Portfolio Management with R

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Package version 0.19.6
17 August 2024

Contents

1 Introduction

1.1 About PMwR

This book describes how to use the PMWR package. PMWR provides a small set of reliable, efficient and convenient tools that help in processing and analysing trade and portfolio data. PMWR grew out of various pieces of software that I have written since 2008, first at the University of Geneva, later during my work at financial firms.

The package has changed considerably over the years – its early years, in particular.[1] This was partly to accommodate my own needs, and partly also reflecting my learning of the R language and changing views how software should work. And while I still consider the package under reasonably-active development, is has in its current form become fairly stable, notably functions such as `btest`, `returns`, `journal` and `position`. I have written so much code that relies on these functions that I cannot afford to change them.

Nevertheless, several parts still need grooming (I think), so I reserve the right to change them. Any such changes will be announced in the NEWS file (including instructions how to adapt exisiting code), and will be reflected in this manual. I am grateful for comments and suggestions. The book itself is written in Org mode. The text was then exported to HTML and LaTeX; the latter processed with TeX Live. The complete tangled code is available from the book's website.

The PMWR package has been on CRAN since 2018; to install the package, simply type

```
install.packages("PMwR")
```

in an R session. The development version of the package is available from `https://enricoschumann.net/R/packages/PMwR/`. To get the development version from within R, use the following command:

[1] The package was called `PM` until 2012. Also, much of its functionality has over the years been moved to separate packages, of which several made their way to CRAN, such as `datetimeutils`, `mailtools`, `textutils` and `tsdb`.

```
install.packages("PMwR",
                 repos = c('https://enricoschumann.net/R',
                           getOption('repos')))
```

The package depends on several other packages, which are automatically obtained from the same repository and from CRAN. The package's source code is also pushed to public repositories at

`https://git.sr.ht/~enricoschumann/PMwR`
and

`https://gitlab.com/enricoschumann/PMwR`
and

`https://github.com/enricoschumann/PMwR`.
Recent versions of the package (since `0.3-4`, released in 2016) are pure R code and can be built without any prerequisites except an R installation; older versions contained C code, so you needed to have the necessary tool chain installed, typically by installing Rtools.

1.2 Principles

small The aim of PMWR is to provide a *small* set of tools.[2] This comes at a price: interfaces might be more complicated, with arguments being overloaded. But with only few functions, it is easier to remember a function name or to find a function in the first place.

flexible and general PMWR aims to be open to different types of instruments, different timestamps, etc. (In this respect, I consider the `zoo` package a rolemodel for how a package should work: blend well with standard data structures, be idiomatic, flexible with regards to date/time classes, ...)

functional To quote from chapter 1 of K&R: 'With properly designed functions, it is possible to ignore *how* a job is done; knowing *what* is done is sufficient'. PMWR emphasizes computations: transforming simple and transparent data structures into other data structures. In R, a computation means calling a function. There are many good reasons for using functions:

[2] A great inspiration for 'smallness' were the principles behind the tools that make working on a Unix-type operating system so productive (and so much fun). In particular, that a programme should do one thing only (but thoroughly). See for instance Raymond (2003) or Gancarz (2003). Another inspiration came from the Lua language, which I used much in the past. Lua even removed functions to make the language even smaller. Closer to finance, there is the Ledger project.

- clearer code; code is easier to reuse and to maintain
- functions provide a clear view of what is needed for a specific computation (i.e. the function arguments), and so functions help doing parallel/distributed computing
- it is easier to test functionality
- because of R's pass-by-value principle, input data is not changed, which makes code more reliable
- clean workspace after function call has ended

There are even more advantages, actually; such as the application of functional techniques such as memoisation. (See e.g. Dominus, 2005, for many examples.)

Computations provided by PMWR do not – for developers: should not – rely on global options/settings. The exception are functions that are used interactively, which essentially means `print` methods. (In scripts or methods, `cat` is preferred.)

matching by name Whenever possible and intuitive, data should be matched by name, not by position. This is most natural with vectors that store scalar information about instruments, such as prices or multipliers. In such cases, data input is preferred in the form of named vectors. (In other languages, we would use a hashtable instead of a vector.)

vectorization Functions should do vectorization when it is beneficial in terms of speed or clarity of code. Likewise, functions should work on matrices directly (typically columnwise) when it simplifies or speeds things up. Otherwise, applying the function (i.e. looping) should be left to the user.

An example may clarify this: `drawdown`, as provided by the NMOF package, is internally computed through `cumsum`, so it will be fast for a single vector. But for a matrix of time series, it would need a loop, which will be left to the user. On the other hand, returns can be computed efficiently for a matrix, so the function `returns` directly handles matrices of prices.

1.3 Setting up R

In this manual, all R output will be presented in English. In case you run R in a different locale, but want to receive messages in English, type this:

```
Sys.setenv(LANGUAGE = "en")
```

Or, since R version 4.2:

```
Sys.setLanguage(lang = "en")
```

1.4 Typographical conventions

R code is shown in a typewriter font like this.

```
1+1
```

The results of a computation are shown as follows:

```
[1] 2
```

Note that R output is marked with a vertical line at the left margin, so that it can more easily be distinguished from the input.

2 Keeping track of transactions: journals

2.1 Overview

The ultimate basis of many financial computations are lists of transactions. PMWR provides an S3 class `journal` for handling such lists. A `journal` is a list of atomic vectors, to which a class attribute is attached. (Thus, a `journal` is similar to a data-frame.[1]) Such a list is created through the function `journal`. Methods should not rely on this list being sorted in any particular way: components of a journal should always be retrieved by name, never by position. (In this respect a journal differs from a data-frame, for which we can meaningfully refer to the *n*-th column.) A journal's components, such as `amount` or `timestamp`, are called *fields* in this manual.

The simplicity of the class is intended, because it is meant for interactive analyses. The user may – and is expected to – dissect the information in a `journal` at will; such dissections may include removing the class attribute.

2.2 Fields

What is actually stored in a `journal` is up to the user. A number of fields are, however, required for certain operations and so it is recommended that they be present:

`amount` The notional amount that is transacted. `amount` is, in a way, the most important property of a journal. When functions compute statistics from the journal (the number of transactions, say), they will often look at `amount`.

[1] Only similar: a data-frame may contain non-atomic vectors, a.k.a. lists.

`timestamp` When did the transaction take place? A numeric or character vector; should be sortable.

`price` Well, price. Well, there are many types of prices. The price specified in a journal can be used to compute profit/loss, so the difference between prices should be proportional to profit/loss for the transactions. Unfortunately, there are many instruments that are not quoted in transaction prices: Options may be quoted in implied volatility, say, or bonds in yield. For such instruments, the net-asset value (NAV) should be used.

`instrument` Description of the financial instrument; typically an identifier, a.k.a. ticker or symbol. That is, a string or perhaps a number;[2] but not a more-complex object (recall that journals are lists of atomic vectors).

`id` A transaction identifier, possibly but not necessarily unique.

`account` Description of the account (a string or perhaps a number).

`...` other fields. They must be named, as in `fees = c(1, 2, 1)`.

All fields except `amount` can be missing. Such missing values will be 'added back' as `NA` with the exception of `id` and `account`, which will be `NULL`. To be clear: `amount` could be a vector of only `NA` values, but it cannot be left out when the journal is created. (This will become clearer with the examples below.)

A journal may have no transactions at all in it. In such a case all fields have length zero, e.g. `amount` would be `numeric(0)`. Such empty journals can be created by saying `journal()` or by coercing a zero-row data-frame to a journal, via a call to `as.journal`.

Transactions in a journal may be organised in hierarchies, such as

```
account => subaccount => subsubaccont => ... => instrument
```

This is useful and necessary when you have traded an instrument for different accounts, say, or as part of different strategies. Such a hierarchy may be completely captured in the instrument field, by concatenating account hierarchy and instrument using a separator pattern such as `::`.[3] The result would be 'namespaced' instruments such as `Pension::Equities::AMZN`. Alternatively, part of the hierarchy may be stored in the `account` field.

[2] Numbers have to be converted to character in some situations, for instance when used as names.
[3] This notation is inspired by the syntax of `ledger` files. See `https://www.ledger-cli.org/` .

2.3 Creating and combining journals

The function `journal` creates journal objects. See `?journal` for details about the function and about methods for `journal` objects. At its very minimum, a journal must contain amounts of something.

```
J <- journal(amount = c(1, 2, -2, 3))
J
```

```
  amount
1      1
2      2
3     -2
4      3

4 transactions
```

Actually, that is not true. Sometimes it is useful to create an empty journal, one with no entries at all. You can do so by saying `journal()`, without any arguments.

```
journal()
```

```
no transactions
```

To see the current balance, which is nothing more than the sum over all amounts, you can use `position`.

```
position(J)
```

```
4
```

Suppose you wanted to note how many bottles of milk and wine you have stored in your cellar. Whenever you add to your stock, you have a positive amount; whenever you retrieve bottles, you have a negative amount. Then, by keeping track of transactions, you do not have to take stock (apart, perhaps, from occasional checking that you did not miss a transaction), as long as you keep track of what you put into your cellar and what you take out.

There may be some analyses you can do on flows alone: you may check your drinking habits for patterns, such as slow accumulation of wine, followed by rapid consumption; or the other way around. But typically, you will want to analyse your transactions later, and then the more information you record about them – when, what, why, at what price, etc. –, the better. Journals allow you to store such information. To show how they are used, let us switch to a financial example.

