DescTools

A Hardworking Assistant for Descriptive Statistics

<preliminary blueprint version>

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R sometimes makes ordinary tasks difficult. Virtually every data analysis project starts with describing data. The first thing to do will often be calculating summary statistics for all variables while listing the occurrence of nonresponse and missing data and producing some kind of graphics. This is a three-click process in SPSS, but regardless of the normality of this task, base R does not contain higher level functions for quickly describing huge datasets (meant regarding the number of variables, not records) adequately in a more or less automated way. There are facilities like summary, describe (Hmisc), stat.desc (library pastecs), but all of them are lacking some functionality or flexibility we would have expected.
Another point is, that there are quite a few commonly used functions, which curiously are not present in the stats package, think e.g. of skewness, kurtosis but also the Gini-coefficent, Cohen's Kappa or Somers' delta. This led to a rank growth of libraries implementing just one specific missing thing. There are plenty of "misc"-libraries out there, containing such functions and tests. We would normally end up using a dozen libraries, each time using just one single function out of it and suffering huge variety concerning NA-handling, recycling rules and so on.
R has been developed in a university environment. This will be clear at the latest then when you find yourself working in an office of an insurance and you realize that only MS-Office (and no LATEX) is installed on your system (and the IT guys won't give you admin rights). We were forced in this situation to write code for doing our reporting in MS-Word. (This works quite well for Windows, but not for Mac unfortunately.)
The first version of "DescTools" arose after completion of a project, where we had to describe a dataset under deadline pressure, and we started to gather our newly created functions and put them together.
This collection has meanwhile grown to a considerably versatile toolset for descriptive statistics, providing rich univariate and bivariate descriptions of data without expecting the user to say much.
There are numerous basic statistic functions and tests, possibly flexible and enriched with different approaches (if existing). Confidence intervals are extensively provided.

Recognizing that most problems can be satisfactorily visualized with bar-, scatter- and dotplots, still some more specific plot types are used in special cases and thus included in the library. Some of them are rather new, and some of them are based on types found scattered in the myriads of R packages found out there (partly rewritten to meet the design goals of the package).

This document describes quickly the essentials of the package DescTools.

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Users, even expert statisticians, do not always screen the data.
B. D. Ripley, Robust statistics (2004)

1 Introduction

The analyst's sacred duty before beginning any sort of statistical analysis is to take a preliminary look at the data with three main goals in mind: first, to check for errors and anomalies; second, to understand the distribution of each of the variables on its own; and third, to begin to understand the nature and strength of relationships among variables.
Errors should, of course, be corrected, since even a small percentage of erroneous data values can drastically influence the results and might completely invalidate the analysis. Understanding the distribution of the variables, especially the outcomes, is crucial to choosing the appropriate multipredictor regression method. Finally, understanding the nature and strength of relationships is the first step in building a more formal statistical model from which to draw conclusions.
To prevent the analyst to bypass this steps the describing process must be quick and simple. The package DescTools has been created with the aim to make data descriptions less costly and time consuming. One outstanding feature of the package is the combination of numerical results and graphical representation which can mostly be automated and reported to the console, but as well quite easily be exported to a Word Document.

The proper description of data depends on the nature of the measurement. The key distinction for statistical analysis is between numerical and categorical variables. The temperature of the pizza is a numerical variable, while the driver delivering it is categorical. The delivery time is numerical, whereas the area of the customer is categorical. A secondary but sometimes important distinction within numerical variables is whether the variable can take on a whole continuum or just a discrete set of values. So the temperature would be continuous, while number of pizzas ordered (count) would be discrete.
A numerical variable taking on a continuum of values is called continuous and one that only takes on a discrete set of values is called discrete. A secondary distinction sometimes made with regard to categorical variables is whether the categories are ordered or unordered. So, for example, categories of quality (low, medium, high) would be ordered, while the operator would be unordered.
A categorical variable is ordinal if the categories can be logically ordered from smallest to largest in a sense meaningful for the question at hand (we need to rule out silly orders like alphabetical); otherwise it is unordered or nominal. Some overlap between types is possible. For example, we may break a numerical variable (such as exact total amount) into ranges or categories. Conversely, we may treat a categorical variable as a numerical score, for example, by assigning values one to three to the ordinal responses Low, Medium, High. Most of the basic analysis methods for numerical scores (e.g., linear regression or t-tests) have interpretations based on average scores. So assigning scores to a categorical variable is effective if average scores are readily interpretable. [3]

The function Desc is designed to describe variables depending on their type with some reasonable statistic measures and an adequate graphic representation. It includes code for describing logical variables, factors (ordered and unordered), integer variables (typically counts), numeric variables, dates and tables and matrices.
Data frames will be split into their variables and the single variable will be described. A formula interface is implemented to easily describe variables in dependence of others.

The output can either be sent to the R-console or as well directly redirected to a MS-Word document.

The latter works only in Windows with MS-Office installed, but Mac users can leave the wrd argument away and add a plotit = TRUE argument to have the full results in the console.

Note: For all the examples in this document, `library(DescTools)` must be declared.

2 Categorical Variables

The first variable is an unordered `factor`. Factors are typically best described by a frequency table of their levels. The default order of the output table is following a pareto rule, the most frequent levels first.
Ordered factors would be sorted after their natural order by default. The default order can be changed by setting the `ord` argument to either `"desc", "asc", "name"` or `"level"`.
The frequency table is by default truncated in the case that there are more than a dozen values (this can be avoided by setting the argument `maxrows=NA`, see: `?Desc.factor` for more details).

Desc

```
Desc(d.pizza$driver, plotit=TRUE)
```

```
  length      n    NAs levels unique  dupes
   1'209  1'204      5      7      7      y


      level freq   perc cumfreq cumperc
1 Carpenter  272  .226      272    .226
2    Carter  234  .194      506    .420
3    Taylor  204  .169      710    .590
4    Hunter  156  .130      866    .719
5    Miller  125  .104      991    .823
6    Farmer  117  .097     1108    .920
7   Butcher   96  .080     1204   1.000
```

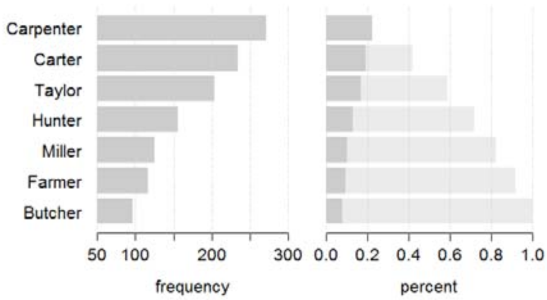


Figure 10.2 Frequency plot of a categorical variable

The graphical representation consists of two horizontal barplots. The left one is displaying the absolute frequencies with truncated x-axis. The left plot will always display the percentages with fixed x-axis limits set to 0 and 1. The cumulative frequencies can be displayed or be left away.

Synopsis

`length`	total number of elements in the vector, NAs are included here
`n`	number of valid cases, NAs, NaNs, Inf etc. are not counted here
`NAs`	number of missing values
`levels`	number of levels
`unique`	number of unique values. Note: This is not necessarily the same value as levels, as there might be empty levels. Thus the number of levels might be higher than the number of unique values (but not the other way round).
`dupes`	y(es) or n(o), reporting if there are any duplicate values in the vector. If “n” (for no) then there are only unique values in the variable.
`freq`	the count (absolute frequency) of the specific level. The order of a factors frequency table is by default chosen as “absolute frequency-decreasing”.
`perc`	the relative frequency of the specific level
`cumfreq`	the cumulative frequencies of the levels
`cumperc`	the same for the percentage values

3 Numerical Variables

3.1 Numeric

The next variable, the temperature of the delivered pizza, is numeric. Numeric variables are described by the most usual statistical measures for location, variation and shape.
Several features of the output are worth consideration. The largest and smallest values should be scanned for outlying or incorrect values, and the mean (or median) and standard deviation (or interquartile range IQR, resp. the median absolute deviation mad) should be assessed as general measures of the location and spread of the data.
The quantiles deliver a good overall impression of the distribution. We note that 90% of the data lie between 26 and 60 degrees and the inner 50% between 42 and 55.
The skewness and kurtosis are usually more easily assessed by the graphical means, though their numerical values are included in the output. A large difference between the mean and median is another cue for the skewness. In right-skewed data, the mean is larger than the median, while in left-skewed data, the mean is smaller than the median.

```
Desc(d.pizza$temperature, main="", plotit=TRUE)
```

```
  length       n     NAs unique      0s    mean meanSE
   1'209   1'170      39    375       0 47.937  0.291

     .05     .10     .25 median     .75     .90     .95
  26.700  33.290  42.225     50  55.300  58.800  60.500

   range      sd   vcoef    mad     IQR    skew    kurt
  45.500   9.938   0.207  9.192  13.075  -0.842   0.051

lowest : 19.3, 19.4, 20, 20.2 (2), 20.35
highest: 63.8, 64.1, 64.6, 64.7, 64.8
```

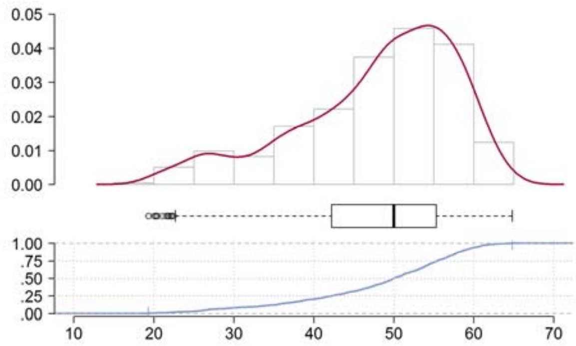


Figure 3.1 Distribution of a numeric variable.

PlotFdist

The plot 3.1 as produced by the function `PlotFdist` combines a histogram with a density plot, a boxplot and the plot of the empirical distribution function ECDF. The scale for the x-axis is synchronized over all plots. The median can thus be found on the boxplot as also in the ecdf-plot. The maximum and the minimum value are tagged with a tiny vertical dash upon the ecdf-line.

Let's enumerate the features in detail. The first measures length, n, NAs, unique have again the same meaning as above. NAs are silently removed from all subsequently calculations.

`0s`	total number of zero values.
`mean`	the arithmetic mean of the vector.
`meanSE`	standard error of the mean, sd(x) / sqrt(n). This can be used to construct the confidence intervals for the mean, defined as `qt(p = 0.025, df = n-1) * sd(x) / sqrt(n)`. (See also: function `MeanCI(…)`)
`.05, .., .95`	quantiles of x, starting with 5%, 10%, 1. quartile, median etc.
`rng`	range of x, `max(x) – min(x)`
`sd`	standard deviation
`vcoef`	variation coefficient, defined as `sd(x) / mean(x)`
`mad`	median absolute deviation
`IQR`	inter quartiles range
`skew`	skewness of x
`kurt`	kurtosis of x
`lowest`	the smallest 5 values. If there are bindings, the frequency of each value will be reported in brackets.
`highest`	same as lowest, but on the other end

Transformations can be entered in place.

```
Desc(1/d.pizza$temperature, digits=3, main="")
title(expression(frac(1,x)))
```

```
 length      n    NAs  unique     0s    mean  meanSE
  1'209  1'170     39     375      0   0.022   0.000

    .05    .10    .25  median    .75     .90     .95
  0.017  0.017  0.018   0.020  0.024   0.030   0.037

  range     sd  vcoef     mad    IQR    skew    kurt
  0.036  0.006  0.289   0.004  0.006   2.027   4.244

lowest : 0.015, 0.015, 0.015, 0.016, 0.016
highest: 0.049, 0.050 (2), 0.050, 0.052, 0.052
```

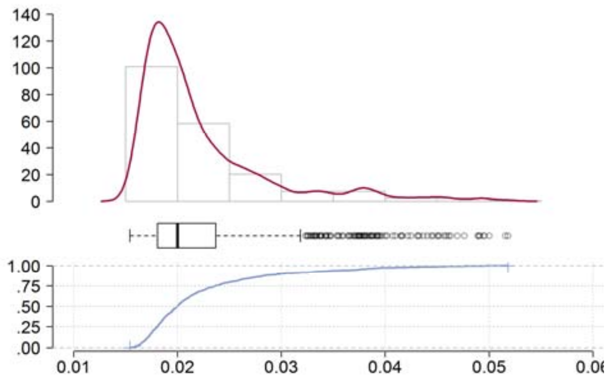


Figure 3.2 Distribution of a numeric variable.

