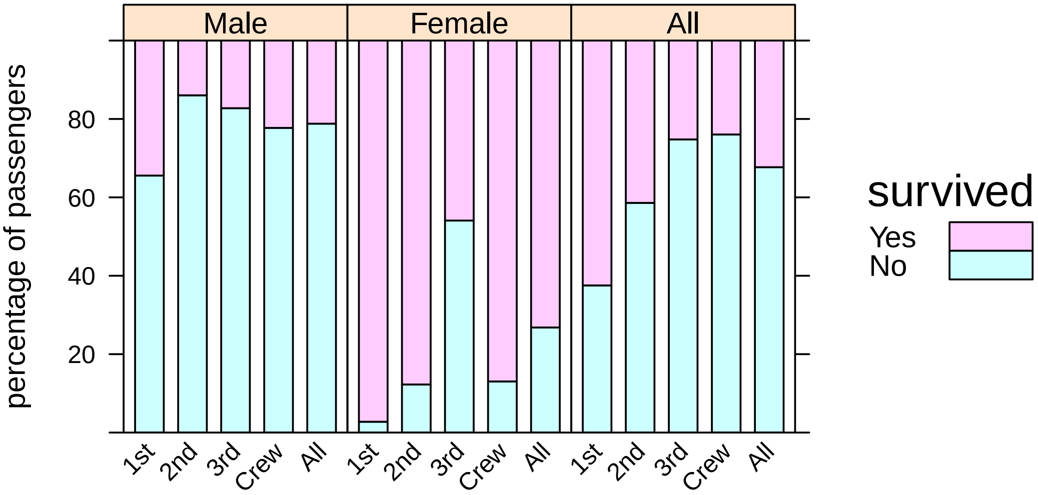

```
tab__(Titanic, ~  Sex + Class + Survived, pct = c(1,2)) %>%
  barchart(ylab = 'percentage of passengers',
```

```
            horizontal = FALSE,
            ylim = c(0,100), layout = c(5,1),
            scales = list(x=list(rot=45)),
            auto.key=list(space='right',title='survived', reverse.row
```




```
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.row
```



Male
Female
All
percentage of passengers
20
40
60
80
1st
2nd
3rd
Crew
All
1st
2nd
3rd
Crew
All
1st
2nd
3rd
Crew
All
survived
Yes
No

9.9.2 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
```

```
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
```

```
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
```

9.10 Frequency data frame —-

From table to frequency data frame:

```
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
```

9.11 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
```

```r
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 = binomi
      data = Titanic.ind, subset = Class != "Crew")

  Coefficients:
                (Intercept)                      Class2nd
                  1.657e+01                    -1.466e-07
                   Class3rd                     SexFemale
                 -1.756e+01                     2.175e-07
                   AgeAdult            Class2nd:SexFemale
                 -1.729e+01                    -1.996e-07
         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
```

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

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

 Coefficients:
                 (Intercept)                     Class2nd
                   1.657e+01                   -1.466e-07
```

```
                 Class3rd                     SexFemale
               -1.756e+01                     2.175e-07
                AgeAdult             Class2nd:SexFemale
               -1.729e+01                    -1.996e-07
       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
fit2 <- glm(Survived ~ (Class + Sex + Age)^2,
           dd, family = binomial)
summary(fit2)
```

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

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.6771  -0.5952  -0.5952   0.3152   2.2293

Coefficients:
                     Estimate Std. Error z value Pr(>|z|)
(Intercept)          16.26450  920.38635   0.018    0.986
Class2nd             -0.82145 1005.81944  -0.001    0.999
Class3rd            -17.25489  920.38641  -0.019    0.985
SexFemale             3.59619    0.74781   4.809 1.52e-06 ***
AgeAdult            -16.99213  920.38637  -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 1005.81949  -0.001    0.999
```

```
Class3rd:AgeAdult     16.34159  920.38643   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
```

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

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

```
Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.6771  -0.5952  -0.5952   0.3152   2.2293

Coefficients:
                             Estimate Std. Error z value
(Intercept)                 1.657e+01  1.073e+03   0.015
Class2nd                   -1.466e-07  1.294e+03   0.000
Class3rd                   -1.756e+01  1.073e+03  -0.016
SexFemale                   2.175e-07  2.629e+03   0.000
AgeAdult                   -1.729e+01  1.073e+03  -0.016
Class2nd:SexFemale         -1.996e-07  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
1      1304     1165.4
2      1306     1165.4 -2 -1.506e-06
```

9.12 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
```

```r
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
    data = Titanic.wide, subset = Class != "Crew")

Deviance Residuals:
```

```
 [1]  0  0  0  0  0  0  0  0  0  0  0  0

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: 3.0911e-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)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.6771  -0.5952  -0.5952   0.3152   2.2293

Coefficients:
                              Estimate Std. Error z value
(Intercept)                  1.657e+01  1.073e+03   0.015
Class2nd                    -1.466e-07  1.294e+03   0.000
Class3rd                    -1.756e+01  1.073e+03  -0.016
SexFemale                    2.175e-07  2.629e+03   0.000
AgeAdult                    -1.729e+01  1.073e+03  -0.016
```

```
Class2nd:SexFemale          -1.996e-07  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.

```r
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:

```r
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.

```r
dim(m)
```

```
[1] 3 4
```

```r
m
```

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

```r
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
```

```
diag(m)
```

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

```
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.