Suppose you have transacted the following trades.

```
|  timestamp | account | instrument | amount |   price | note        |
|------------+---------+------------+--------+---------+-------------|
| 2017-08-01 | Pension | AMZN       |     10 | 1001.00 |             |
| 2017-08-01 | Pension | MSFT       |    220 |   73.10 |             |
| 2017-07-14 | Trading | AMZN       |     10 | 1001.50 |             |
| 2017-07-31 | Trading | AMZN       |     -5 | 1014.00 | take profit |
| 2017-08-15 | Trading | AMZN       |     10 |  985.50 |             |
| 2017-10-05 | Pension | MSFT       |     70 |   74.40 |             |
```

This table is formatted in Org syntax, and throughout this chapter we will present trade information in this format. The function `org_journal` converts such a table into a `journal`.

```
org_journal <-
function(file, text, timestamp.as.Date = TRUE) {
  ans <- orgutils::readOrg(text = text)
  if (timestamp.as.Date && "timestamp" %in% colnames(ans))
    ans$timestamp <- as.Date(ans$timestamp)
  ans <- as.journal(ans)
  ans
}
```

We read the table into a journal `J`.

```
J
```

```
   instrument   timestamp  amount   price  account         note
1        AMZN  2017-08-01      10  1001.0  Pension
2        MSFT  2017-08-01     220    73.1  Pension
3        AMZN  2017-07-14      10  1001.5  Trading
4        AMZN  2017-07-31      -5  1014.0  Trading  take profit
5        AMZN  2017-08-15      10   985.5  Trading
6        MSFT  2017-10-05      70    74.4  Pension

6 transactions
```

A `print` method defines how a journal is displayed. See `?print.journal` for details. In general, you can always get help for methods for generic functions by saying `?<generic_function>.journal`, e.g. `?print.journal` or `?as.data.frame.journal`.

```
print(J, max.print = 2, exclude = c("account", "note"))
```

```
   instrument   timestamp  amount   price
1        AMZN  2017-08-01      10  1001.0
2        MSFT  2017-08-01     220    73.1
[ .... ]

6 transactions
```

A `str` method shows the fields in the journal.

```
str(J)
```

```
'journal':       6 transactions
 $ instrument: chr [1:6] "AMZN" "MSFT" "AMZN" "AMZN" ...
 $ account   : chr [1:6] "Pension" "Pension" "Trading" ...
 $ timestamp : Date[1:6], format: "2017-08-01" ...
 $ amount    : int [1:6] 10 220 10 -5 10 70
 $ price     : num [1:6] 1001 73.1 1001.5 1014 985.5 ...
 $ note      : chr [1:6] "" "" "" "take profit" ...
```

You may notice that the output is similar to that of a `data.frame` or `list`. That is because `J` is a `list` of atomic vectors, with a class attribute. Essentially, it is little more than a list of the columns of the above table.

But note that `journal` would silently have added required fields such as `price`, initialised as `NA`.

```
str(journal(amount = 1))
```

```
'journal':     1 transaction
 $ instrument: chr NA
 $ timestamp : num NA
 $ amount    : num 1
 $ price     : num NA
```

In the example, the timestamps are of class `Date`. But essentially, any vector of mode character or numeric can be used, for instance `POSIXct`, or other classes. Here is an example that uses the `nanotime` package (Eddelbuettel, 2017).

```
library("nanotime")
journal(amount = 1:3, timestamp = nanotime(Sys.time()) + 1:3)
```

```
                            timestamp  amount
1  2020-08-09T08:27:19.812951001+00:00       1
2  2020-08-09T08:27:19.812951002+00:00       2
3  2020-08-09T08:27:19.812951003+00:00       3

3 transactions
```

Journals can be combined with `c`.

```
J2 <- J
J2$note <- rep("copy", length(J))
c(J, J2)
```

```
    instrument   timestamp  amount   price  account          note
1         AMZN  2017-08-01      10  1001.0  Pension
2         MSFT  2017-08-01     220    73.1  Pension
3         AMZN  2017-07-14      10  1001.5  Trading
4         AMZN  2017-07-31      -5  1014.0  Trading  take profit
5         AMZN  2017-08-15      10   985.5  Trading
6         MSFT  2017-10-05      70    74.4  Pension
7         AMZN  2017-08-01      10  1001.0  Pension          copy
8         MSFT  2017-08-01     220    73.1  Pension          copy
9         AMZN  2017-07-14      10  1001.5  Trading          copy
10        AMZN  2017-07-31      -5  1014.0  Trading          copy
11        AMZN  2017-08-15      10   985.5  Trading          copy
12        MSFT  2017-10-05      70    74.4  Pension          copy

12 transactions
```

The new combined journal will not be sorted by date. In general, a journal need not be sorted in any particular way. There is a `sort` method for journals, whose default is to sort by timestamp. We can also sort by other fields, for instance by amount.

```
sort(c(J, J2), by = c("amount", "price"), decreasing = FALSE)
```

```
    instrument   timestamp  amount   price  account          note
1         AMZN  2017-07-31      -5  1014.0  Trading  take profit
2         AMZN  2017-07-31      -5  1014.0  Trading          copy
3         AMZN  2017-08-15      10   985.5  Trading
4         AMZN  2017-08-15      10   985.5  Trading          copy
5         AMZN  2017-08-01      10  1001.0  Pension
6         AMZN  2017-08-01      10  1001.0  Pension          copy
7         AMZN  2017-07-14      10  1001.5  Trading
8         AMZN  2017-07-14      10  1001.5  Trading          copy
9         MSFT  2017-10-05      70    74.4  Pension
10        MSFT  2017-10-05      70    74.4  Pension          copy
11        MSFT  2017-08-01     220    73.1  Pension
12        MSFT  2017-08-01     220    73.1  Pension          copy

12 transactions
```

You can query the number of transactions in a journal with `length`.

2.4 Selecting transactions

In an interactive session, you can use `subset` to select transactions.

```
subset(J, amount > 10)
```

```
   instrument   timestamp  amount  price  account  note
1        MSFT  2017-08-01     220   73.1  Pension
2        MSFT  2017-10-05      70   74.4  Pension

2 transactions
```

With `subset`, you need not quote the expression that selects trades and you can directly access a journal's fields. Because of the way `subset` evaluates its arguments, it should not be used within functions. (See the Examples section in `?journal` for what can happen then.)

More generally, to extract or change a field, use its name, either through the `$` operator or double brackets `[[...]]`.[4]

```
J$amount
```

```
[1]  10 220  10  -5  10  70
```

You can also replace specific fields.

```
J$note[1] <-  "some␣note"
J
```

```
   instrument   timestamp  amount   price  account         note
1        AMZN  2017-08-01      10  1001.0  Pension    some note
2        MSFT  2017-08-01     220    73.1  Pension
3        AMZN  2017-07-14      10  1001.5  Trading
4        AMZN  2017-07-31      -5  1014.0  Trading  take profit
5        AMZN  2017-08-15      10   985.5  Trading
6        MSFT  2017-10-05      70    74.4  Pension

6 transactions
```

The `` `[` `` method works with integers or logicals, returning the respective transactions.

```
J[2:3]
```

```
   instrument   timestamp  amount   price  account  note
1        MSFT  2017-08-01     220    73.1  Pension
2        AMZN  2017-07-14      10  1001.5  Trading

2 transactions
```

[4]The behaviour of '[[' may change in the future: it may then be used to iterate over the transactions in a journal, not the fields. This would be motivated by `https://developer.r-project.org/blosxom.cgi/R-devel/NEWS/2016/03/09` even though the commit was reversed two days later `https://developer.r-project.org/blosxom.cgi/R-devel/NEWS/2016/03/11`

```
J[J$amount < 0]
```

```
   instrument   timestamp  amount  price  account         note
1        AMZN  2017-07-31      -5   1014  Trading  take profit

1 transaction
```

You can also pass a string, which is then interpreted as a regular expression that is matched against all character fields in the journal.

```
J["Pension"]
```

```
   instrument   timestamp  amount   price  account       note
1        AMZN  2017-08-01      10  1001.0  Pension  some note
2        MSFT  2017-08-01     220    73.1  Pension
3        MSFT  2017-10-05      70    74.4  Pension

3 transactions
```

By default, case is ignored, but you can set `ignore.case` to `FALSE`. (Also supported are arguments `fixed`, `perl` and `useBytes`, to be passed to `grepl`, with default `FALSE`.)

```
J["pension", ignore.case = FALSE]
```

```
no transactions
```

You can also specify the fields to match the string against.

```
J["Pension", match.against = "instrument"]
```

```
no transactions
```

Finally, you can invert the selection with `invert`.

```
J["Pension", invert = TRUE]
```

```
   instrument   timestamp  amount   price  account         note
1        AMZN  2017-07-14      10  1001.5  Trading
2        AMZN  2017-07-31      -5  1014.0  Trading  take profit
3        AMZN  2017-08-15      10   985.5  Trading

3 transactions
```

The split method breaks up a journal according to a 'factor' (here, the `instrument` field) into a list of journals. In interactive sessions, this can be used to have information per sub-journal printed.

```
split(J, J$instrument)
```

```
$AMZN
   instrument   timestamp  amount   price  account         note
1        AMZN  2017-08-01      10  1001.0  Pension    some note
2        AMZN  2017-07-14      10  1001.5  Trading
3        AMZN  2017-07-31      -5  1014.0  Trading  take profit
4        AMZN  2017-08-15      10   985.5  Trading

4 transactions

$MSFT
   instrument   timestamp  amount  price  account  note
1        MSFT  2017-08-01     220   73.1  Pension
2        MSFT  2017-10-05      70   74.4  Pension

2 transactions
```

2.5 Computing balances

2.5.1 Computing positions from journals

The function `position` gives the current balance of all instruments.

```
position(J)
```

```
AMZN  25
MSFT 290
```

To get the position at a specific date, use the `when` argument.

```
position(J, when = as.Date("2017-08-10"))
```

```
     2017-08-10
AMZN         15
MSFT        220
```

If you do not like such a tabular view, consider splitting the journal.

```
lapply(split(J, J$instrument),
       position, when = as.Date("2017-08-10"))
```

```
$AMZN
     2017-08-10
AMZN         15

$MSFT
     2017-08-10
MSFT        220
```

To get a time series of positions, you can use specific keywords for `when`: `all` will print the position at all timestamps in the journal.

```
position(J, when = "all")
```

```
           AMZN MSFT
2017-08-01   15  220
2017-07-14   10    0
2017-07-31    5    0
2017-08-15   25  220
2017-10-05   25  290
```

Keywords `first` and `last` give you the first and last position. (The latter is the default; so if `when` is not specified at all, the last position is computed.) `endofday` computes the positions at the ends of calendar days in the journal. `endofmonth` and `endofyear` print the positions at the ends of all calendar months and years between the first and the last timestamp. (The function `nth_day` in package `datetimeutils` offers more options.)