There are several approaches commonly used for graphical comparing the variable's distribution to a reference distribution. The two most seen are firstly superposing the reference density curve over the variable's histogram and second using a Q-Q-plot. A QQ plot is used to compare the shapes of distributions, providing a graphical view of how properties such as location, scale, and skewness are similar or different in the two distributions

LinScale

```
z <- LinScale(z, newlow=0, newhigh = 32)[,1]
PlotFdist(z, args.curve = list(expr="dchisq(x, df=5)", col="darkgreen"),
          args.boxplot=NA, args.ecdf=NA)
legend(x="topright", legend=c("kernel density", expression(chi["df=5"]^2-distribution)),
       fill=c(getOption("col1", hred), "darkgreen"), text.width = 5)
```

We get

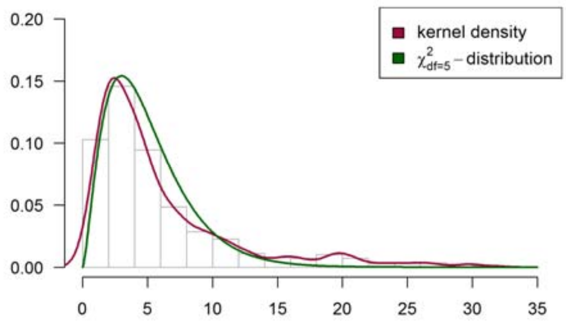


Figure 3.3 Overlay of fitted χ^2-function.

This makes it clear, that this is not the best way to decide, whether the red curve follows our hypothesized distribution or not. Where does random start?
The better approach is to use a QQ-plot, which by the way solves the x-axis scaling problem we had in the overlay solution. The function PlotQQ is a wrapper for plotting QQ-plots with other than normal distributions. A qqline is inserted on which the points are likely to lie (approximately) if the two distributions being compared are similar.

PlotQQ

```
# get some data
set.seed(81)
z <- rchisq(100, df=5)

for(i in 1:20){
  zz <- rchisq(100, df=5)
```

```
  PlotQQ(zz, function(p) qchisq(p, df=5), add=(i!=1), args.qqline = NA,
         col="grey", type="l", lty="dotted", main=NA)
}

PlotQQ(z, function(p) qchisq(p, df=5), add=TRUE, args.qqline=list(col=2, probs=c(0.1,
0.6)))
title(main=expression("Q-Q plot for" ~~ {chi^2}[nu == 3]))
```

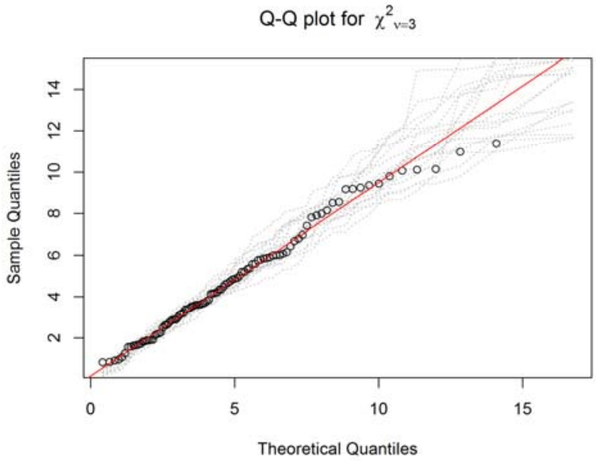


Figure 3.4 QQ plot for a χ^2-distributed variable.

It might sometimes be hard to judge, if the points are too far from the qqline or not.
An idea to check the general variability is to add 20 sets, simulated with the desired distribution. If our points are an extreme path, something is likely to be wrong. In our example above all is ok, of course, as we sampled from the tested distribution.

3.2 Numeric data with few unique values

If there's a numeric variable with only one or two handfuls of unique values then a description by means of a histogram and a density curve is not really adequate. The density curve will start oscillating and the bins in the histograms would lose their continuous nature.
Therefore we change the graphic representation from a histogram to a histogram like h-type plot without density curve.

In the numerical results the extreme values will be replaced by a frequency representation with absolute values and percentages.

```
Desc(d.pizza$weekday, plotit=TRUE)
```

```
length      n    NAs  unique     0s   mean  meanSE
 1'209  1'177     32       7      0   4.44    0.06

   .05    .10    .25  median    .75    .90     .95
  1.00   1.00   3.00    5.00   6.00   7.00    7.00

 range     sd  vcoef     mad    IQR   skew    kurt
  6.00   2.02   0.45    2.97   3.00  -0.34   -1.17

   level  freq   perc  cumfreq   cumperc
1      1   144  12.2%      144     12.2%
2      2   117   9.9%      261     22.2%
3      3   134  11.4%      395     33.6%
4      4   147  12.5%      542     46.0%
5      5   171  14.5%      713     60.6%
6      6   244  20.7%      957     81.3%
7      7   220  18.7%    1'177    100.0%
```

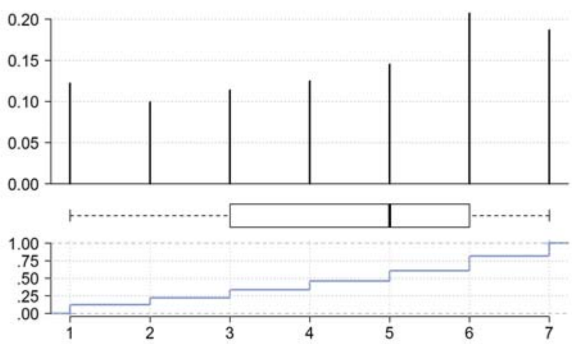


Figure 3.5 Distribution of a numeric variable.

3.3 Count data (discrete)

The next variable is a count variable, whose nature is somewhat between numeric and factors as far as descriptive measures are concerned. In fact, if there are only just a few unique values, then the factor representation (frequencies) might be more appropriate than the numeric description (with densities etc.). We draw the line between factor and numeric representation at a dozen of unique values in x. Beyond that number, the numeric description will be reported and for fewer values the factor representation will be used.

```
Desc(d.pizza$count, plotit=TRUE)
```

```
  length      n    NAs unique     0s   mean meanSE
   1'209  1'197     12      8      0  3.444  0.045

     .05    .10    .25 median    .75    .90    .95
       1      2      2      3      4      6      6

     rng     sd  vcoef    mad    IQR   skew   kurt
       7  1.556  0.452  1.483      2  0.454 -0.363


  level freq  perc cumfreq cumperc
1     1  108  .090     108    .090
2     2  259  .216     367    .307
3     3  300  .251     667    .557
4     4  240  .201     907    .758
5     5  152  .127    1059    .885
6     6   97  .081    1156    .966
7     7   34  .028    1190    .994
8     8    7  .006    1197   1.000
```

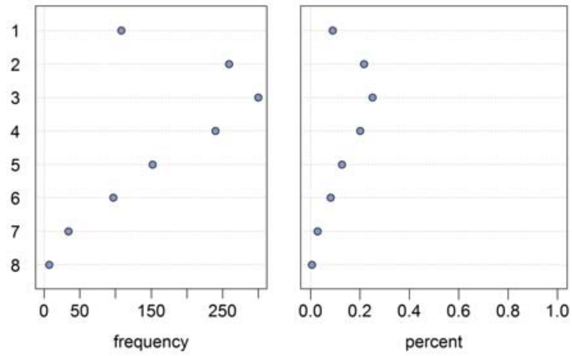


Figure 3.6 Distribution of a count variable.

The plot is produced as a (horizontal) dotchart. More than 12 unique values are truncated (a warning is placed in the plot area). The `maxrows` argument can be used to override this default (NA for all).

Two dotcharts are created, the left one shows the absolute frequencies, the right one the percentages. On the left plot the x-axis might be adapted to the data (as R does by default). The percentages will always be displayed on a 0:1-range.
The plot width is adapted to the length of the labels. If the labels get too long, they will be truncated and displayed with ellipsis (…).

4 Logical values

Dichotomous variables do not have real dense (univariate) information. The variable `wine_ordered` for example contains only two values, 0 and 1. Still it is usually interesting to know, how many NAs there are, besides the frequencies of course. The individual frequencies are reported together with a confidence interval, calculated by `BinomCI` using the option `"Wilson"`.

```
Desc(d.pizza$wine_ordered, plotit=TRUE)
```

```
  length      n    NAs unique
   1'209  1'197     12      2

  freq  perc lci.95 uci.95¹
0 1010  .844   .822   .863
1  187  .156   .137   .178

¹ 95%-CI Wilson
```

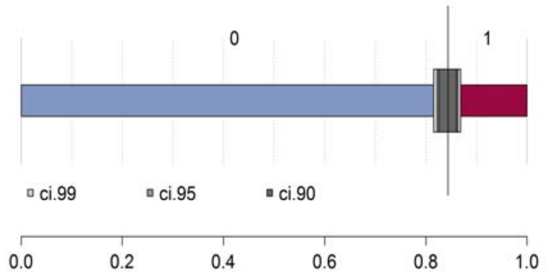


Figure 4.1 Distribution of a numeric variable.

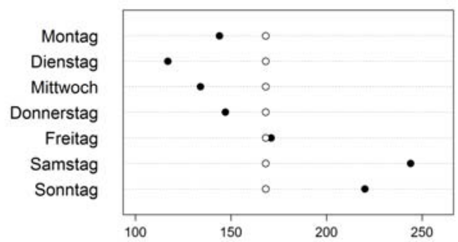
This is basically a univariate horizontal stacked barplot, with confidence intervals on the confidence levels of 0.90, 0.95 and 0.99. The vertical line denominates the point estimator.

5 Time variables

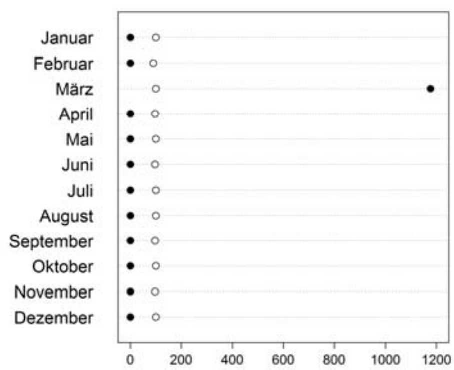
5.1 Dates

A date variable is harder to describe as single variable. What characteristics would one want to know from a date? We would normally choose a description similar to numeric values, supplemented by an analysis of the weekday and month for grasping anomalies concerning extreme, invalid or missing values.

```
Desc(d.pizza$date, plotit=TRUE)

  length      n    NAs unique
   1'209  1'177     32     31

lowest : 2014-03-01 (42), 2014-03-02 (46), 2014-03-03 (26), 2014-03-04 (19)
highest: 2014-03-28 (46), 2014-03-29 (53), 2014-03-30 (43), 2014-03-31 (34)

Weekdays:
       level freq  perc cumfreq cumperc   exp  res
1     Montag  144  .122     144    .122 168.1 -1.9
2   Dienstag  117  .099     261    .222 168.1 -3.9
3   Mittwoch  134  .114     395    .336 168.1 -2.6
4 Donnerstag  147  .125     542    .460 168.1 -1.6
5    Freitag  171  .145     713    .606 168.1   .2
6    Samstag  244  .207     957    .813 168.1  5.9
7    Sonntag  220  .187    1177   1.000 168.1  4.0

        Chi-squared test for given probabilities

data:  table(xd)
X-squared = 78.8785, df = 6, p-value = 6.09e-15
```



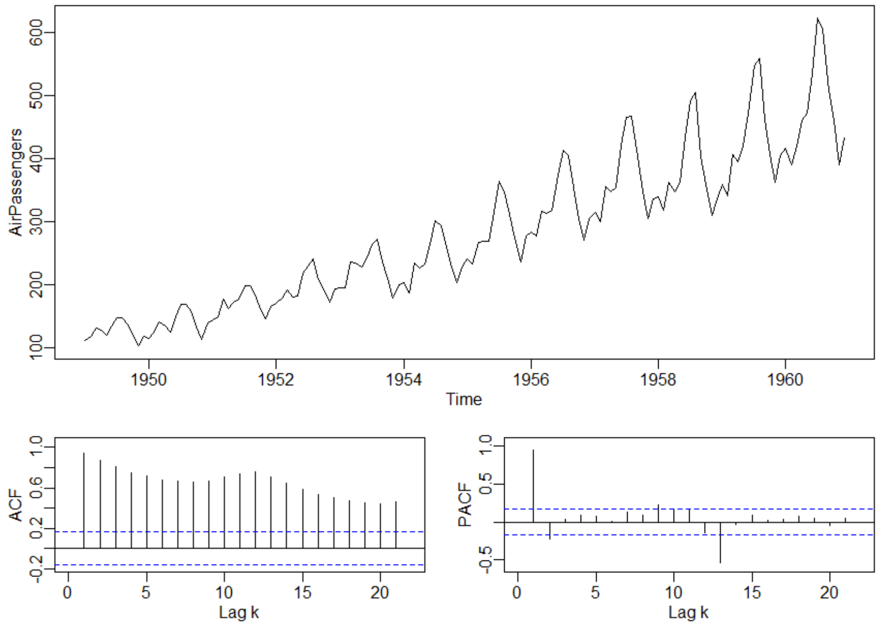

```
Months:
       level freq perc cumfreq cumperc  exp prs.res
1     Januar    0    0       0       0 99.7   -10.0
2    Februar    0    0       0       0 93.3    -9.7
3       März 1177    1    1177       1 99.7   107.9
4      April    0    0    1177       1 96.5    -9.8
5        Mai    0    0    1177       1 99.7   -10.0
6       Juni    0    0    1177       1 96.5    -9.8
7       Juli    0    0    1177       1 99.7   -10.0
8     August    0    0    1177       1 99.7   -10.0
9  September    0    0    1177       1 96.5    -9.8
10   Oktober    0    0    1177       1 99.7   -10.0
11  November    0    0    1177       1 96.5    -9.8
12  Dezember    0    0    1177       1 99.7   -10.0

        Chi-squared test for given probabilities

data:  tab
X-squared = 12719.19, df = 11, p-value < 2.2e-16
```



5.2 Timeseries PlotACF

This produces a combined plot of a time series and its autocorrelation and partial autocorrelation, which is used in every introductory course for time-series.

```
PlotACF(AirPassengers)
```



6 data.frames

After that, every single variable will be described according to the type of its class.