We are not limited to the timestamps that exist in the journal.

```
position(J, when = seq(from = as.Date("2017-07-25"),
                       to   = as.Date("2017-08-05"),
                       by   = "1␣day"))
```

```
           AMZN MSFT
2017-07-25   10    0
2017-07-26   10    0
2017-07-27   10    0
2017-07-28   10    0
2017-07-29   10    0
2017-07-30   10    0
2017-07-31    5    0
2017-08-01   15  220
2017-08-02   15  220
2017-08-03   15  220
2017-08-04   15  220
2017-08-05   15  220
```

By default, `position` will show you positions of all instruments, even if they are zero.

```
position(J, when = as.Date("2017-7-15"))
```

```
     2017-07-15
AMZN         10
MSFT          0
```

You can suppress such positions with `drop.zero`.

```
position(J, when = as.Date("2017-7-15"), drop.zero = TRUE)
```

```
     2017-07-15
AMZN         10
```

`drop.zero` can also be a numeric value, in which case is it interpreted as an absolute tolerance. This is useful in cases such as this one:

```
position(journal(instrument = "USD",
                 timestamp  = as.Date("2012-01-05"),
                 amount     = c(0.1, 0.1, 0.1, -0.3)),
         drop.zero = TRUE)
```

```
USD 2.775558e-17
```

```
position(journal(instrument = "USD",
                 timestamp  = as.Date("2012-01-05"),
                 amount     = c(0.1, 0.1, 0.1, -0.3)),
         drop.zero = 1e-12)
```

```
## (Note that there is no output.)
```

When accounts are specified, we may also aggregate positions by account.

```
position(J, use.account = TRUE)
```

```
         [,1]
Pension
|-- AMZN   10
`-- MSFT  290
Trading
`-- AMZN   15
```

As described above, each instruments gets its 'namespace'.

```
as.data.frame(position(J, use.account = TRUE))
```

```
           Pension.AMZN Pension.MSFT Trading.AMZN
2017-10-05           10          290           15
```

position is a generic method. Its default method does not require a journal.

```
amount <- c(10, 20, -10)
position(amount)

all.t <- seq_along(amount)
position(amount,
         timestamp = all.t,
         when = all.t)

position(amount,
         timestamp = all.t,
         when = "all")
```

2.5.2 Algorithms for computing balances

We have three vectors: when, timestamp and amount. Vectors when and timestamp are of the same type and are both sorted in increasing order; timestamp and amount have the same length. The result of the computation is a vector position with the same length as when.

```
i, j = 0  /* i loops over when; j loops over amount/timestamp */
for (i = 0; i < length(when); i++) {
  if (i == 0)
    pos[i] = 0;
  else
    pos[i] = pos[i - 1];
  while (timestamp[j] <= when[i] && j < length(j))
    position[i] += amount[j++];
}
```

Below follow two Perl snippets that compute positions from list of trades. (Perl syntax is similar to C syntax; in particular, array indices start at 0. This makes Perl very useful to test algorithms that are later to be coded in C.)

when and timestamp sorted

```
use warnings;
use strict;
use v5.14;

my @when = (0,1,2,7);         ## when to compute position
my @timestamp = (0,0,0,2);    ## timestamps of trades
my @amount = (1,1,1,-2);      ## traded amounts
```

```
## when and timestamp sorted
my @pos = (0) x @when; ## same length as @when
my $i = 0;
my $j = 0;


## /* i loops over when; j loops over amount/timestamp */
for ($i = 0; $i < @when; $i++) {
    if ($i == 0) {
        $pos[$i] = 0;
    } else {
        $pos[$i] = $pos[$i - 1];
    }
    while ($j < @amount && $timestamp[$j] <= $when[$i]) {
        $pos[$i] += $amount[$j];
        $j += 1;
    }
}
say "@pos";
```

```
3 3 1 1
```

when and timestamp unsorted

```
use warnings;
use strict;
use v5.14;

my @when = (0,1,2,7);         ## when to compute position
my @timestamp = (0,0,0,2);    ## timestamps of trades
my @amount = (1,1,1,-2);      ## traded amounts


my @pos = (0) x @when; ## same length as @when
my $i = 0;
my $j = 0;
@pos = (0,0);
for ($i = 0; $i < @when; $i++) {
    for ($j = 0; $j < @timestamp; $j++) {
        if ($timestamp[$j] <= $when[$i]) {
            $pos[$i] += $amount[$j];
        }
    }
}
say "@pos";
```

```
3 3 1 1
```

2.6 Aggregating and transforming journals

Often the data provided by journals needs to be processed in some way. A straightforward strategy is to call `as.data.frame` on the journal and then to use one of the many functions and methods that can be used for data-frames, such as `aggregate` or `apply`.

Even without coercion to a data-frame: A journal is a list of atomic vectors and hence already very similar to a data-frame. As a consequence, many computations can also be done directly on the journal, in particular with `tapply`. An example: you have a journal `trades` and want to compute monthly turnover (two-way). If there is only one instrument or all instruments may be added without harm (typically when they are denominated in the same currency), you can use this expression:

```
tapply(trades,
       INDEX = format(trades$timestamp, "%Y-%m"),
       FUN = function(x) sum(abs(x$amount)))
```

To break it down by instrument, just add instrument as a second grouping variable to the `INDEX` argument.

```
tapply(trades,
       INDEX = list(format(trades$timestamp, "%Y-%m"),
                    trades$instrument),
       FUN = function(x) sum(abs(x$amount)))
```

A special case is when a journal is to be processed into a new journal. For this, PMwR defines an `aggregate` method for journals:

```
aggregate.journal(x, by, FUN, ...)
```

The method splits the journal according to the grouping argument `by`, which can be a `list` (as in the default method) or an atomic vector. The argument `FUN` can either be a function or list. If a function, it should receive a journal and also evaluate to a journal. (Note that this is different from R's `aggregate.data.frame`, which calls `FUN` on all columns, but in turn cannot address specific columns of the `data.frame`.) If `FUN` is a list, its elements should be named functions. The names should match fields in the journal.

An example: we have a journal covering two trading days and wish to create a summary journal, which aggregates buys and sells for every day.

```
  J <- org_journal(text = "
␣␣␣␣|␣instrument␣|␣timestamp␣␣␣␣␣␣␣|␣amount␣|␣price␣|
␣␣␣␣|------------+----------------+--------+-------|
␣␣␣␣|␣A␣␣␣␣␣␣␣␣␣␣|␣2013-09-02␣Mon␣|␣␣␣␣␣-3␣|␣␣␣102␣|
␣␣␣␣|␣B␣␣␣␣␣␣␣␣␣␣|␣2013-09-02␣Mon␣|␣␣␣␣␣-3␣|␣␣␣104␣|
```

```
␣␣␣␣|␣B␣␣␣␣␣␣␣␣␣␣|␣2013-09-02␣Mon␣|␣␣␣␣␣␣3␣|␣␣␣106␣|
␣␣␣␣|␣B␣␣␣␣␣␣␣␣␣␣|␣2013-09-02␣Mon␣|␣␣␣␣␣-2␣|␣␣␣104␣|
␣␣␣␣|␣A␣␣␣␣␣␣␣␣␣␣|␣2013-09-03␣Tue␣|␣␣␣␣␣-1␣|␣␣␣110␣|
␣␣␣␣|␣A␣␣␣␣␣␣␣␣␣␣|␣2013-09-03␣Tue␣|␣␣␣␣␣␣1␣|␣␣␣104␣|
␣␣␣␣|␣A␣␣␣␣␣␣␣␣␣␣|␣2013-09-03␣Tue␣|␣␣␣␣␣␣5␣|␣␣␣108␣|
␣␣␣␣|␣A␣␣␣␣␣␣␣␣␣␣|␣2013-09-03␣Tue␣|␣␣␣␣␣␣3␣|␣␣␣107␣|
␣␣␣␣|␣B␣␣␣␣␣␣␣␣␣␣|␣2013-09-03␣Tue␣|␣␣␣␣␣-4␣|␣␣␣102␣|
␣␣␣␣|␣B␣␣␣␣␣␣␣␣␣␣|␣2013-09-03␣Tue␣|␣␣␣␣␣␣3␣|␣␣␣106␣|
␣␣")
```

```
  fun <- function(x) {
    journal(timestamp = as.Date(x$timestamp[1]),
            amount = sum(x$amount),
            price = sum(x$amount*x$price)/sum(x$amount),
            instrument = x$instrument[1L])
  }

  aggregate(J,
            by = list(J$instrument,
                      sign(J$amount),
                      as.Date(J$timestamp)),
            FUN = fun)
```

The results is a journal, but with at most a single buy or sell transaction per instrument per day: see the buy transaction for instrument `A` on September, 3.

```
  instrument   timestamp  amount     price
1          A  2013-09-02      -3  102.0000
2          B  2013-09-02      -5  104.0000
3          B  2013-09-02       3  106.0000
4          A  2013-09-03      -1  110.0000
5          B  2013-09-03      -4  102.0000
6          A  2013-09-03       9  107.2222
7          B  2013-09-03       3  106.0000

7 transactions
```

3 Computing profit and loss

In this chapter we will deal with computing profit and loss (P/L) measured in amounts of currency. If you are interested in computing returns, see Section Computing returns.

3.1 Simple cases

3.1.1 Total profit/loss

We buy one unit of an asset at a price of 100 euro and we sell it for 101. We have made a profit of 1 euro.

This simple case is frequent enough that we should make the required computation simple as well. The PMwR package provides a function `pl`, which for this case may be called as follows.

```
pl(price  = c(100, 101),
   amount = c(1, -1))
```

```
P/L total       1
average buy   100
average sell  101
cum. volume     2‘

P/L ’total is in units of instrument;‘’
volume is sum of /absolute/ amounts.
```

Instead of a vectors `price` and `amount`, you could also have passed a journal to `pl`.

In principle, profit/loss (P/L) is straightforward to compute. Let x be a vector of the absolute amounts traded, and let p be a vector of the prices at which we traded.

Then P/L is just the difference between what we received when selling and what we paid when buying.

$$\sum x_i^{\text{sell}} p_i^{\text{sell}} - \sum x_i^{\text{buy}} p_i^{\text{buy}} \tag{3.1}$$

This can be simplified when we impose the convention that sold amounts are negative.

$$\begin{aligned} \text{P/L} &= -\sum_{x<0} x_i p_i - \sum_{x>0} x_i p_i && (3.2)\\ &= -\sum x_i p_i && (3.3) \end{aligned}$$

The function `pl` also expects this convention: in the code example we had $x = [1, -1]'$.

There are several ways to perform this basic (or fundamental, rather) computation. Here are some, along with some timing results.

```
amount <- rep(c(-100, 100), 500)
price <- rep(100, length(amount))

library("rbenchmark")
benchmark(
    ## variations
    amount %*% price,
    sum(amount*price),
    crossprod(amount, price),
    t(amount*price) %*% rep(1, length(amount)),  ## matrix summing

    ## settings
    columns = c("test", "elapsed", "relative"),
    order = "relative",
    replications = 50000)
```

```
                                       test elapsed relative
1                            amount %*% price   0.126    1.000
3                  crossprod(amount, price)   0.138    1.095
2                       sum(amount * price)   0.172    1.365
4 t(amount * price) %*% rep(1, length(amount))   0.440    3.492
```

`pl` uses the straightforward `sum(amount * price)` variant; only when very long vectors are used, it switches to `crossprod`.