Let's start with a quick description of some variables out of the integrated `data.frame` `d.pizza`.

```
library(DescTools)

# the results (and the plots) will either be displayed in the console
Desc(d.pizza[,c("driver","temperature","count","weekday","wine_ordered","date")],
plotit=TRUE)

# ... or we can start a new word instance and send the results directly to a word document
wrd <- GetNewWrd()
Desc(d.pizza[,c("driver","temperature","count","weekday","wine_ordered","date")], wrd=wrd)
```

```
'data.frame':   1209 obs. of  4 variables:
 1 $ driver      : Factor w/ 7 levels "Butcher","Carpenter",..: 7 1 1 7 3 7 7 7 7 3 ...
 2 $ temperature : num  53 56.4 36.5 NA 50 27 33.9 54.8 48 54.4 ...
 3 $ count       : int  5 2 3 2 5 1 4 NA 3 6 ...
 4 $ weekday     : num  6 6 6 6 6 6 6 6 6 6 ...
 5 $ wine_ordered: int  0 0 0 0 0 0 1 NA 0 1 ...
 6 $ date        : Date, format: "2014-03-01" "2014-03-01" "2014-03-01" "2014-03-01" ...
```

First a simple `Str()` of the `data.frame` is performed. The result is no more than that of a `str()` command, extended with an enumeration of the variables.

Str

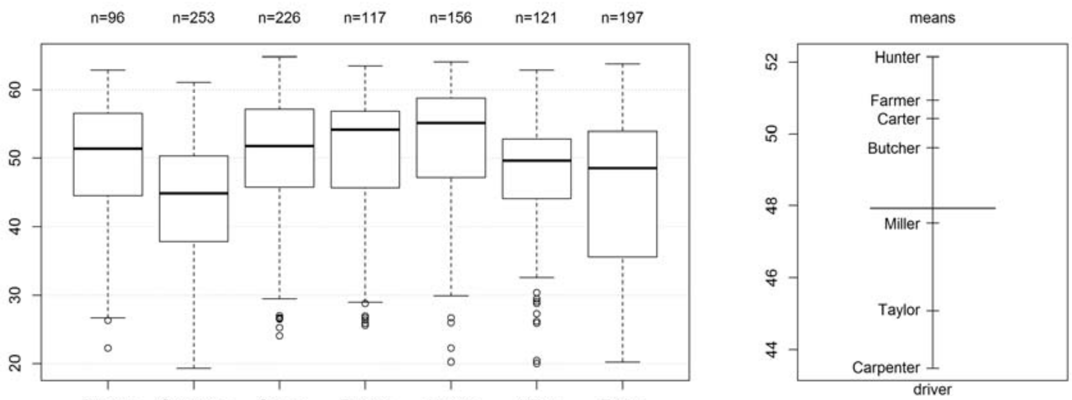
7 Pairwise Numeric ~ Categorical

7.1 Boxplot and Designplot

`Desc` implements a formula interface allowing to define bivariate descriptions straight forward.

A numeric variable vs. a categorical is best described by group wise measures. Here the valid pairs are reported first. Missing values in the single groups are documented in the results table and missing values on the grouping factor are mentioned with a warning at the end of the table, if existing at all.

```
Desc(temperature ~ driver, d.pizza, digits=1, plotit=TRUE)

Summary:
n pairs: 1'209, valid: 1'166 (96%), missings: 43 (4%), groups: 7

         Butcher Carpenter   Carter   Farmer   Hunter   Miller   Taylor
mean        49.6     43.5¹     50.4     50.9    52.1²     47.5     45.1
median      51.4     44.8¹     51.8     54.1    55.1²     49.6     48.5
sd           8.8       9.4      8.5      9.0      8.9      8.9     11.4
IQR         12.0      12.5     11.3     11.2     11.6      8.8     18.4
n             96       253      226      117      156      121      197
np         0.082     0.217    0.194    0.100    0.134    0.104    0.169
NAs            0        19        8        0        0        4        7
0s             0         0        0        0        0        0        0

¹ min, ² max

Kruskal-Wallis rank sum test:
  Kruskal-Wallis chi-squared = 141.9349, df = 6, p-value < 2.2e-16
Warning:
  Grouping variable contains 5 NAs (0.414%).
```



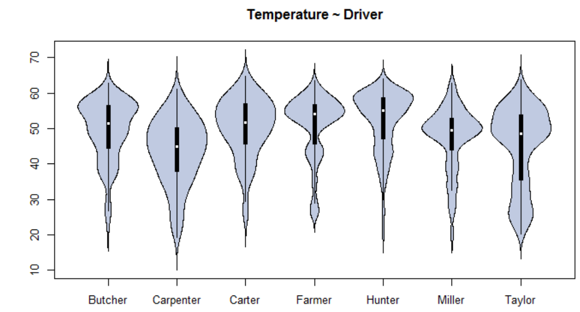
a boxplot combined with a means-plot as used in anova

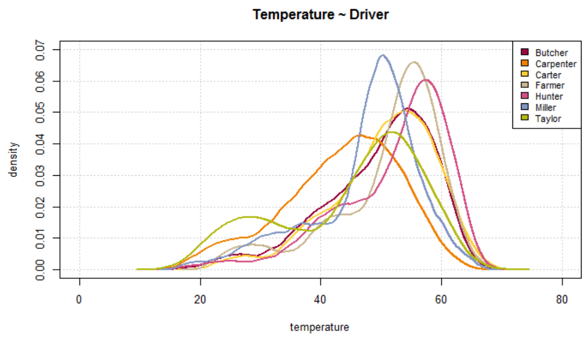
7.2 Comparing distributions

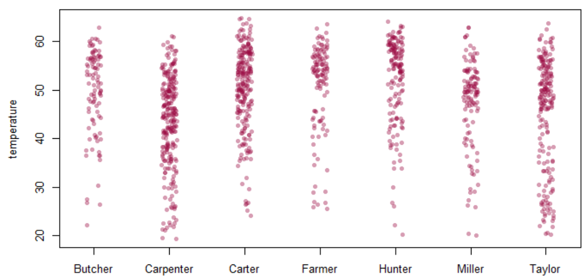
How should we compare distributions graphically, moving beyond a simple boxplot? PlotViolin serves the same utility as a side-by-side boxplot, but provides more detail about the single distribution. We started with John Verzani's Violinplot and rewrote it so that it takes exactly the same parameters as the boxplot-function.

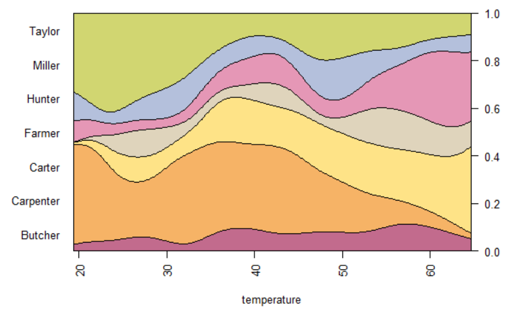
Another idea is to plot several densities within the same plot. PlotMultiDens does this while setting the xlim- and ylim-values to an appropriate value, ensuring all density lines are fully visible. For a smaller number of variables, say up to two handfuls, this will be the most direct way to compare their distributions. (Note: For violins this limit lies much higher as they do not overlap and so mutually hide.)

```
PlotViolin(temperature ~ driver, data=d.pizza, col = SetAlpha(hblue,0.5),
           main="Temperature ~ Driver")

PlotMultiDens(temperature ~ driver, data=d.pizza, xlab="temperature",
              main="Temperature ~ Driver", panel.first=grid(),
              col=PalHelsana(), lwd=2 )
```









For small datasets a stripchart might be the best way to plot the data.
The conditional density-plot at the right allows to grasp the proportions within the total density.

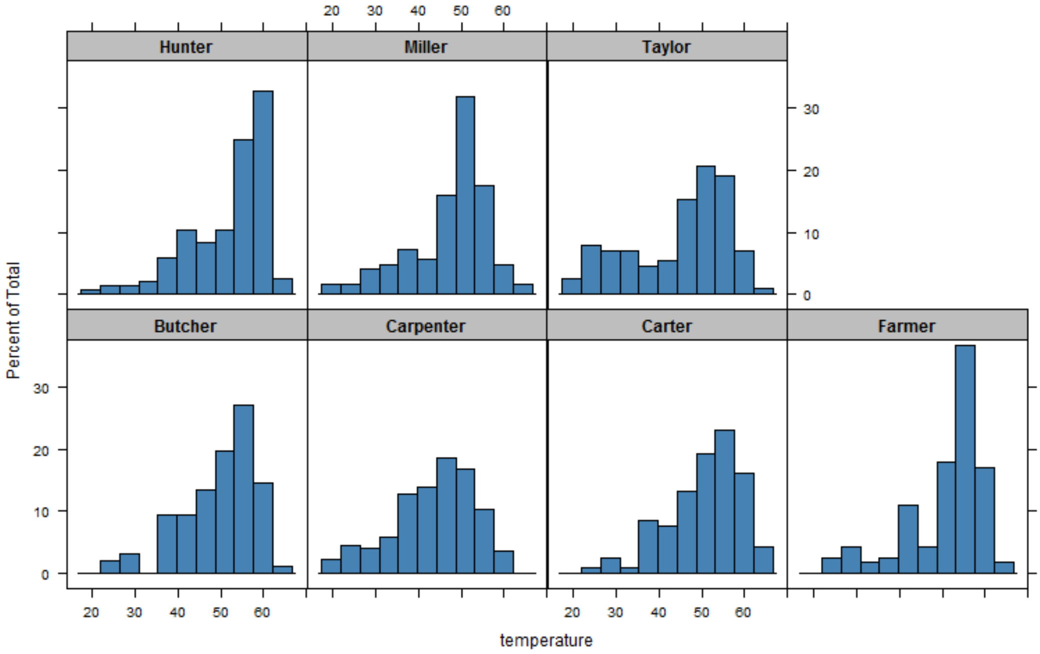
```
stripchart(temperature ~ driver, d.pizza, vertical=TRUE,
           method="jitter", pch=16, col=SetAlpha(hred,0.4))

d.frm <- na.omit(d.pizza[,c("temperature","driver")])
par(las=2, mar=c(4.1,10.1,5.1, 5.1))
cdplot(x=d.frm$temperature, y=d.frm$driver, ylab="", xlab="temperature",
       col=SetAlpha(PalHelsana(), 0.6))
```

7.3 Trellis

The classic way is to spend a full plot for every single variable. There's an interesting link, demonstrating this technique: http://www.statmethods.net/advgraphs/trellis.html