`pl` also accepts an argument `instrument`: if it is available, `pl` computes and reports P/L for each instrument separately. As an example, suppose you traded shares of two German companies, Adidas and Commerzbank. We collect the transactions in a journal.

```
J <- readOrg(text = "
| instrument  | amount | price |
|-------------+--------+-------|
| Adidas      |     50 |   100 |
| Adidas      |    -50 |   102 |
| Commerzbank |    500 |     8 |
| Commerzbank |   -500 |     7 |
")
J <- as.journal(J)
J
```

```
    instrument  amount  price
1       Adidas      50    100
2       Adidas     -50    102
3  Commerzbank     500      8
4  Commerzbank    -500      7

4 transactions
```

We now pass the journal directly to `pl`.

```
pl(J)
```

```
Adidas
  P/L total     100
  average buy   100
  average sell  102
  cum. volume   100

Commerzbank
  P/L total     -500
  average buy      8
  average sell     7
  cum. volume   1000‘

P/L ’total is in units of instrument;‘’
volume is sum of /absolute/ amounts.
```

An aside: since the shares are denominated in the same currency (euro), total profit is the same even if we had left out the instruments; however, average buying and selling prices becomes less informative.

Financial instruments differ not only in the currencies in which they are denominated. Many derivatives have multipliers, which you may also specify. Suppose you have traded FGBL (German Bund futures) and FESX (EURO STOXX 50 futures). One point of the FGBL translates into 1000 euros; for the FESX it is 10 euros.

```
J <- readOrg(text = "
```

```
␣␣|␣instrument␣␣|␣amount␣|␣␣price␣|
␣␣|-------------+--------+--------|
␣␣|␣FGBL␣MAR␣16␣|␣␣␣␣␣␣1␣|␣165.20␣|
␣␣|␣FGBL␣MAR␣16␣|␣␣␣␣␣-1␣|␣165.37␣|
␣␣|␣FGBL␣JUN␣16␣|␣␣␣␣␣␣1␣|␣164.12␣|
␣␣|␣FGBL␣JUN␣16␣|␣␣␣␣␣-1␣|␣164.13␣|
␣␣|␣FESX␣JUN␣16␣|␣␣␣␣␣␣5␣|␣␣␣2910␣|
␣␣|␣FESX␣JUN␣16␣|␣␣␣␣␣-5␣|␣␣␣2905␣|
␣␣")

  J <- as.journal(J)
  futures_pl <- pl(J,
                   multiplier = c("^FGBL" = 1000, "^FESX" = 10),
                   multiplier.regexp = TRUE)
  futures_pl
```

```
FESX JUN 16
  P/L total        -250
  average buy      2910
  average sell     2905
  cum. volume        10

FGBL JUN 16
  P/L total          10
  average buy    164.12
  average sell   164.13
  cum. volume         2

FGBL MAR 16
  P/L total         170
  average buy     165.2
  average sell   165.37
  cum. volume         2‘

P/L ’total is in units of instrument;‘’
volume is sum of /absolute/ amounts.
```

Note that we used a named vector to pass the multipliers. Per default, the names of this vector need to exactly match the instruments' names. Setting `multiplier.regexp` to `TRUE` causes the names of the multiplier vector to be interpreted as (Perl-style) regular expressions.

At this point, it may be helpful to describe how we can access the results of such P/L computations (other than having them printed to the console, that is). The function `pl` always returns a list of lists – one list for each instrument.

```
str(futures_pl)
```

```
List of 3
 $ FESX JUN 16:List of 6
  ..$ pl         : num -250
  ..$ realised   : logi NA
  ..$ unrealised: logi NA
  ..$ buy        : num 2910
  ..$ sell       : num 2905
  ..$ volume     : num 10
 $ FGBL JUN 16:List of 6
  ..$ pl         : num 10
  ..$ realised   : logi NA
  ..$ unrealised: logi NA
  ..$ buy        : num 164
  ..$ sell       : num 164
  ..$ volume     : num 2
 $ FGBL MAR 16:List of 6
  ..$ pl         : num 170
  ..$ realised   : logi NA
  ..$ unrealised: logi NA
  ..$ buy        : num 165
  ..$ sell       : num 165
  ..$ volume     : num 2
 - attr(*, "class")= chr "pl"
 - attr(*, "along.timestamp")= logi FALSE
 - attr(*, "instrument")= chr [1:3] "FESX JUN 16" "FGBL JUN 16" "FGBL MAR 16"
```

Each such list contains numeric vectors: 'pl', 'realised', 'unrealised', 'buy', 'sell', 'volume'. There may also be an additional vector, `timestamp`, to be described later in Section PL over time. The vectors 'realised' and 'unrealised' will be `NA` unless `along.timestamp` is not `FALSE`, also described in Section PL over time. Data can be extracted by standard methods.

```
unlist(futures_pl[["FESX␣JUN␣16"]])
```

```
  pl   realised unrealised        buy       sell     volume
-250         NA          NA       2910       2905         10
```

```
unlist(lapply(futures_pl, `[[`, "volume"))
```

```
FESX JUN 16 FGBL JUN 16 FGBL MAR 16
         10           2           2
```

You may prefer `sapply(...)` instead of `unlist(lapply(...))`. Also, extracting the raw P/L numbers of each instrument is so common that you can say `pl(pl(...))`. So you could have written:

```
pl(pl(J,
      multiplier = c("FGBL" = 1000, "FESX" = 10),
      multiplier.regexp = TRUE))
```

```
FESX JUN 16 FGBL JUN 16 FGBL MAR 16
       -250          10         170
```

It is often more convenient to have the data presented as a table, which we can create with `as.data.frame`.

```
as.data.frame(futures_pl)
```

```
              pl     buy    sell volume
FESX JUN 16 -250 2910.00 2905.00     10
FGBL JUN 16   10  164.12  164.13      2
FGBL MAR 16  170  165.20  165.37      2
```

Or if you like ASCII tables, with `toOrg`.

```
toOrg(as.data.frame(futures_pl), row.names = "instrument")
```

```
| instrument   |   pl |    buy |   sell | volume |
|--------------+------+--------+--------+--------|
| FESX JUN 16 | -250 |   2910 |   2905 |     10 |
| FGBL JUN 16 |   10 | 164.12 | 164.13 |      2 |
| FGBL MAR 16 |  170 |  165.2 | 165.37 |      2 |
```

We can also use `pl` when there are open positions. The simplest example is a journal of just one trade.

```
pl(amount = 1, price = 100)
```

```
P/L total      NA
average buy   100
average sell  NaN
cum. volume     1‘

P/L ’total is in units of instrument;‘’
volume is sum of /absolute/ amounts.‘
sum(amount’) is not zero: specify ‘’vprice to compute P/L.
```

There can be no P/L number since the position is not closed. But the message that is shown tells us what to do: we need to specify a price at which the open position is to be valued. This valuation price is passed as argument `vprice` (`v` as in `valuation`).

```
pl(amount = 1, price = 100, vprice = 105)
```

```
P/L total       5
average buy   100
average sell  105
cum. volume     1

'P/L total' is in units of instrument;
'volume' is sum of /absolute/ amounts.
 average sell includes 'vprice'
```

Note that `average sell` takes into account the valuation price that we specified.[1] But `cum. volume` has remained 1 since only 1 unit was actually traded.

A common task is to compute P/L over a specified period of time such as one trading day. The procedure for such a case requires three ingredients:

1. the initial position and its valuation prices,
2. the trades during the period,
3. the final position and its prices.

Suppose yesterday, at market close, we had the following positions.

```
yesterday_position <- c("FESX JUN 16" =  -20, "FGBL JUN 16" = 10)
yesterday_prices   <- c("FESX JUN 16" = 2912, "FGBL JUN 16" = 164.23)
```

Note that, as with the multipliers above, we use named vectors for both the position and the prices: the names indicate the instruments.

Trading just ended, and we have done the following trades.

```
J
```

```
    instrument  amount    price
1  FGBL MAR 16       1   165.20
2  FGBL MAR 16      -1   165.37
3  FGBL JUN 16       1   164.12
4  FGBL JUN 16      -1   164.13
5  FESX JUN 16       5  2910.00
6  FESX JUN 16      -5  2905.00

6 transactions
```

Now we pass the three ingredients – initial position, trades during the period, and valuation prices for the final, open positions – to `pl`.

```
pl(J,
   initial.position = yesterday_position,
   initial.price = yesterday_prices,
   vprice = c("FESX JUN 16" = 2902, "FGBL JUN 16" = 164.60),
   multiplier = c("FGBL" = 1000, "FESX" = 10),
   multiplier.regexp = TRUE)
```

[1] In an earlier version of the code, average buy/sell price did not take into account `vprice`. But specifying `vprice` creates a fiction, anyway (P/L 'as if' the trade was closed), and this fiction is more informative if the average buy/sell price is adjusted.

```
FESX JUN 16
  P/L total       1750
  average buy   2903.6
  average sell  2910.6
  cum. volume       10

FGBL JUN 16
  P/L total       3710
  average buy   164.22
  average sell  164.56
  cum. volume        2

FGBL MAR 16
  P/L total        170
  average buy    165.2
  average sell  165.37
  cum. volume        2‘

P/L ’total is in units of instrument;‘’
volume is sum of /absolute/ amounts.
 for FESX JUN 16: average buy includes ‘’vprice
 for FGBL JUN 16: average sell includes ‘’vprice
```

An aside: we could have simulated this computation by creating one journal of the initial position and another journal (with reversed `amount` signs) for the final position, merging all three journals and then computing P/L.

3.1.2 P/L over time

In the examples above, we computed *total* P/L. It is also illuminating to see how P/L evolved over time. Suppose that a stock trader bought one share at 50, one share at 90 and sold two shares at 100. These trades resulted in a profit of 60, or an average return of more than +40% (bought at an average price of 70, and sold at 100).

```
J <- journal(price  = c( 90, 50, 100),
             amount = c(  1,  1,  -2))
pl(J)
```

```
P/L total      60
average buy    70
average sell  100
cum. volume     4

'P/L total' is in units of instrument;
'volume' is sum of /absolute/ amounts.
```

That may appear like some pretty good trading. Yet suppose that the order of the trades was

```
buy at 90  =>  buy at 50  =>  sell at 100.
```

You may have noticed that the `journal` that we created above already has the trades ordered this way. We may not know what was traded and when, but there is clearly some information in the order of the trades and the drawdown that it implies: namely a mark-to-market loss of at least 40 before it recovered. For situations like this, the argument `along.timestamp` can be used.

```
pl(J, along.timestamp = TRUE)
```

```
timestamp       1   2   3
P/L total       0 -40  60
__ realised     0   0  60
__ unrealised   0 -40   0
average buy    70
average sell  100
cum. volume     1   2   4

'P/L total' is in units of instrument;
'volume' is sum of /absolute/ amounts.
```

Note that we do not provide an actual timestamp, in which case the function uses integers 1, 2, ..., `length(J)`. With no further arguments, as here, the function computes the running position and evaluates it at every trade with the trade's price. This may not be totally accurate because of bid–ask spreads or other transaction costs. But it provides more information than only computing the aggregate P/L for the trades.

```
str(pl(J, along.timestamp = TRUE))
```

```
List of 1
 $ :List of 7
  ..$ timestamp : int [1:3] 1 2 3
  ..$ pl        : num [1:3] 0 -40 60
  ..$ realised  : num [1:3] 0 0 60
  ..$ unrealised: num [1:3] 0 -40 0
  ..$ buy       : num 70
  ..$ sell      : num 100
  ..$ volume    : num [1:3] 1 2 4
 - attr(*, "class")= chr "pl"
 - attr(*, "along.timestamp")= logi TRUE
 - attr(*, "instrument")= logi NA
```

As described above, `pl` object is a list of lists: one list for each instrument. But now the components `pl`, `realised` and so on actually hold time-series, with the times given by `timestamp`.

In the previous section, we used `vprice` to value a final open position. We can also use it to value a position over time. See Profit/Loss for Open Positions, and this example on quant.stackexchange.com.

3.2 More-complicated cases

Unfortunately, in real life computing P/L is often more complicated:

- One asset-price unit may not translate into one currency unit: there may be multipliers a.k.a. contract factors; there are even instruments with variable multipliers, e.g. Australian government-bond futures.
- Asset positions may map into cashflows in non-obvious ways. The simple case is the delay in actual payment and delivery of an asset, which is often two or three days. The more problematic cases are derivatives with daily adjustments of margins. In such cases, one may need to model (i.e. keep track of) the actual account balances.
- Assets may be denominated in various currencies.
- Currencies themselves may be assets in the portfolio. Depending on how they are traded (cash, forwards, *&c.*), computing P/L may not be straightforward.

How – or, rather, to what degree – these complications are handled is, as always, up to the user. For a single instrument, computing P/L in units of the instrument is usually meaningful, though perhaps not always intuitive. But *adding up* the profits and losses of several assets will in general not work because of multipliers or different currencies. A simple and transparent way is then to manipulate the journal before P/L is computed (e.g., multiply notionals by their multipliers).

4 Computing returns

This chapter is about computing returns. For computing profit/loss in currency units, see Section Computing profit and (or) loss.

4.1 Arithmetic and geometric returns

Let P_t be the price at point in time t, then returns r_t are defined as

$$r_t \equiv R_t - 1 = \frac{P_t}{P_{t-1}} - 1 = \frac{P_t - P_{t-1}}{P_{t-1}} \tag{4.1}$$

with $1 + r_t \equiv R_t$. Such returns are called simple or discrete returns. Over N periods, we can chain-link such returns.

$$(1 + r_1)(1 + r_2)\ldots = \prod_{i=1}^{N} 1 + r_i \tag{4.2}$$

The **geometric average** r_g is a number chosen so that the equation

$$(1 + r_g)^N = \prod_{i=1}^{N} 1 + r_i \tag{4.3}$$

holds.

The **arithmetic average** is computed as

$$\frac{1}{N}\sum_{i=1}^{N} 1 + r_i\,. \tag{4.4}$$

Typically, in R, we transform a whole series $P_{t_1}, P_{t_2}, P_{t_3}, \ldots$ (i.e. a numeric vector) into returns $R_{t_2}, R_{t_3}, \ldots$, which is a one-liner in R:

```
simple_returns <- function(x)
    x[-1L]/x[-length(x)] - 1
```

(You could argue that these are two lines: yet even a one-liner, if used repeatedly, should be written as a function.)

This works because we can write the computation of Equation (4.1) as

$$\begin{array}{lcll} & & P_t & \\ R_{t+1} & = & P_{t+1} & / \quad P_t \\ R_{t+2} & = & P_{t+2} & / \quad P_{t+1} \\ R_{t+3} & = & P_{t+3} & / \quad P_{t+2} \\ R_{t+4} & = & \underbrace{P_{t+4}}_{\texttt{x}} & / \quad P_{t+3} \\ & & & \quad \underbrace{P_{t+4}}_{\texttt{x}} \end{array}$$

Many types of return computations are implemented in function `returns`. The function always computes discrete returns, as defined above.[1]

Let us try it. PMwR comes with two small datasets, DAX and REXP. DAX stands for *Deutscher Aktienindex* (German Equity Index), and REXP stands for *Rentenindex (Performance)*. Both datasets are data-frames of one column that contains the price for the day, with the timestamps stored as rownames in format `YYYY-MM-DD`.

```
head(DAX)
```

```
               DAX
2014-01-02 9400.04
2014-01-03 9435.15
2014-01-06 9428.00
2014-01-07 9506.20
2014-01-08 9497.84
2014-01-09 9421.61
```

We extract the prices for the first five business days of 2014 and put them into a vector P.

```
P <- head(DAX[[1]], n = 5)
P
```

```
[1] 9400.04 9435.15 9428.00 9506.20 9497.84
```

Now we call `simple_returns`.

```
simple_returns(P)
```

[1]The function never computes logarithmic returns.

```
[1]  0.00373509 -0.00075780  0.00829444 -0.00087943
```

In fact, using `returns` as provided by PMWR would have given the same result.

```
returns(P)
```

```
[1]  0.00373509 -0.00075780  0.00829444 -0.00087943
```

PMWR's `returns` function offers more convenience than `simple_returns`. For instance, it will recognise when the input argument has several columns, such as a matrix or a data-frame. In such a case, it computes returns for each column.[2]

```
returns(cbind(P, P))
```

```
             P         P
[1,]  0.003735  0.003735
[2,] -0.000758 -0.000758
[3,]  0.008294  0.008294
[4,] -0.000879 -0.000879
```

The argument `pad` determines how the initial observation is handled. The default, `NULL`, means that the first observation is dropped. It is often useful to use `NA` instead, since in this way the returns series keeps the same length as the original price series.

```
data.frame(price = P, returns = returns(P, pad = NA))
```

```
   price     returns
1 9400.0          NA
2 9435.1  0.00373509
3 9428.0 -0.00075780
4 9506.2  0.00829444
5 9497.8 -0.00087943
```

Setting `pad` to 0 can also be useful, because then it is easy to 'rebuild' the original series with `cumprod`. (But see Section Scaling series for a description of the function `scale1`, which is even more convenient.)

```
P[1] * cumprod(1 + returns(P, pad = 0))
```

```
[1] 9400.04 9435.15 9428.00 9506.20 9497.84
```

`returns` also has an argument `lag`, with default 1. This can be used to compute rolling returns, such as 30-day returns, etc. `lag`

`returns` is a generic function, which goes along with some overhead. If you need to compute returns on simple data structures as in the examples above and need fast computation, then you may also use `.returns`. The function is the actual workhorse `.returns`

[2] See Vectorization.

that performs the raw return calculation.

Besides having methods for numeric vectors (which includes those with a dim attribute, i.e. matrices) and data-frames, `returns` also understands `zoo` objects. So let us create two `zoo` series, `dax` and `rex`.

```
library("zoo")
dax <- zoo(DAX[[1]], as.Date(row.names(DAX)))
rex <- zoo(REXP[[1]], as.Date(row.names(REXP)))

str(dax)
```

```
'zoo' series from 2014-01-02 to 2015-12-30
  Data: num [1:505] 9400 9435 9428 9506 9498 ...
  Index:  Date[1:505], format: "2014-01-02" "2014-01-03" ...
```

```
str(rex)
```

```
'zoo' series from 2014-01-02 to 2015-12-30
  Data: num [1:502] 441 441 442 442 442 ...
  Index:  Date[1:502], format: "2014-01-02" "2014-01-03" ...
```

```
  returns(head(dax, 5), pad = NA)
```

```
2014-01-02 2014-01-03 2014-01-06 2014-01-07 2014-01-08
        NA   0.003735  -0.000758   0.008294  -0.000879
```

Matrices work as well. We combine both series into a two-column matrix `drax`.[3]

```
  drax <- cbind(dax, rex)
  returns(head(drax, 5))
```

```
                dax       rex
2014-01-03  0.003735  0.000611
2014-01-06 -0.000758  0.001704
2014-01-07  0.008294  0.000621
2014-01-08 -0.000879 -0.000131
```

As you see, just as for a numeric matrix, the function computes the returns for each column.

In fact, `zoo` objects bring another piece of information – timestamps – that `returns` can use. (Since `xts` series inherit from `zoo`, they will work as well.)

[3] In case you did not know: `drax` is not only the name of a dataset in this book, but also the name of Marvel-comics superhero and of the villain of a James Bond novel. The latter is actually German, which makes it obvious to choose the name for representing German indices. `:-)`

4.2 Arithmetic and geometric *excess* returns

The arithmetic excess return is the difference in final wealth as a proportion of initial wealth. The geometric excess return is the difference in final wealth as a proportion of final wealth as produced by the benchmark.

4.3 Logarithmic returns

As defined above, given a financial instrument's price P_t, the discrete return~r_{t+1} between t and $t+1$ is defined as

$$r_{t+1} = \frac{P_{t+1} - P_t}{P_t} = \frac{\Delta P_{t+1}}{P_t}$$

where $\Delta P_{t+1} \equiv P_{t+1} - P_t$. Log returns are given by

$$r_{t+1}^{(\log)} = \log P_{t+1} - \log P_t \,.$$

Here, log always refers to the natural logarithm, i.e. the logarithm with base~e.

Practically, the difference between these two types of returns is small. We have

$$\begin{aligned}\frac{\Delta P_{t+1}}{P_t} - \log\left(\frac{\Delta P_{t+1}}{P_t} + 1\right) &= \frac{\Delta P_{t+1}}{P_t} - \left[\frac{\Delta P_{t+1}}{P_t} - \frac{1}{2}\left(\frac{\Delta P_{t+1}}{P_t}\right)^2 + \frac{1}{3}\left(\frac{\Delta P_{t+1}}{P_t}\right)^3 - \ldots\right] \\ &= \frac{1}{2}\left(\frac{\Delta P_{t+1}}{P_t}\right)^2 - \mathcal{O}\left[\left(\frac{\Delta P_{t+1}}{P_t}\right)^3\right].\end{aligned}$$

We have used the fact that the Taylor expansion of $\log(1+x)$ is

$$x - \frac{x^2}{2} + \frac{x^3}{3} - \frac{x^4}{4} + \cdots$$

For many practical purposes there is no difference between log returns and discrete returns; any error arising from choosing the wrong method will be swamped by data uncertainty.