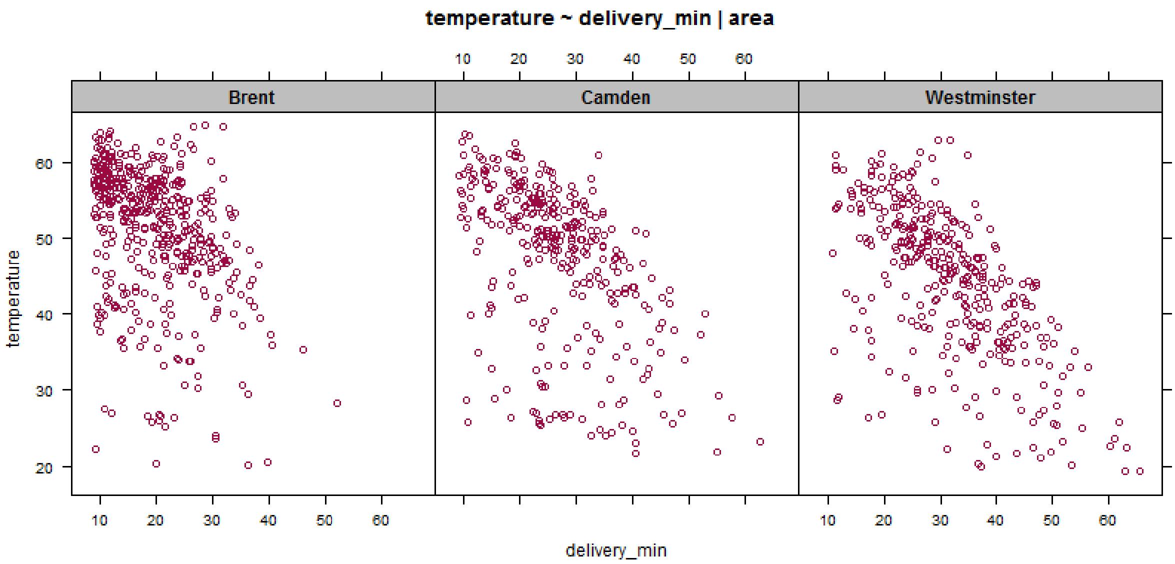
```
library(lattice)
trellis.par.set(strip.background = list(col = gray(0.5)), add.text = list(col =
'white'))

myStripStyle <- function(which.panel, factor.levels, ...) {
  panel.rect(0, -0.5, 1, 1,
             col = "grey",
             border = 1)
```

```
  panel.text(x = 0.5, y = 0.25,
             font=2,
             lab = factor.levels[which.panel],
             col = "black")
}

histogram( ~ temperature | driver, data=d.pizza, col="steelblue", strip=myStripStyle)
```



Again here a scatterplot is highly informative.

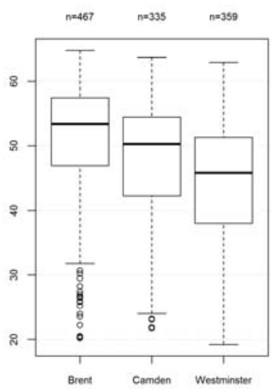
```
xyplot(temperature ~ delivery_min | area, d.pizza,
       main='temperature ~ delivery_min | area', col=hred, strip=myStripStyle)
```

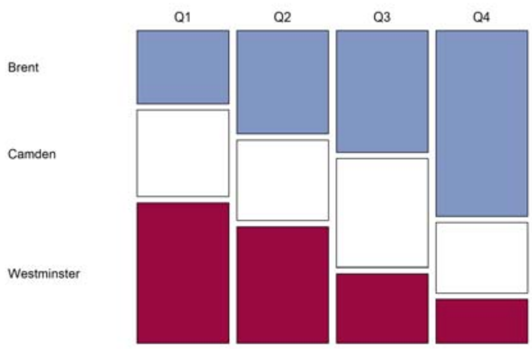


8 Pairwise Categorical ~ Numeric

No, it's not the same as numeric ~ categorical. The design is such, that the response variable is categorical and the predictor numeric. With a model one would set up a multinomial regression (or logistic in the case of 2 categories).

```
Desc(area ~ temperature, data=d.pizza, digits=1, wrd=wrd)

Summary:
n pairs: 1'209, valid: 1'161 (96%), missings: 48 (4%), groups: 3


              Brent      Camden  Westminster
mean          51.1²        47.4        44.3¹
median        53.4²        50.3        45.9¹
sd             8.7         10.1         9.8
IQR           10.5         12.2        13.2
n              467          335         359
np           0.402        0.289       0.309
NAs              7            9          22
0s               0            0           0

¹ min, ² max

Kruskal-Wallis rank sum test:
  Kruskal-Wallis chi-squared = 115.83, df = 2, p-value < 2.2e-16
Warning:
  Grouping variable contains 10 NAs (0.827%).


Proportions of area in the quantiles of temperature:

                Q1    Q2    Q3    Q4
  Brent       0.244 0.345 0.405 0.618
  Camden      0.289 0.266 0.363 0.236
  Westminster 0.467 0.389 0.232 0.146
```





9 Pairwise Categorical ~ Categorical

Two categorical variables are described by a contingency table, as shown in the vignette Tables.

10 Pairwise Numeric ~ Numeric

10.1 Boxplot and Designplot

Two numerical variables have no obvious standard description as their relationship can have many forms. We report therefore only the simple correlation coefficients (Pearson, Spearman and Kendall).

The variables are plotted as xy-scatterplots with interchanging mutual dependency, supplemented with a LOESS smoother.

```
Desc(temperature ~ delivery_min, d.pizza, plotit=TRUE)
```

```
Summary:
n pairs: 1'209, valid: 1'170 (97%), missings: 39 (3%)


Pearson corr. : -0.575
Spearman corr.: -0.573
Kendall corr. : -0.422
```

Scatterplots for two numeric variables:

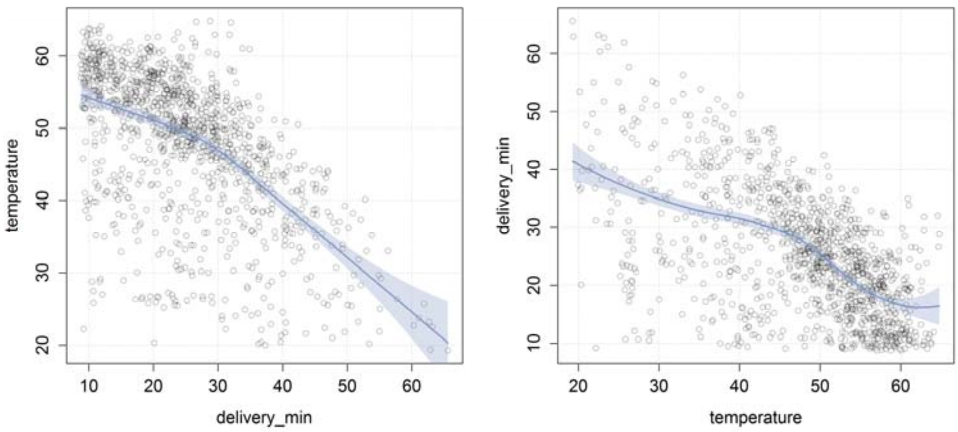
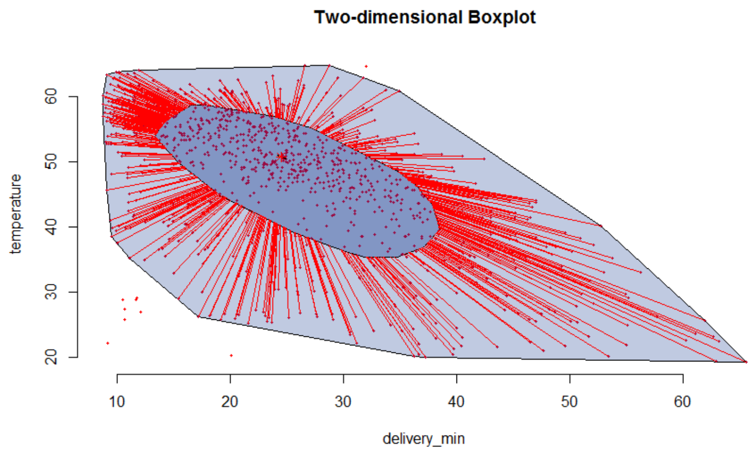


Figure 10.2 Mosaicplot of Eye colour ~ Hair colour.

10.2 Boxplot on 2 dimensions: PlotBag

This function transposes the boxplot idea in the 2-dimensional space. The points are outliers, the lightblue area is the area within the fences in a normal boxplot and the darkblue area is the inner quartile range.
The median is plotted as orange point in the middle.
This code is taken verbatim from Peter Wolf's aplpack package.

```
d.frm <- d.pizza[complete.cases(d.pizza[,c("temperature","delivery_min")]),]

PlotBag(x=d.frm$delivery_min, y=d.frm$temperature, xlab="delivery_min",
        ylab="temperature", main="Two-dimensional Boxplot")
```

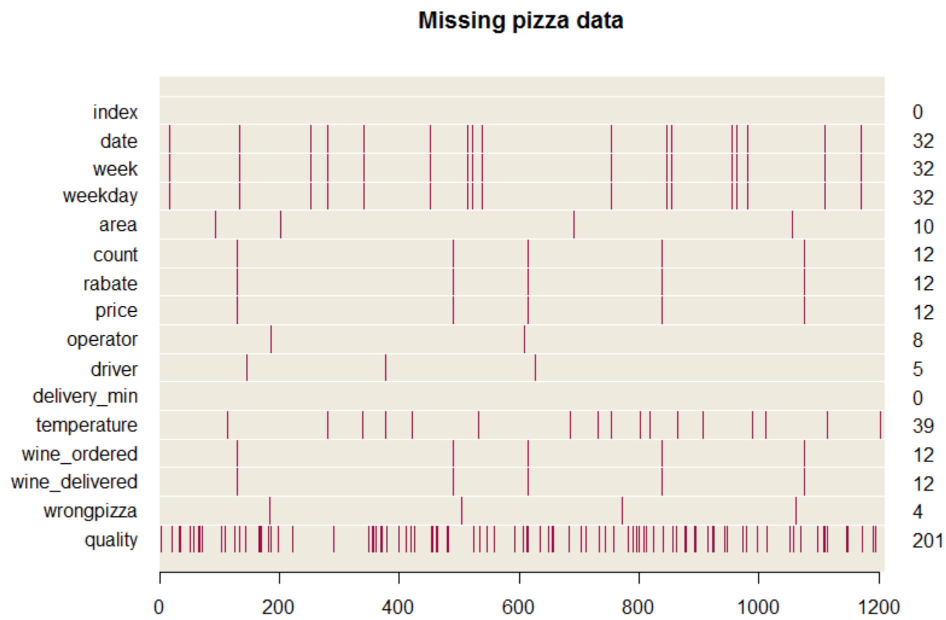


11 Multiple pairwises

```
Desc(temperature ~ ., data=d.pizza[,c("temperature","driver","operator","area")],
     digits=1)
```

12 Plot missing data

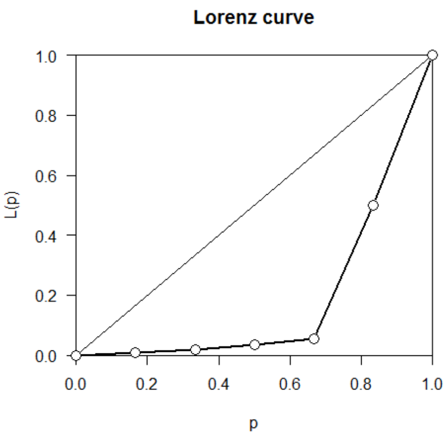
An interesting idea for creating a visual representation of missing data was brought to my attention by Henk Harmsen. The following plot symbolize each missing value with a vertical line. The x-axis represents the index of the record. On the right side are the numbers of missings noted.