So, when should you use log returns, and when simple returns? Whenever you compute returns, or a function of them, for an investor (for a factsheet, say), use simple returns. If the portfolio had a drawdown of -70%, then the log return will be $log(1-0.7) = -120\%$, which practical people simply have a hard time to understand.

If you do research, however, you are of course entitled to apply any transformation to your data. And then working with log returns might have advantages.

- For currencies, log returns are often preferred because they enforce symmetry: if EURUSD drops 10%, then the levels of the currencies won't be compatible a rise of 10% of USDEUR.
- Log returns can be added, so many nice properties of sums can be applied (such as the Central Limit Theorem, in its many guises)

4.4 Time-weighted returns

4.5 Holding-period returns

When a timestamp is available, `returns` can compute returns for specific calendar periods. As an example, we use the daily DAX levels in 2014 and 2015 and compute monthly returns from them.

```
returns(dax, period = "month")
```

```
      Jan Feb  Mar  Apr  May  Jun  Jul  Aug  Sep  Oct Nov  Dec YTD
2014 -1.0 4.1 -1.4  0.5  3.5 -1.1 -4.3  0.7  0.0 -1.6 7.0 -1.8 4.3
2015  9.1 6.6  5.0 -4.3 -0.4 -4.1  3.3 -9.3 -5.8 12.3 4.9 -5.6 9.6
```

If you prefer to not use `zoo` or `xts`, you may also pass the timestamp explicitly to `returns`.

```
returns(coredata(dax), t = index(dax), period = "month")
```

```
      Jan Feb  Mar  Apr  May  Jun  Jul  Aug  Sep  Oct Nov  Dec YTD
2014 -1.0 4.1 -1.4  0.5  3.5 -1.1 -4.3  0.7  0.0 -1.6 7.0 -1.8 4.3
2015  9.1 6.6  5.0 -4.3 -0.4 -4.1  3.3 -9.3 -5.8 12.3 4.9 -5.6 9.6
```

Despite the way these monthly returns are printed: the result of the function call is a numeric vector (the return numbers), with additional information added through attributes. There is also a `class` attribute, which has value `p_returns`. The advantage of this data structure is that it is 'natural' to compute with the returns, e.g. to calculate means, extremes and other quantities.

```
range(returns(dax, period = "month"))
```

```
[1] -0.0928  0.1232
```

Most useful, however, is probably the `print` method, whose results you have seen above. You may also compute monthly returns for matrices, i.e. for more than one asset. But now the `print` method will behave differently. The function's assumption is that now it would be more convenient to print the returns aligned by date in a table.

```
returns(drax, period = "month")
```

```
             dax   rex
2014-01-31  -1.0   1.8
2014-02-28   4.1   0.4
2014-03-31  -1.4   0.1
2014-04-30   0.5   0.3
2014-05-30   3.5   0.9
2014-06-30  -1.1   0.4
2014-07-31  -4.3   0.4
2014-08-29   0.7   1.0
2014-09-30   0.0  -0.1
2014-10-31  -1.6   0.1
2014-11-28   7.0   0.4
2014-12-30  -1.8   1.0
2015-01-30   9.1   0.3
2015-02-27   6.6   0.1
2015-03-31   5.0   0.3
2015-04-30  -4.3  -0.5
2015-05-29  -0.4  -0.2
2015-06-30  -4.1  -0.8
2015-07-31   3.3   0.7
2015-08-31  -9.3   0.0
2015-09-30  -5.8   0.4
2015-10-30  12.3   0.4
2015-11-30   4.9   0.3
2015-12-30  -5.6  -0.6
```

If you rather wanted the other, one-row-per-year display, just call the function separately for each series.

```
lapply(list(DAX = dax, REXP = rex),
       returns, period = "month")
```

```
$DAX
      Jan Feb  Mar  Apr  May  Jun  Jul  Aug  Sep  Oct Nov  Dec YTD
2014 -1.0 4.1 -1.4  0.5  3.5 -1.1 -4.3  0.7  0.0 -1.6 7.0 -1.8 4.3
2015  9.1 6.6  5.0 -4.3 -0.4 -4.1  3.3 -9.3 -5.8 12.3 4.9 -5.6 9.6

$REXP
     Jan Feb Mar  Apr  May  Jun Jul Aug  Sep Oct Nov  Dec YTD
2014 1.8 0.4 0.1  0.3  0.9  0.4 0.4 1.0 -0.1 0.1 0.4  1.0 7.1
2015 0.3 0.1 0.3 -0.5 -0.2 -0.8 0.7 0.0  0.4 0.4 0.3 -0.6 0.5
```

See `?print.p_returns` for more display options. For instance:

```
print(returns(dax, period = "month"),
      digits = 2, year.rows = FALSE, plus = TRUE,
      month.names = 1:12)
```

```
      2014    2015
1    -1.00   +9.06
2    +4.14   +6.61
3    -1.40   +4.95
4    +0.50   -4.28
5    +3.54   -0.35
6    -1.11   -4.11
7    -4.33   +3.33
8    +0.67   -9.28
9    +0.04   -5.84
10   -1.56  +12.32
11   +7.01   +4.90
12   -1.76   -5.62
YTD  +4.31   +9.56
```

Sweave

There are methods `toLatex` and `toHTML` for monthly returns. In Sweave documents, you need to use `results = tex` and `echo = false` in the chunk options:

```
\begin{tabular}{rrrrrrrrrrrrr}
<<results=tex,echo=false>>=
toLatex(returns(dax, period = "month"))
\end{tabular}
```

(There is also a vignette that gives examples for `toLatex`; say `vignette("FinTeX", package = "PMwR")` to open it.)

To get annualised returns, use period `ann` (or actually any string matched by the regular expression `^ann`; case is ignored).

```
returns(dax, period = "ann")
```

```
6.9%  [02 Jan 2014 -- 30 Dec 2015]
```

Now let us try a shorter period.

```
returns(window(dax, end = as.Date("2014-1-31")),
        period = "ann")
```

```
-1.0%  [02 Jan 2014 -- 31 Jan 2014;
        less than one year, not annualised]
```

The function did *not* annualise: it refuses to do so if the time period is shorter than one year. (You may verify the return for January 2014 in the tables above.) To force annualising, add a `!`. The exclamation mark serves as a mnenomic that it is now imperative to annualise.

```
returns(window(dax, end = as.Date("2014-1-31")),
        period = "ann!")
```

```
-11.8%  [02 Jan 2014 -- 31 Jan 2014;
         less than one year, but annualised]
```

There are several more accepted values for `period`, such as `year`, `quarter`, month-to-date (`mtd`), year-to-date (`ytd`) or inception-to-date (`total`). The help page of `returns` lists all options. Note that any such setting for `period` requires that the timestamp can be coerced to `Date`; for instance, intraday time-series with `POSIXct` timestamps would work as well.

4.6 Portfolio returns

Sometimes we may need to compute returns for a portfolio of fixed weights, given an assumption when the portfolio is rebalanced. For instance, we may want to see how a constant allocation of 10%, 50% and 40%. to three funds would have done, assuming that a portfolio is rebalanced once a month. If more detail is necessary, then function `btest` can be used; see Chapter Backtesting. But the simple case can be done with `returns` already. Here is an example.

```
prices <- c(100, 102, 104, 104, 104.5,
              2, 2.2, 2.4, 2.3,   2.5,
            3.5,   3, 3.1, 3.2,   3.1)

dim(prices) <- c(5, 3)
prices
```

```
     [,1] [,2] [,3]
[1,] 100.0  2.0  3.5
[2,] 102.0  2.2  3.0
[3,] 104.0  2.4  3.1
[4,] 104.0  2.3  3.2
[5,] 104.5  2.5  3.1
```

Now suppose we want a constant weight vector, $[0.1, 0.5, 0.4]'$, but only rebalance at times 1 and 4. (That is, we rebalance the portfolio only with the prices at timestamps 1 and 4.)

```
returns(prices,
        weights = c(10, 50, 40)/100,
        rebalance.when = c(1, 4))
```

```
[1] -0.0051429  0.0637565 -0.0128240  0.0314590
attr(,"holdings")
           [,1]    [,2]    [,3]
[1,] 0.00100000 0.25000 0.11429
[2,] 0.00100000 0.25000 0.11429
```

```
[3,] 0.00100000 0.25000 0.11429
[4,] 0.00096154 0.21739 0.12500
[5,] 0.00096154 0.21739 0.12500
attr(,"contributions")
           [,1]      [,2]      [,3]
[1,] 0.00200000  0.050000 -0.057143
[2,] 0.00201034  0.050258  0.011488
[3,] 0.00000000 -0.023623  0.010799
[4,] 0.00048077  0.043478 -0.012500
```

The result also contains, as attributes, the imputed holdings and the single period contributions.

Argument `weights` does not have to be a vector. It can also be a matrix. In such a case, each row is interpreted as a portfolio. Instead of weights, we could also specify fixed positions. See `?returns` for different possibilities to call `returns`.

4.7 Return contribution

Let $w(t,i)$ be the weight of portfolio segment i at the beginning of period t, and let $r(t,i)$ be the return of segment i over period t. Then the portfolio return over period t, $r_{\mathrm{P}}(t)$ is a weighted sum of the N segment returns.

$$r_{\mathrm{P}}(t) = \sum_{i=1}^{N} r(t,i)w(t,i)\,. \tag{4.5}$$

When the weights sum to unity, we may also write

$$1 + r_{\mathrm{P}}(t) = \sum_{i=1}^{N} \big(1 + r(t,i)\big)w(t,i) \tag{4.6}$$

or, defining $1 + r \equiv R$,

$$R_{\mathrm{P}}(t) = \sum_{i=1}^{N} R(t,i)w(t,i)\,. \tag{4.7}$$

The total return contribution of segment i over time equals

$$\sum_{t=1}^{T-1} \left(R(t,i)w(t,i) \prod_{s=t+1}^{T} R_{\mathrm{P}}(s) - 1 \right) + \underbrace{r(T,i)\,w(T,i)}_{\text{final period}}\,. \tag{4.8}$$

In this way, a segment's return contribution in one period is reinvested in the overall portfolio in succeeding periods. See Feibel (2003) and Christopherson, Cariño, and Ferson (2009).