13 Concentration

Lorenz-curves can be found in other libraries. This implementation starts with that from the library `ineq`, adding some value by calculating confidence intervals for the Gini coefficient.

```
x <- c(10, 10, 20, 20, 500, 560)

lc <- Lc(x)
plot(lc)
points(lc$p, lc$L, cex=1.5, pch=21, bg="white", col="black", xpd=TRUE)

Gini(x)
Gini(x, unbiased = FALSE)

Gini(x, conf.level = 0.95)
```



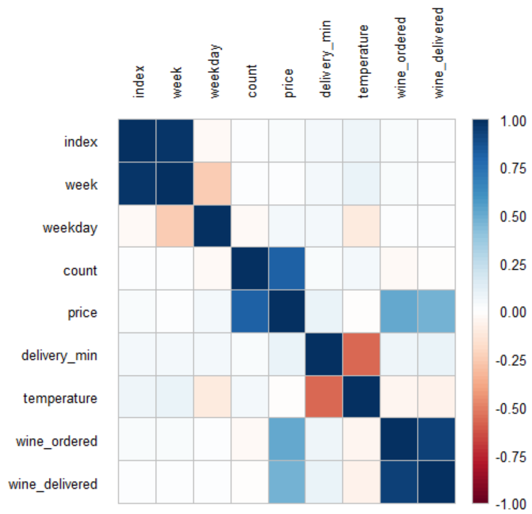

```
> Gini(x)
[1] 0.7535714

> Gini(x, unbiased = FALSE)
[1] 0.6279762

> Gini(x, conf.level=0.95)
     gini    lwr.ci    upr.ci
0.7535714 0.2000000 0.8967742
```

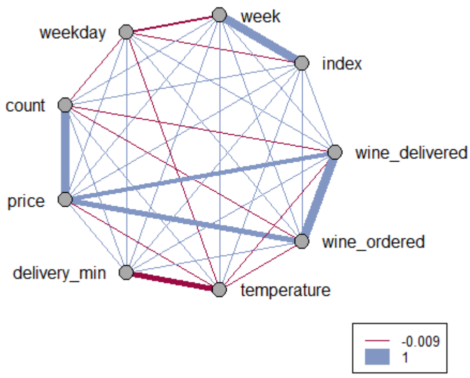
14 Multivariate graphical description

14.1 Correlation plot

These functions produce a graphical display of a correlation matrix. In the classic matrix representation the cells of the matrix can be shaded or coloured to show the correlation value. In the right circular representation the correlations are coded in the line width of the connecting lines. Red means a negative correlation, blue a positive one.

```
par(mfrow=c(1,2))
m <- cor(d.pizza[,which(sapply(d.pizza, is.numeric))], use="pairwise.complete.obs")

PlotCorr(m, col=PalDescTools("RedWhiteBlue1", 100), border="grey",
        args.colorlegend=list(labels=Format(seq(1,-1,-.25), 2), frame="grey"))

PlotWeb(m, col=c(hred, hblue))
```



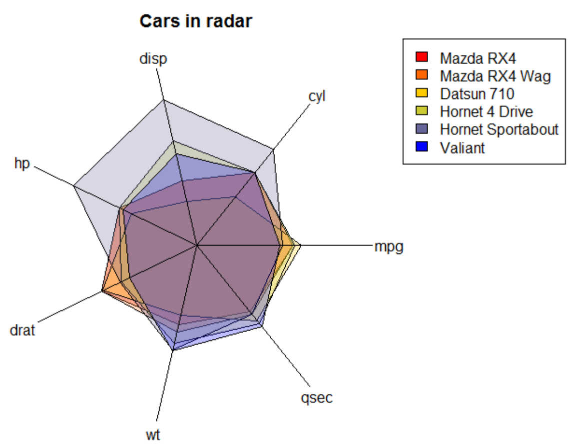


14.2 PlotPolar (Radarplot)

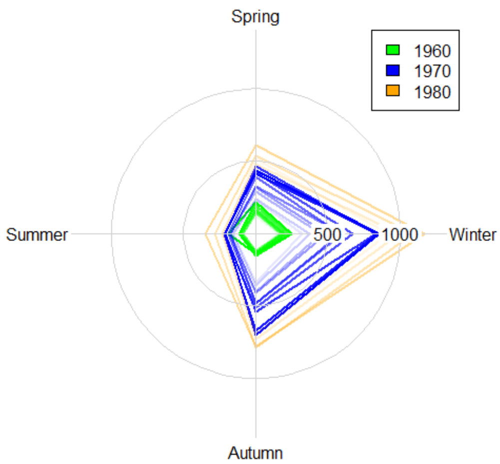
This function produces a polar plot but can also be used to draw radarplots or spiderplots.

A)

```
d.car <- scale(mtcars[1:6,1:7], center=FALSE)

# let's have a palette with thransparent colors
cols <- SetAlpha(colorRampPalette(c("red","yellow","blue"), space = "rgb")(6), 0.25)

PlotPolar(d.car, type="l", fill=cols, main="Cars in radar")
PolarGrid(nr=NA, ntheta=ncol(d.car), alabels=colnames(d.car), lty="solid", col="black")
legend(x=2, y=2, legend=rownames(d.car), fill=SetAlpha(cols, NA))
```



A)



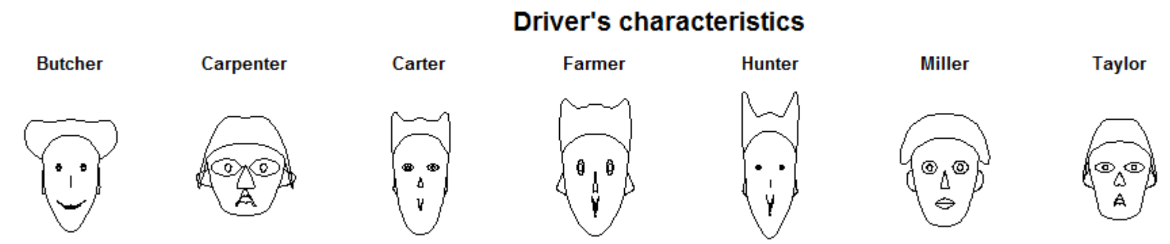
B)

```
B)

m <- matrix(UKgas, ncol=4, byrow=TRUE)

cols <- c(SetAlpha(rep("green", 10), seq(0,1,0.1)),
          SetAlpha(rep("blue", 10), seq(0,1,0.1)),
          SetAlpha(rep("orange", 10), seq(0,1,0.1)))

PlotPolar(r=m, type="l", col=cols, lwd=2 )
PolarGrid(ntheta=4, alabels=c("Winter","Spring","Summer","Autumn"), lty="solid")

legend(x="topright", legend=c(1960,1970,1980), fill=c("green","blue","orange"))
```

14.3 PlotFaces

A nice idea for the concrete representation of your customer's profile is to produce a Chernoff faces plot. The rows of a data matrix represent cases and the columns the variables.

```
m <- data.frame( lapply(
d.pizza[,c("temperature","price","delivery_min","wine_ordered","weekday")]
                         , tapply, d.pizza$driver, mean, na.rm=TRUE))

PlotFaces(m, ncol=7, nrow=1, main="Driver's characteristics")
```

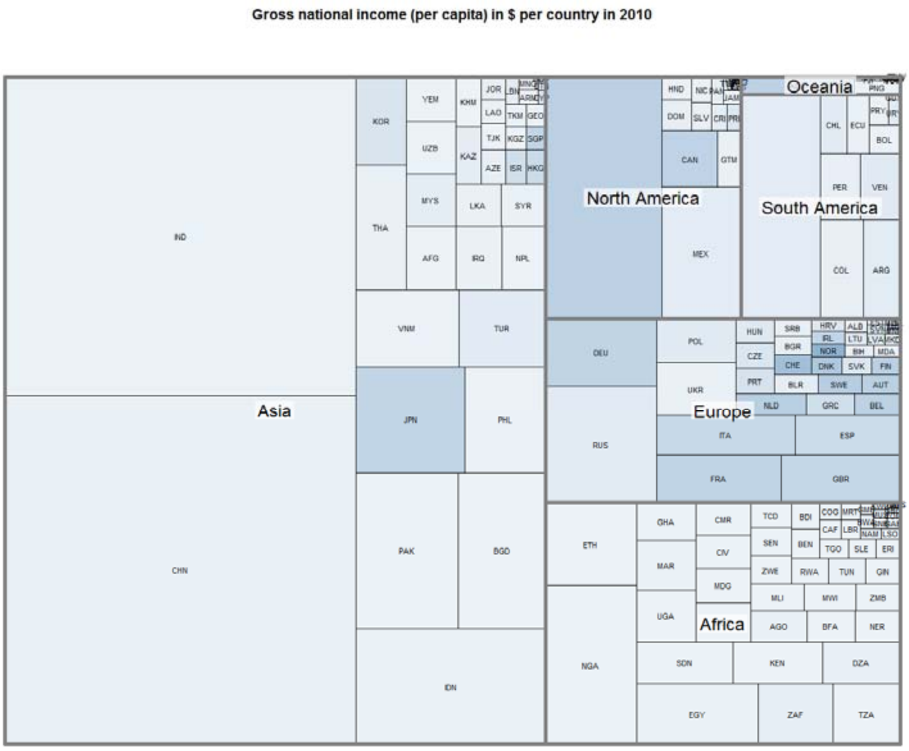


14.4 PlotTreemap

This function produces a treemap.

```
# get some data
data(GNI2010, package="treemap")
gn <- GNI2010[,c("iso3","population","continent","GNI")]
gn <- gn[gn$GNI!=0,]

# define a color
gn$col1 <- SetAlpha("steelblue", LinScale(gn$GNI, newlow=0.1, newhigh=0.6))


b <- PlotTreemap(x=gn$population, grp=gn$continent, col=gn$col1, labels=gn$iso3,
                 main="Gross national income (per capita) in $ per country in 2010",
                 labels.grp=NA, cex=0.7)

# get the midpoints
mid <- do.call(rbind, lapply(lapply(b, "[", 1), data.frame))

# and write the continents' text
```

```
DrawBoxedText(x=mid$grp.x, y=mid$grp.y, labels=rownames(mid), cex=1.5, bold=TRUE,
              border=NA, col=SetAlpha("white",0.7) )
```



15 Supplements to base R plots

15.1 Lineplots

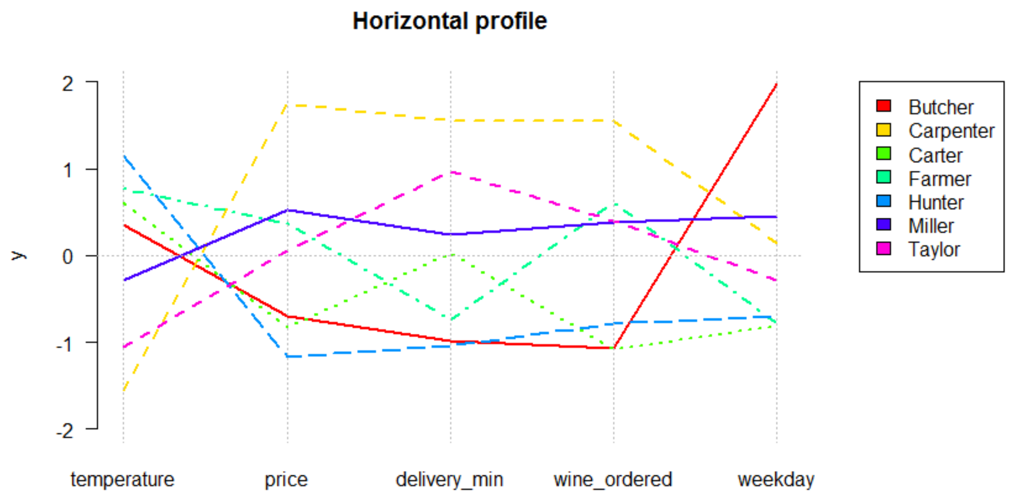
There are many flavours of line plots. Most (all?) of them can be handled by the function `matplot`.
We generally desist from defining own functions, that only set suitable arguments for another already existing function, as we fear we would run into a forest of new functions, loosing overview.

Yet the parametrization of `matplot` can be a haunting experience and so we integrate some common examples here in the sense of a “How-To” tutorial.

Let’s for example have a horizontal profile of the driver’s characteristics.

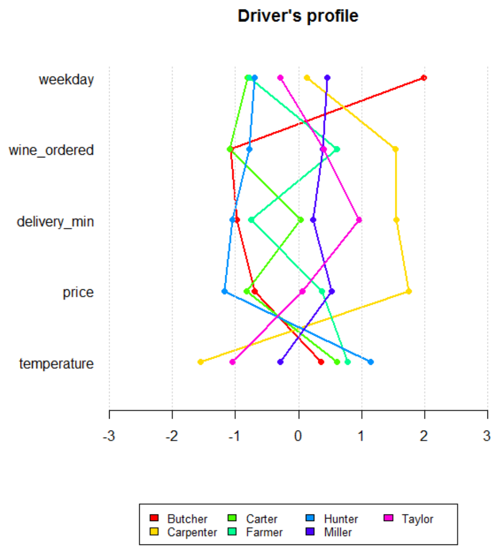
```
m <-
data.frame(lapply(d.pizza[,c("temperature","price","delivery_min","wine_ordered","weekday")],
                tapply, d.pizza$driver, mean, na.rm=TRUE))
(ms <- data.frame(lapply(m, scale)))         # lets scale that

          temperature       price delivery_min wine_ordered    weekday
Butcher     0.3605689 -0.69917381  -0.98046684   -1.0738446  1.9826284
Carpenter  -1.5481318  1.74805901   1.54851320    1.5445402  0.1389367
Carter      0.6105633 -0.82596309   0.02841316   -1.0840337 -0.8062020
Farmer      0.7718643  0.36562860  -0.74842415    0.6105001 -0.7800183
```

```
Hunter      1.1473246 -1.16829499  -1.04738479   -0.7792855 -0.7038441
Miller     -0.2918676  0.52072004   0.23662429    0.3794541  0.4596817
Taylor     -1.0503216  0.05902424   0.96272512    0.4026695 -0.2911825

x <- 1:ncol(ms)
y <- t(ms)

windows(8.8,5)
par(mar=c(5,4,4,10)+.1)
matplot(x, y, type="l", col=rainbow(nrow(ms)), xaxt="n", las=1, lwd=2, frame.plot=FALSE,
ylim=c(-2,2),
        xlab="", main="Horizontal profile")
abline(h=0, v=1:5, lty="dotted", col="grey")
par(xpd=TRUE)
legend(x=5.5, y=2, legend=rownames(ms), fill=rainbow(nrow(ms)))
axis(side=1, at=1:5, labels=colnames(ms), las=1, col="white")
```

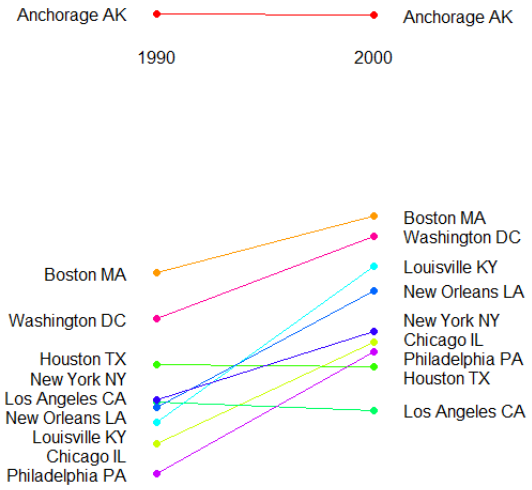


And the same, but on the vertical axis. (A)

```
par(mar=c(8,8,5,2))
matplot(x=y, y=x, type="l", pch=1:5, frame.plot=FALSE, axes=FALSE, xlab="", ylab="",
lty="solid",
        col=rainbow(nrow(ms)), xlim=c(-3,3), ylim=c(0.5,ncol(ms)), main="Driver's profile",
lwd=2)
matpoints(x=y, y=x, col=rainbow(nrow(ms)), pch=16)
grid(ny=NA)
axis(side=1, las=1)
mtext(colnames(ms), side=2, at=1:ncol(ms), las=2)
par(xpd=TRUE)
legend(x=0, y=-1, legend=rownames(ms), fill=rainbow(nrow(ms)), xjust=0.5, ncol=4, cex=0.8)
```



A)



B)

15.2 "Bumpchart"

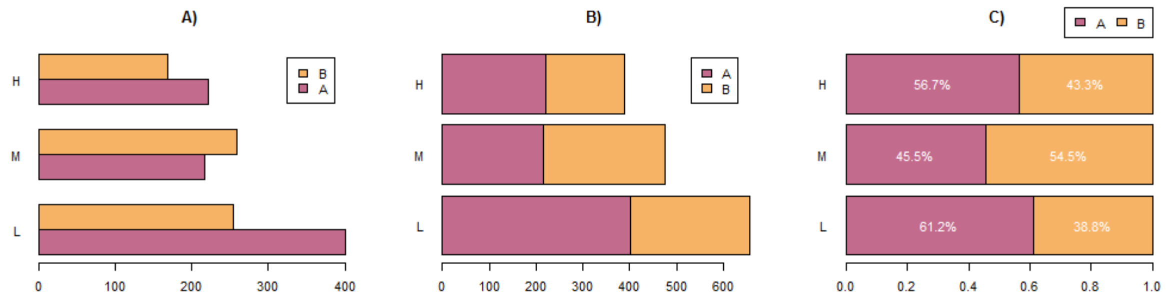
Plot B is sometimes called bumpchart (Jim Lemon).

```
# example from plotrix (bumpchart)
edu <- matrix(c(90.4,90.3,75.7,78.9,66,71.8,70.5,70.4,68.4,67.9,
                67.2,76.1,68.1,74.7,68.5,72.4,64.3,71.2,73.1,77.8), ncol=2, byrow=TRUE)
rownames(edu) <- c("Anchorage AK","Boston MA","Chicago IL",
                   "Houston TX","Los Angeles CA","Louisville KY","New Orleans LA",
                   "New York NY","Philadelphia PA","Washington DC")
colnames(edu) <- c(1990,2000)

par(mar=c(5,10,5,10))
matplot(x=1:2, y=t(edu), type="l", frame.plot=FALSE, axes=FALSE, xlab="",
        ylab="", lty="solid", col=rainbow(10))
matpoints(x=1:2, y=t(edu), pch=16, frame.plot=FALSE, axes=FALSE, xlab="",
          ylab="", lty="solid", col=rainbow(10))

sapply( 1:2, function(i) mtext(rownames(edu), side=2*i,
                      at=SpreadOut(edu[,i], mindist=1.1), line=1, las=1 ))
mtext(colnames(edu), side=3, at=1:2, line=-3.5, las=1 )
```

15.3 Barplot horizontal

A simple barplot, once with absolute values, once with percentages.

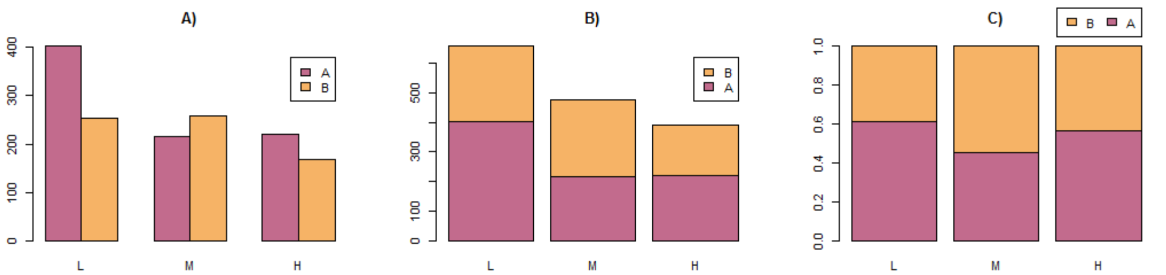
```
windows(height=3, width=11); par(mfrow=c(1,3))
col <- SetAlpha(PalHelsana(), 0.6)
tab <- matrix(c(401,216,221,254,259,169), nrow=2, byrow=TRUE,
       dimnames=list(wool=c("A","B"), tension=c("L","M","H")))
ptab <- prop.table(tab, 2)

# A)
barplot(tab, beside = TRUE, horiz=TRUE, main="A)",
        col = col[1:2], las = 1, legend = rownames(tab))
# B)
barplot(tab, beside = FALSE, horiz=TRUE, main="B)",
        col = col[1:2], las = 1, legend = rownames(tab))
# C)
b <- barplot(ptab, beside = FALSE, horiz=TRUE, main="C)",
             col = col[1:2], las = 1, legend.text = rownames(tab),
             args.legend = list(x=1, y=4.4, bg="white", ncol=2))

x <- t(apply(ptab, 2, Midx, incl.zero=TRUE, cumulate=TRUE))
text(paste(round(t(ptab),3) * 100, "%",sep=""), x=x, y=b, col="white")
```



15.4 Barplot vertical

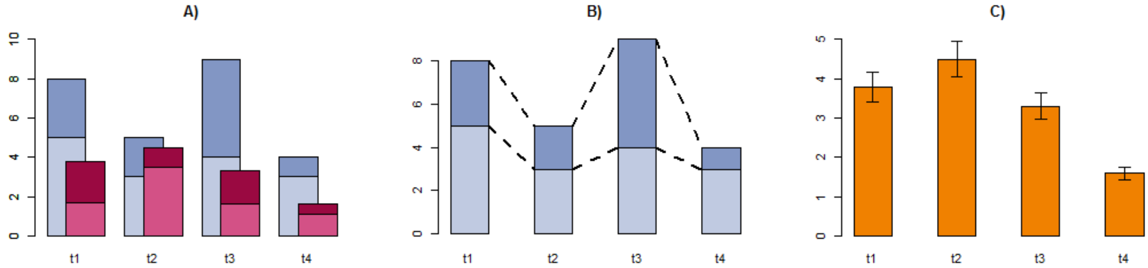
This same as above but with vertical bars.

```
# A)
barplot(tab, beside = TRUE, main="A)",
        col = col[1:2], legend = rownames(tab))
# B)
barplot(tab, beside = FALSE, main="B)",
        col = col,  legend = rownames(tab))
# C)
barplot(ptab, beside = FALSE, main="C)",
        col = col, legend.text = rownames(tab),
        args.legend = list(x=3.6, y=1.2, bg="white", ncol=2))
```



15.5 Barplot (specials)

Some specials like overlapping bars, connecting lines or error bars in combination with a barplot.

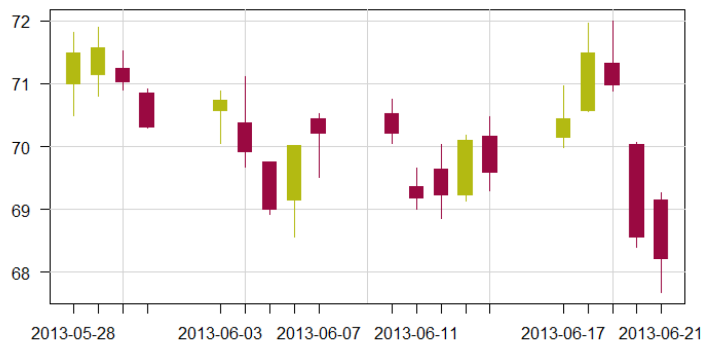



```
windows(height=3,11)
par(mfrow=c(1,3))

# A) Overlapping bars -----------------------------
blue <- rbind(c(5, 3, 4, 3),
              c(3, 2, 5, 1))
dimnames(blue) <- list(c("A","B"),c("t1","t2","t3","t4"))
red <- rbind(c(1.7,3.5,1.6,1.1),
              c(2.1,1.0,1.7,0.5))
dimnames(red) <- list(c("A","B"),c("t1","t2","t3","t4"))

# Set parameters
osp <- 0.5                # overlapping part in %
sp <- 1                   # spacing between the bars

nbars <- dim(blue)[2]   # how many bars do we have?

# Create first barplot
b <- barplot( blue, col=SetAlpha(hblue, c(0.5,1)), main="A)"
              , beside=FALSE, ylim=c(0,10), axisnames=FALSE
              , xlim=c(0, nbars*2-osp )       # enlarge x-Axis
              , space=c(0, rep(sp, nbars-1) ) # set spacing=1, starting with 0
             )
# Draw the red series
barplot( red, col= c(PalHelsana()[5], hred), beside=FALSE
         , space=c(1-osp, rep(1, nbars-1)) # shift to right by 1-osp
         , axisnames=FALSE, add=TRUE)

# Create axis separately, such that labels can be shifted to the left
axis(1, labels=colnames(red), at=b+(1-osp)/2, tick=FALSE, las=1)


# B) Connecting lines -----------------------------
barplot(blue, col= SetAlpha(hblue, c(0.5,1)), space=1.2, main="B)" )
ConnLines(blue, lwd=2, lty="dashed", space=1.2)


# C) Add error bars -------------------------------
cred <- apply(red, 2, sum)
b <- barplot(cred, col=horange, space=1.2, ylim=c(0,5), main="C)" )
ErrBars(from=cred * .90, to=cred * 1.1, pos=b)
```

15.6 PlotCandlestick

This plot is used primarily to describe price movements of a security, derivative or currency over time. Candlestick charts are a visual aid for decision making in stock, foreign exchange, commodity, and option trading.

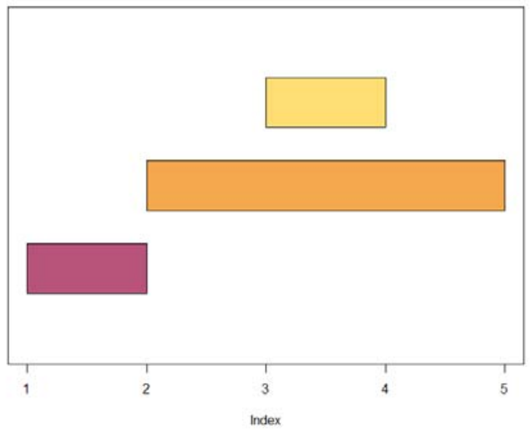
```
example(PlotCandlestick)
PlotCandlestick(x=as.Date(rownames(nov)), y=nov, border=NA, las=1, ylab="")
```



15.7 PlotHorizBar

This is a simple function for plotting flowing horizontal or vertical bars.