The calculation is provided in the function `rc` ('return contribution').

```
weights <- rbind(c( 0.25, 0.75),  ## the assets' weights
                 c( 0.40, 0.60),  ## during three periods
                 c( 0.25, 0.75))

R <- rbind(c( 1   ,    0),        ## the assets' returns
           c( 2.5, -1.0),         ## during these periods
           c(-2  ,  0.5))/100

rc(R, weights, segment = c("equities", "bonds"))
```

```
$period_contributions
  timestamp equities    bonds    total
1         1   0.0025  0.00000  0.00250
2         2   0.0100 -0.00600  0.00400
3         3  -0.0050  0.00375 -0.00125

$total_contributions
equities    bonds    total
 0.00749 -0.00224  0.00525
```

4.8 Returns when there are external cashflows

External cashflows (or transfers of positions) can be handled just like dividends. The following table shows the values and cashflows of a hypothetical portfolio.

timestamp	value	cashflow	value with cashflow
1	0	+100	100
2	101	0	101
3	104	0	104
4	103	+100	203
5	204	-200	4

A total-return series, based on column value with cashflow but excluding column cashflow, can be computed with `div_adjust`.

```
cf <- c(100, 100, -200)
t <- c(1, 4, 5)
x <- c(100, 101, 104, 203, 4)
div_adjust(x, t, div = -cf, backward = FALSE)
```

```
[1] 100.00 101.00 104.00 103.00 103.51
```

More conveniently, the function `unit_prices` helps to compute so-called time-weighted returns of a portfolio when there are inflows and outflows. (The term

time-weighted returns is a misnomer, since returns are not weighted at all. They are only time-weighted if time-periods are of equal length.) We repeat the previous example.

```
NAV <- data.frame(timestamp = 1:5,
                  NAV = x)

cf <- data.frame(timestamp = t,
                 cashflow = cf)
unit_prices(NAV, cf)
```

```
  timestamp NAV  price    units
1         1 100 100.00 1.000000
2         2 101 101.00 1.000000
3         3 104 104.00 1.000000
4         4 203 103.00 1.970874
5         5   4 103.51 0.038645
```

The function returns a data-frame: to compute returns, use the `price` column.

In general, valuation (i.e. the computation of the NAV) must take place before external cashflows. Fairness suggests that: what price would you give an external investor if you had not valued the positions? And even if fairness mattered not: suppose we traded on a specific day, had a positive PL, and ended the day in cash. We could then not differentiate any more between a cash increase because of an external inflow and a cash increase because of a profitable trade.

5 Backtesting

This chapter explains how to test trading strategies with the `btest` function. A recent tutorial is available from SSRN.

5.1 Decisions

At a given instant in time (in actual life, 'now'), a trader needs to answer the following questions:

1. Do I want to compute a new target portfolio, yes or no? If yes, go ahead and compute the new target portfolio.
2. Given the target portfolio and the actual portfolio, do I want to rebalance (i.e. close the gap between the actual portfolio and the target portfolio)? If yes, rebalance.

If such a decision is not just hypothetical, then the answer to the second question may lead to a number of orders sent to a broker. Note that many traders do not think in terms of *stock* (i.e. balances) as we did here; rather, they think in terms of *flow* (i.e. orders). Both approaches are equivalent, but the described one makes it easier to handle missed trades and synchronise accounts.

During a backtest, we will simulate the decisions of the trader. How precisely we simulate depends on the trading strategy. The `btest` function is meant as a helper function to simulate these decisions. The logic for the decisions described above must be coded in the functions `do.signal`, `signal` and `do.rebalance`.

Implementing `btest` required a number of decision too: (i) what to model (i.e. how to simulate the trader), and (ii) how to code it. As an example for point (i): how precisely do we want to model the order process (e.g. use limit orders?, allow partial fills?) Example for (ii): the backbone of `btest` is a loop that runs through the data.

Loops are slow in R when compared with compiled languages,[1] so should we vectorise instead? Vectorisation is indeed often possible, namely if trading is not path-dependent. If we have already a list of trades, we can efficiently transform them into a profit-and-loss in R without relying on an explicit loop (see Section Computing profit and (or) loss). Yet, one advantage of looping is that the trade logic is more similar to actual trading; we may even be able to reuse some code in live trading.

Altogether, the aim for `btest` is to stick to the functional paradigm as much as possible. Functions receive arguments and evaluate to results; but they do not change their arguments, nor do they assign or change other variables 'outside' their environment, nor do the results depend on some variable outside the function. This creates a problem, namely how to keep track of state. If we know what variables need to be persistent, we could pass them to the function and always have them returned. But we would like to be more flexible, so we can pass an environment; examples are below. To make that clear: functional programming should not be seen as a yes-or-no decision; it is a matter of degree. And more of the functional approach can help already.

5.2 Data structure

All computations of `btest` will be based on one or several price series of length `T`. Internally, these prices are stored in numeric matrices.

Prices are passed as argument `prices`. For a single asset, this must be a matrix of prices with four columns: open, high, low and close.

For `n` assets, you need to pass a `list` of length four: `prices[[1]]` must be a matrix with `n` columns containing the open prices for the assets; `prices[[2]]` is a matrix with the high prices, and so on. For instance, with two assets, you need four matrices with two columns each:

```
 open      high      low       close
+-+-+     +-+-+     +-+-+     +-+-+
| | |     | | |     | | |     | | |
| | |     | | |     | | |     | | |
| | |     | | |     | | |     | | |
| | |     | | |     | | |     | | |
| | |     | | |     | | |     | | |
+-+-+     +-+-+     +-+-+     +-+-+
```

[1] Unqualified statements such as 'R is slow' or 'loops are slow' are not useful. In the current version of PMwR, the overhead of running a backtest with `btest` with 500 assets and 5000 observations (and rebalancing each of those assets at each of those 5000 timestamps) is less than five seconds; if only few assets are touched, overhead is less than one second.

If only close prices are used, then for a single asset, use either a matrix of one column or a numeric vector. For multiple assets a `list` of length one must be passed, containing a matrix of close prices. For example, with 100 close prices of 5 assets, the prices should be arranged in a matrix `p` of size 100 times 5; and `prices = list(p)`.

The `btest` function runs from `b+1` to `T`. The variable `b` is the burn-in and it needs to be a positive integer. When we take decisions that are based on past data, we will lose at least one data point. In rare cases `b` may be zero.

Here is an important default: at time =t=, we can use information up to time `t-1`. Suppose that `t` were 4. We may use all information up to time 3, and trade at the `open` in period 4:

```
t    time      open  high  low   close
1    HH:MM:SS                            <--\
2    HH:MM:SS                            <-- - use information
3    HH:MM:SS  --------------------------  <--/
4    HH:MM:SS     X                      <- trade here
5    HH:MM:SS
```

We could also trade at the `close`:

```
t    time      open  high  low   close
1    HH:MM:SS                            <-- \
2    HH:MM:SS                            <-- - use information
3    HH:MM:SS  --------------------------  <-- /
4    HH:MM:SS                        X   <-- trade here
5    HH:MM:SS
```

No, we cannot trade at the high or low. (Some people like the idea, as a robustness check, to always buy at the high, sell at the low. Robustness checks – forcing a bit of bad luck into the simulation – are a good idea, notably bad executions. High/low ranges can inform such checks, but using these ranges does not go far enough, and is more of a good story than a meaningful test.)

5.3 Function arguments

5.3.1 Available information within functions

`btest` expects as arguments a number of functions, such as `signal`; see the next section for a complete list. The default is to specify no arguments to these functions, because they can all access the following 'objects'. These objects actually are, with the exception of `Globals`, themselves functions that can access certain data. These

functions can only read; there are no replacement functions. The exception is `Globals`, which is an environment, and which can explicitly be used for writing (i.e. storing data).

Open open prices

High high prices

Low low prices

Close close prices

Wealth the total wealth (cash plus positions) at a given point in time

Cash cash (in accounting currency)

Time current time (an integer)

Timestamp the `timestamp` when that is specified (i.e. when the argument `timestamp` is supplied); if not, it defaults to `Time`

Portfolio the current portfolio

SuggestedPortfolio the currently-suggested portfolio

Globals an environment (not a function)

All functions take as their first argument a `lag`, which defaults to `1`. So to get the most recent close price, say

```
Close()
```

which is the same as `Close(lag = 1)`.

The `lag` can be a vector, too: the expression

```
Close(Time():1)
```

for instance will return all available close prices. So in period 11, say, you want close prices for lags 10, 9, ..., 1. Hence, to receive prices in their correct order, the lag sequence must always be in reverse order.

If you find it awkward to specify the lag in this reverse order, you may use the argument `n` instead, which specifies to retrieve the last n data points. So the above `Close(Time():1)` is equivalent to

```
Close(n = Time())
```

and saying

```
Close(n = 10)
```

will get you the last ten closing prices in their actual temporal order.

5.3.2 Function arguments

signal The function signal uses information until and including t-1 and returns the suggested portfolio (a vector) to be held at t. This position should be in units of the instruments; if you prefer to work with weights, then you should set convert.weights to TRUE. Then, the value returned by signal will be interpreted as weights and will be automatically converted to position sizes.

do.signal do.signal uses information until and including t-1 and must return TRUE or FALSE to indicate whether a signal (i.e. new suggested position) should be computed. This is useful when the signal computation is costly and only be done at specific points in time. If the function is not specified, it defaults to function() TRUE. Instead of a function, this may also be

- a vector of integers, which then indicate the points in time when to compute a position; or
- a vector of logical values, which then indicate the points in time when to compute a position; or
- a vector that inherits from the class of timestamp (e.g. Date); or
- one of the keywords firstofmonth, lastofmonth, firstofuqarter or lastofmonth. In this case, timestamp must inherit from Date or be coercible to Date. (Options can easily be specified with function nth_day in package datetimeutils.)

do.rebalance just like do.signal, but refers to the actual trading. If the function is not specified, it defaults to function() TRUE. Note that rebalancing can typically not take place at a higher frequency than implied by signal. That is because calling signal leads to a position, and when this position does not change (i.e. signal was not called), there is actually no need to rebalance. So do.rebalance is normally used when rebalancing should be done less often that signal computation, e.g. when the decision whether to trade or not is conditional on something.

print.info The function is called at the end of an iteration. Whatever it returns will be ignored since it is called for its side effect: print information to the screen, into a file or into some other connection.

cashflow The function is called at the end of each iteration; its value is added to the cash. The function provides a clean way to, for instance, add accrued interest to or subtract fees from a strategy.