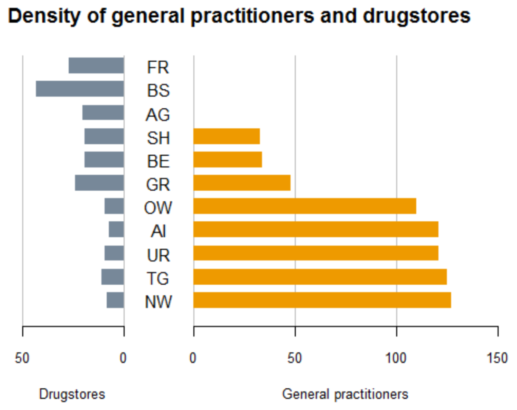
```
PlotHorizBar(from=c(1,2,3), to=c(2,5,4), grp=c(1,2,3), col=PalHelsana()[1:3])
```



15.8 PlotPyramid

A special kind of horizontal barplot is a "pyramid plot", where the bars are plotted back to back. This is sometimes needed, when your boss has specific and strict ideas how his presentation should look like.

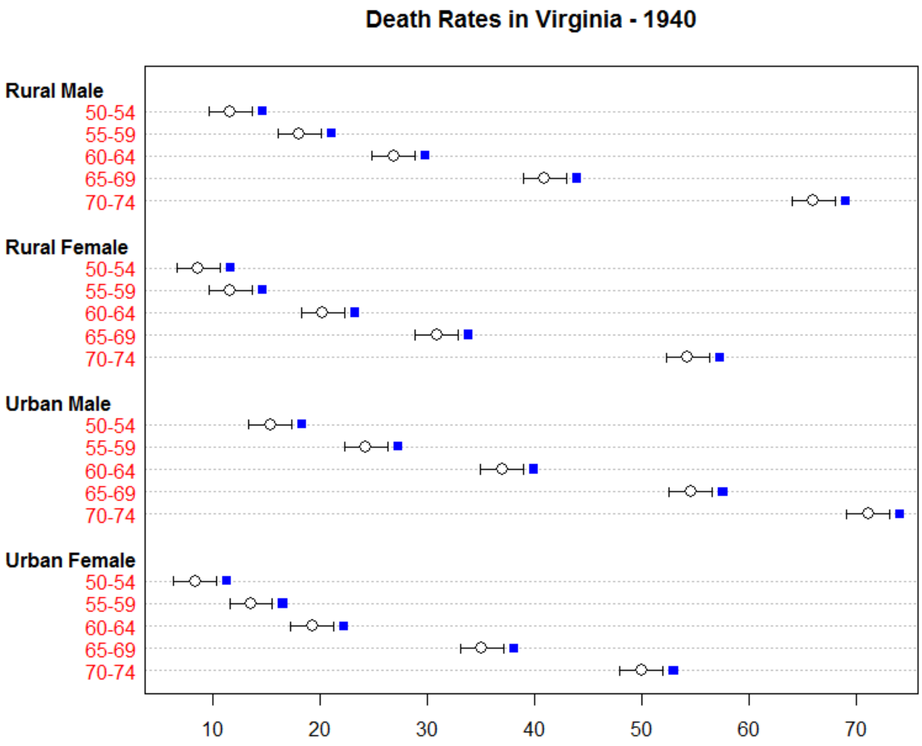
```
d.sda <- data.frame(
  kt_x  = c("NW","TG","UR","AI","OW","GR","BE","SH","AG","BS","FR"),
  apo_n = c(  8,  11,   9,   7,   9,  24,  19,  19,  20,  43,  27 ),
  sda_n = c(127, 125, 121, 121, 110,  48,  34,  33,   0,   0,   0 ))

PlotPyramid(lx=d.sda[,c("apo_n","sda_n")], ylab=d.sda$kt_x,
            col=c("lightslategray", "orange2"), border = NA, ylab.x=0, xlim=c(-110,250),
            gapwidth = NULL, cex.lab = 0.8, cex.axis=0.8, xaxt = TRUE,
            lxlab="Drugstores", rxlab="General practitioners",
            main="Density of general practitioners and drugstores",
            space=0.5, args.grid=list(lty=1))
```



15.9 PlotDot

The base function dotchart has been improved but still has some potential for extensions. Especially an add argument is sometimes useful and returning the y-coordinates for the points would allow to add elements.
PlotDot implements these extensions and allows adding error bars. This is interesting, as the calculation of the x-limits should be done with respect to the bars and not only to the points.

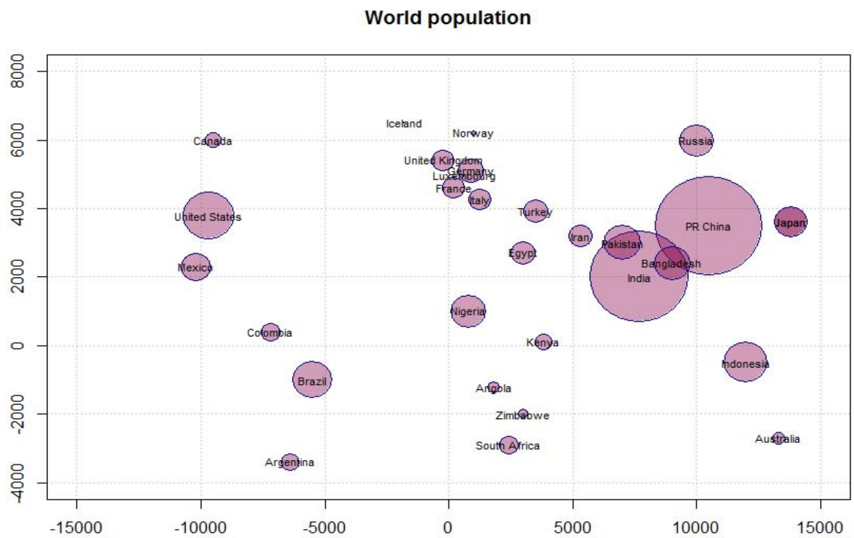
```
# add some error bars
PlotDot(VADeaths, main="Death Rates in Virginia - 1940", col="red", pch=NA,
        args.errbars = list(from=VADeaths-2, to=VADeaths+2, mid=VADeaths,
        pch=21, cex=1.4))

# add some other values
PlotDot(VADeaths+3, pch=15, col="blue", add=TRUE, labels=NA)
```



15.10 PlotBubble

Bubbles can actually easily be produced with the standard plot function. This function here helps you defining appropriate axis limits.

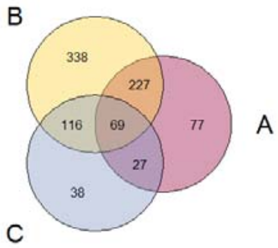
```
PlotBubble(d.world$x, d.world$y, area=d.world$pop/90, col=SetAlpha("deeppink4",0.4),
border="darkblue",
           xlab="", ylab="", panel.first=grid(), main="World population")
text(d.world$x, d.world$y, labels=d.world$country, cex=0.7, adj=0.5)
```



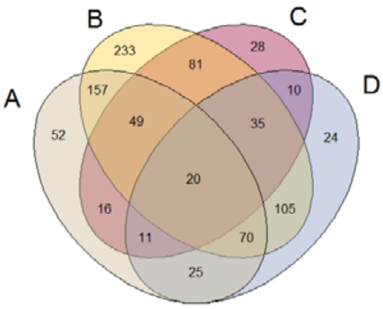
15.11 Venn plots

In rare cases one might want to plot a Venn diagram. This function does this for up to 5 datasets using the simple proposed geometric representations.
(For more than 5 datasets the Venn representation loses its simplicity and other plot types become more adequate.)

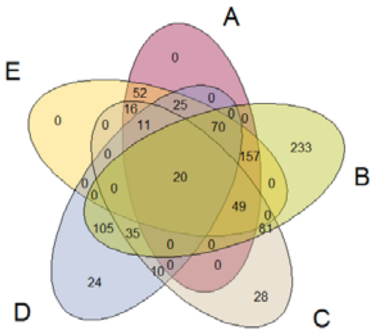
```
example(PlotVenn)
PlotVenn(x=x[1:3], col=SetAlpha(c(PalHelsana()[c(1,3,6)]), 0.4))
PlotVenn(x=x[1:4], col=SetAlpha(c(PalHelsana()[c(1,3,6,4)]), 0.4))
PlotVenn(x=x[1:5], col=SetAlpha(c(PalHelsana()[c(1,3,6,4,7)]), 0.4))
```



3 sets



4 sets



5 sets

15.12 Areaplot

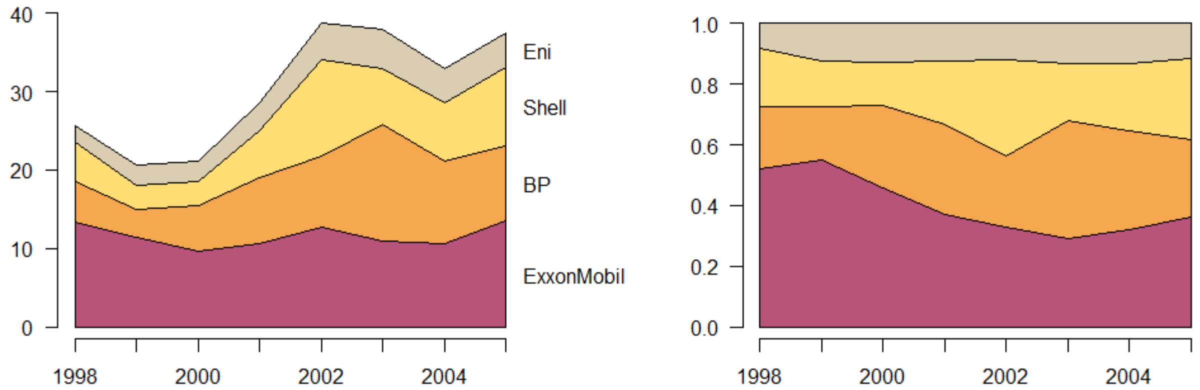
Areaplots have a high “ink factor”[1], say they use much ink to display the information and are therefore rarely the best way of representing data. But again, when your boss wants it this way, here’s a function to produce it easily.

```
t.oil <- t(matrix(c(13.3,11.4, 9.7,10.6,12.7,11.0,10.6,13.5,
                    5.3, 3.6, 5.8, 8.4, 9.1,14.8,10.6, 9.6,
                    4.9, 3.1, 3.0, 6.0,12.2, 7.1, 7.3,10.0,
                    2.1, 2.6, 2.7, 3.5, 4.7, 5.0, 4.4, 4.3), nrow=4, byrow=TRUE,
   dimnames = list(c("ExxonMobil","BP","Shell","Eni"),
                      c("1998","1999","2000","2001","2002","2003","2004","2005"))))
t(t.oil)

par(mfrow=c(1,2), mar=c(5,4,5,5))
col <- SetAlpha(PalHelsana(), 0.7)
PlotArea(t.oil, col = col, las = 1, frame.plot=FALSE)
mtext(side=4, text=colnames(t.oil), las=1,
      at=Midx(tail(t.oil, 1)[,], incl.zero=TRUE, cumulate=TRUE))

PlotArea(prop.table(t.oil, 1), col = col, las = 1, frame.plot=FALSE)
```

```
tab (absolute values)
> t(t.oil)
           1998 1999 2000 2001 2002 2003 2004 2005
ExxonMobil 13.3 11.4  9.7 10.6 12.7 11.0 10.6 13.5
BP          5.3  3.6  5.8  8.4  9.1 14.8 10.6  9.6
Shell       4.9  3.1  3.0  6.0 12.2  7.1  7.3 10.0
Eni         2.1  2.6  2.7  3.5  4.7  5.0  4.4  4.3
```

[1] Tufte, Edward R (2001) [1983], The Visual Display of Quantitative Information (2nd ed.), Cheshire, CT: Graphics Press, ISBN 0-9613921-4-2.

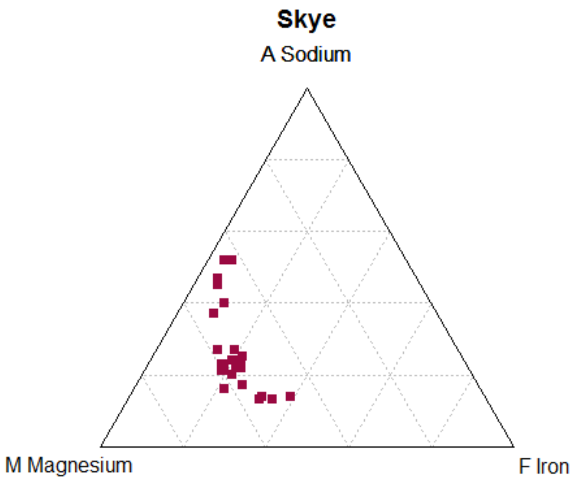
```
ptab (relative values)
            1998  1999  2000  2001  2002  2003  2004  2005
ExxonMobil 0.520 0.551 0.458 0.372 0.328 0.290 0.322 0.361
BP         0.207 0.174 0.274 0.295 0.235 0.391 0.322 0.257
Shell      0.191 0.150 0.142 0.211 0.315 0.187 0.222 0.267
Eni        0.082 0.126 0.127 0.123 0.121 0.132 0.134 0.115
```



15.13 PlotTernary

This produces a ternary or triangular plot.

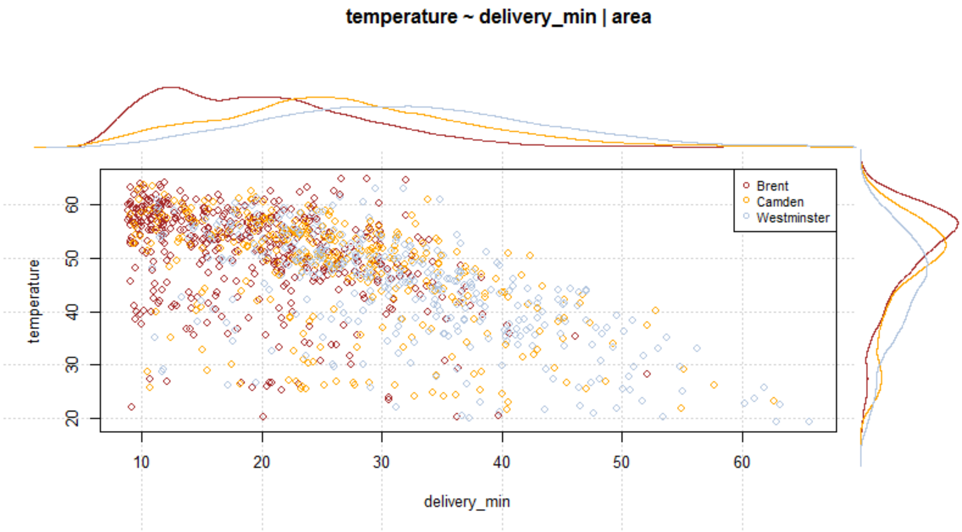
```
data(Skye, package="MASS")
PlotTernary(Skye[c(1,3,2)], pch=15, col=hred, main="Skye",
            lbl=c("A Sodium", "F Iron", "M Magnesium"))
```



15.14 PlotMarDens

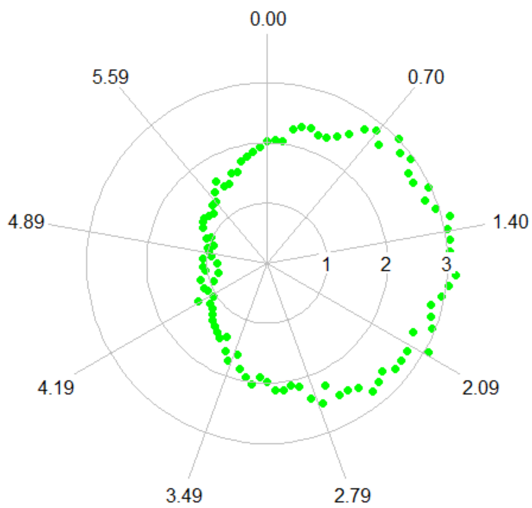
This plot shows a scatterplot of two numerical variables temperature and delivery_time, by area. On the margins the density curves of the specific variable are plotted, also stratified by area.

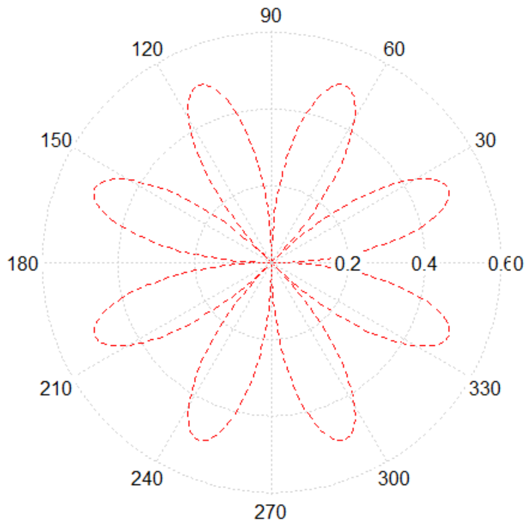
```
PlotMarDens(y=d.pizza$temperature, x=d.pizza$delivery_min, grp=d.pizza$area,
            xlab="delivery_min", ylab="temperature",
            col=c("brown","orange","lightsteelblue"), panel.first=grid(),
            main="temperature ~ delivery_min | area"  )
```



15.15 Polar plots

```
testlen <- c(sin(seq(0, 1.98*pi, length=100)) + 2 + rnorm(100)/10)
testpos <- seq(0, 1.98*pi, length=100)
# start at 12 o'clock and plot clockwise
PlotPolar(testlen, -(testpos - pi/2), type="p", main="Test Polygon", col="green", pch=16)

PolarGrid(ntheta = rev(seq(0, 2*pi, by=2*pi/9) + pi/2),
          alabels=Format(seq(0, 2*pi, by=2*pi/9),2)[-10], col="grey",
          lty="solid", lblradians=TRUE)

# just because of its beauty
t <- seq(0,2*pi,0.01)

PlotPolar(r=sin(2*t)*cos(2*t), theta=t, type="l", lty="dashed", col="red")
PolarGrid()
```

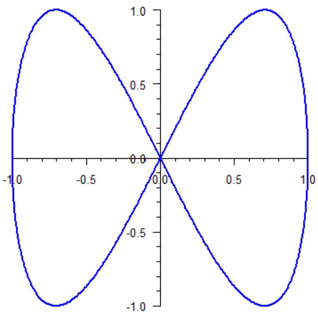


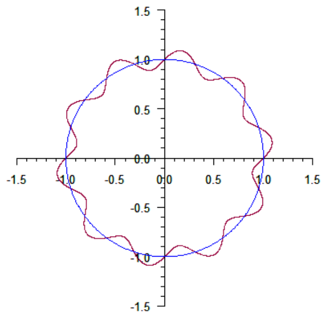


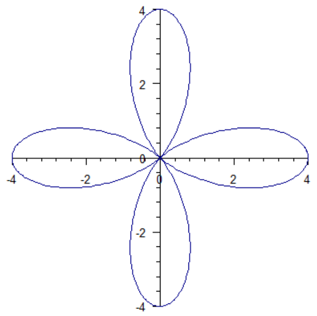
15.16 Plot Functions

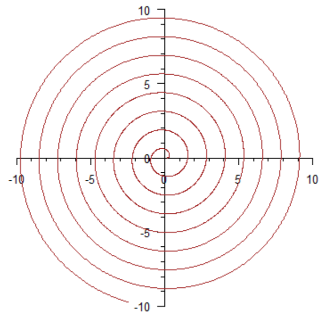
Functions can be plotted a bit more comfortable by means of the function PlotFct. The idea is to be able to use the formula interface, for example x^2 ~ x, and let the function choose appropriate defaults for the rest. (This would be the best case scenario…;-).
There can as well be further parameters defined for plotting more than one function at once.

```
# get some data
par(mfrow=c(2,2))
PlotFun(sin(2*t) ~ sin(t), from=0, to=2*pi, by=0.01, col="blue", lwd=2)

PlotFun(1+ 1/10 * sin(10*x) ~ x, polar=TRUE, from=0, to=2*pi, by=0.001, col=hred)
PlotFun(sin(x) ~ cos(x), polar=FALSE, from=0, to=2*pi, by=0.01, add=TRUE, col="blue")

# lemniscate of Bernoulli
PlotFun((2*a^2*cos(2*t))^2 ~ t, args=list(a=1), polar=TRUE, from=0, to=2*pi+0.1, by=0.01,
        col="darkblue")

# evolving circle
PlotFun(a*(sin(t) - t*cos(t)) ~ a*(cos(t) + t*sin(t)), args=list(a=0.2), from=0, to=50,
by=0.01,
        col="brown")
```


1.0
0.5
0.0
-0.5
-1.0
-1.0
-0.5
0.0
0.5
1.0


1.5
1.0
0.5
0.0
-0.5
-1.0
-1.5
-1.5
-1.0
-0.5
0.0
0.5
1.0
1.5

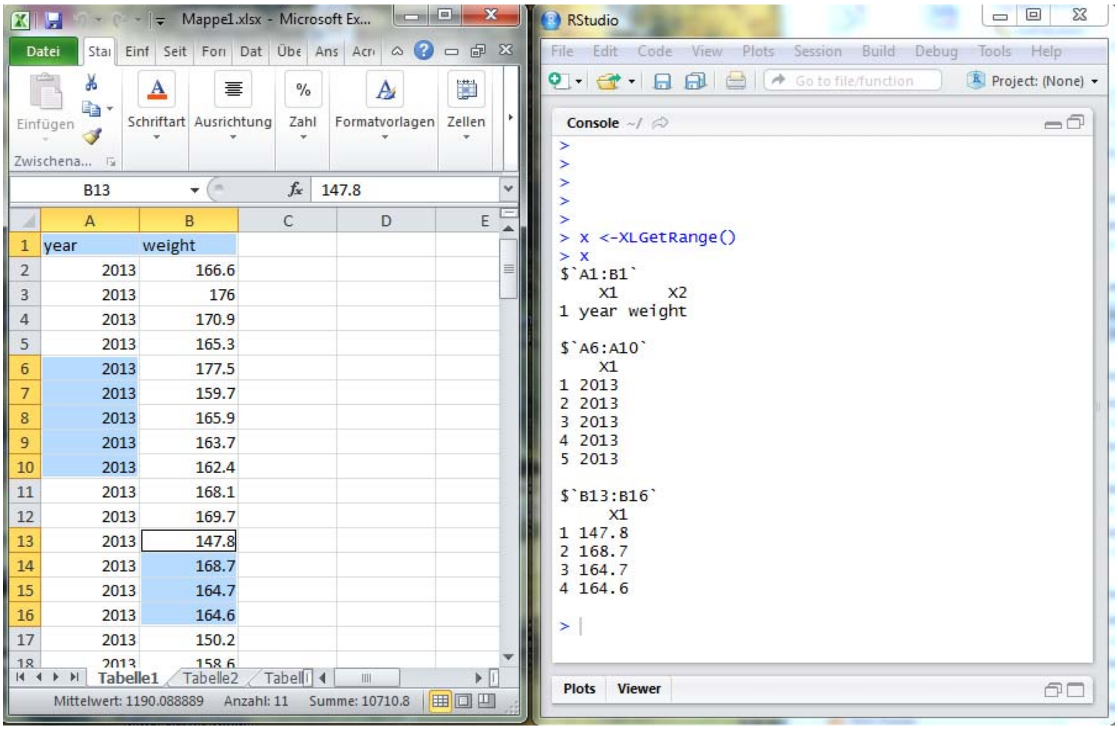

4
2
0
-2
-4
-4
-2
0
2
4


10
5
0
-5
-10
-10
-5
0
5
10

16 Import – Export

16.1 Import data via Excel

The function XLGetRange allows a quick import of data from an Excel-Sheet. The user can either specify a number of cell-references (including a path- and filename) or just select the regions which are to be imported.
The following command will return a list with the contents of the selected cell ranges.



XLView(d.frm) can be used to view a data.frame d.frm in Excel.

16.2 Import SAS datalines

The function ParseSASDatalines can be used to import the SAS data like the following:

```
sas <- "
  data FatComp;
  input Exposure Response Count;
  label Response='Heart Disease';
  datalines;
    0 0  6
    0 1  2
    1 0  4
    1 1 11
 ;"

(FatComp <- ParseSASDatalines(sas))

  Exposure Response Count
1        0        0     6
2        0        1     2
3        1        0     4
4        1        1    11
```

17 References

http://cran.r-project.org/web/packages/vcdExtra/vignettes/vcd-tutorial.pdf

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Vittinghoff, E., Glidden, D. V., Shiboski, S. C., and Mcculloch, C. E. (2005) Regression Methods in Biostatistics: Linear, Logistic, Survival, and Repeated Measures Models. Springer, New York

http://support.sas.com/documentation/cdl/en/statugfreq/63124/PDF/default/statugfreq.pdf

http://www.stat.ufl.edu/~presnell/Courses/sta4504-2011sp/Notes/icda-notes-3x2.pdf

Agresti, A. (2002) Categorical Data Analysis. John Wiley & Sons.

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