5.4 Examples: A single asset

It is best to describe the `btest` function through a number of simple examples.

5.4.1 A useless first example

I really like simple examples. Suppose we have a single instrument, and we use only close prices. The trading rule is to buy, and then to hold forever. All we need is the time series of the prices and the signal function. As an instrument we use the EURO STOXX 50 future with expiry September 2015.

```
timestamp <- structure(c(16679L, 16680L, 16681L, 16682L,
                         16685L, 16686L, 16687L, 16688L,
                         16689L, 16692L, 16693L),
                       class = "Date")
prices <- c(3182, 3205, 3272, 3185, 3201,
            3236, 3272, 3224, 3194, 3188, 3213)
data.frame(timestamp, prices)
```

```
    timestamp prices
1  2015-09-01   3182
2  2015-09-02   3205
3  2015-09-03   3272
4  2015-09-04   3185
5  2015-09-07   3201
6  2015-09-08   3236
7  2015-09-09   3272
8  2015-09-10   3224
9  2015-09-11   3194
10 2015-09-14   3188
11 2015-09-15   3213
```

The `signal` function is very simple indeed.

```
signal <- function()
    1
```

`signal` must be written so that it returns the suggested position in units of the asset. In this first example, the suggested position always is 1 unit. It is only a *suggested* portfolio because we can specify rules whether or not to trade. Examples follow below.

To test this strategy, we call `btest`. The initial cash is zero per default, so initial wealth is also zero in this case. We can change it through the argument `initial.cash`.

```
(solution <- btest(prices = prices, signal = signal))
```

```
initial wealth 0  =>  final wealth  8
```

The function returns a list with a number of components, but they are not printed. Instead, a simple print method displays some information about the results. In this case, it tells us that the total equity of the strategy increased from 0 to 8.

We arrange more details into a `data.frame`. `suggest` is the suggested position; `position` is the actual position.

```
trade_details <- function(solution, prices)
    data.frame(price    = prices,
               suggest  = solution$suggested.position,
               position = unname(solution$position),
               wealth   = solution$wealth,
               cash     = solution$cash)

trade_details(unclass(solution), prices)
```

```
   price suggest position wealth  cash
1   3182       0        0      0     0
2   3205       1        1      0 -3205
3   3272       1        1     67 -3205
4   3185       1        1    -20 -3205
5   3201       1        1     -4 -3205
6   3236       1        1     31 -3205
7   3272       1        1     67 -3205
8   3224       1        1     19 -3205
9   3194       1        1    -11 -3205
10  3188       1        1    -17 -3205
11  3213       1        1      8 -3205
```

We bought in the second period because the default setting for the burnin `b` is 1. Thus, we lose one observation. In this particular case here, we do not rely in any way on the past; hence, we set `b` to zero. With this setting, we buy at the first price and hold until the end of the data.

```
solution <- btest(prices = prices, signal = signal,
                  b = 0)
trade_details(solution, prices)
```

```
   price suggest position wealth  cash
1   3182       1        1      0 -3182
2   3205       1        1     23 -3182
3   3272       1        1     90 -3182
4   3185       1        1      3 -3182
5   3201       1        1     19 -3182
6   3236       1        1     54 -3182
7   3272       1        1     90 -3182
```

```
8   3224       1         1     42 -3182
9   3194       1         1     12 -3182
10  3188       1         1      6 -3182
11  3213       1         1     31 -3182
```

If you prefer the trades only, i.e. not the position series, the solution also contains a `journal`. (See Keeping track of transactions: journals for more on journals.)

```
journal(solution)
```

```
   instrument  timestamp  amount  price
1     asset 1          1       1   3182

1 transaction
```

To make the journal more informative, we can pass `timestamp` and `instrument` information when we call `btest`.

```
journal(btest(prices = prices, signal = signal, b = 0,
              timestamp = timestamp, ## defined above,
                                     ## together with prices
              instrument = "FESX␣SEP␣2015"))
```

```
      instrument   timestamp  amount  price
1  FESX SEP 2015  2015-09-01       1   3182

1 transaction
```

Before we go to the next examples, a final remark, on data frequency. I have used daily data here, but any other frequency, also intraday data, is fine. `btest` will not care of what frequency your data are or whether your data are regularly spaced; it will only loop over the observations that it is given. It is your own responsibility to write `signal` (and other functions) in such a way that they encode a meaningful trade logic.

5.4.2 More-useful examples

Now we make our strategy slightly more selective. The trading rule is to have a position of 1 unit of the asset whenever the last observed price is below 3200 and to have no position when it the price is above 3200. The `signal` function could look like this.

```
signal <- function() {
    if (Close() < 3200)
        1
    else
        0
}
```

If you like to write clever code, you may as well have written this:

```
signal <- function()
    Close() < 3200
```

The `logical` value of the comparison `Close() < 3200` would be converted to either 0 or 1. But the more verbose version above is clearer.[2]

We call `btest` and check the results.

```
solution <- btest(prices = prices, signal = signal)

trade_details(solution, prices)
```

```
   price suggest position wealth  cash
1   3182       0        0      0     0
2   3205       1        1      0 -3205
3   3272       0        0     67    67
4   3185       0        0     67    67
5   3201       1        1     67 -3134
6   3236       0        0    102   102
7   3272       0        0    102   102
8   3224       0        0    102   102
9   3194       0        0    102   102
10  3188       1        1    102 -3086
11  3213       1        1    127 -3086
```

(Yes, this strategy works better than the simple buy-and-hold, but I hope you agree that this is only because of luck.)

The argument `initial.position` specifies the initial position; default is no position. Suppose we had already held one unit of the asset.

```
solution <- btest(prices = prices, signal = signal,
                  initial.position = 1)
```

Then the results would have looked as follows.

```
trade_details(solution, prices)
```

```
   price suggest position wealth cash
1   3182       1        1   3182    0
2   3205       1        1   3205    0
3   3272       0        0   3272 3272
4   3185       0        0   3272 3272
5   3201       1        1   3272   71
6   3236       0        0   3307 3307
```

[2] Remember what Brian Kernighan said: *Everyone knows that debugging is twice as hard as writing a program in the first place. So if you're as clever as you can be when you write it, how will you ever debug it?*

```
7   3272       0         0   3307 3307
8   3224       0         0   3307 3307
9   3194       0         0   3307 3307
10  3188       1         1   3307  119
11  3213       1         1   3332  119
```

In the example above, we use the close price, but we do not access the data directly. A function `Close` is defined by `btest` and passed as an argument to `signal`. Note that we do not add it as a formal argument to `signal` since this is done automatically. In fact, doing it manually would trigger an error message:

```
signal <- function(Close = NULL)   ## ERROR: argument name
    1                              ## 'Close' not allowed
```

```
Error in btest(prices = prices, signal = signal) :
  'Close' cannot be used as an argument name for 'signal'
```

Similarly, we have functions `Open`, `High` and `Low`; see Section 5.3 above for all functions.

Suppose we wanted to add a variable: a `threshold` that tells us when to buy. This would need to be an argument to `signal`; it would also need to be passed with the `...` argument of `btest`.

```
signal <- function(threshold) {
    if (Close() < threshold)
        1
    else
        0
}

solution <- btest(prices = prices,
                  signal = signal,
                  threshold = 3190)

trade_details(solution, prices)
```

```
   price suggest position wealth  cash
1   3182       0        0      0     0
2   3205       1        1      0 -3205
3   3272       0        0     67    67
4   3185       0        0     67    67
5   3201       1        1     67 -3134
6   3236       0        0    102   102
7   3272       0        0    102   102
8   3224       0        0    102   102
9   3194       0        0    102   102
10  3188       0        0    102   102
11  3213       1        1    102 -3111
```

So far we have treated `Close` as a function without arguments, but actually it has an argument `lag` that defaults to `1`. Suppose the rule were to buy if the last close is below the second-to-last close. `signal` could look like this.

```
signal <- function() {
    if (Close(1L) < Close(2L))
        1
    else
        0
}
```

We could also have written `(Close() < Close(2L))`. In any case, the rule uses the close prices of yesterday and of the day before yesterday, so we need to increase `b`.

```
trade_details(btest(prices = prices, signal = signal, b = 2),
              prices)
```

```
   price suggest position wealth  cash
1   3182       0       NA     NA     0
2   3205       0        0      0     0
3   3272       0        0      0     0
4   3185       0        0      0     0
5   3201       1        1      0 -3201
6   3236       0        0     35    35
7   3272       0        0     35    35
8   3224       0        0     35    35
9   3194       1        1     35 -3159
10  3188       1        1     29 -3159
11  3213       1        1     54 -3159
```

If we want to trade a different size, we have `signal` return the desired value.

```
signal <- function()
    if (Close() < 3200)
        2 else 0

trade_details(btest(prices = prices, signal = signal), prices)
```

```
   price suggest position wealth  cash
1   3182       0        0      0     0
2   3205       2        2      0 -6410
3   3272       0        0    134   134
4   3185       0        0    134   134
5   3201       2        2    134 -6268
6   3236       0        0    204   204
7   3272       0        0    204   204
8   3224       0        0    204   204
9   3194       0        0    204   204
10  3188       2        2    204 -6172
11  3213       2        2    254 -6172
```

A often-used way to specify a trading strategy is to map past prices into `+1`, `0` or `-1` for long, flat or short. A signal is often only given at a specified point (like in 'buy one unit now'). Example: suppose the third day is a Thursday, and our rule says 'buy after Thursday'.

```
signal <- function()
    if (Time() == 3L)
        1 else 0

trade_details(btest(prices = prices, signal = signal),
              prices)
```

```
   price suggest position wealth  cash
1   3182       0        0      0     0
2   3205       0        0      0     0
3   3272       0        0      0     0
4   3185       1        1      0 -3185
5   3201       0        0     16    16
6   3236       0        0     16    16
7   3272       0        0     16    16
8   3224       0        0     16    16
9   3194       0        0     16    16
10  3188       0        0     16    16
11  3213       0        0     16    16
```

But this is not what we wanted. If the rule is to buy and then keep the long position, we should have written it like this.

```
signal <- function()
    if (Time() == 3L)
        1 else Portfolio()
```

The function `Portfolio` evaluates to last period's portfolio. Like `Close`, its first argument sets the time `lag`, which defaults to 1.

```
trade_details(btest(prices = prices, signal = signal), prices)
```

```
   prices sp asset.1 wealth  cash
1    3182  0       0      0     0
2    3205  0       0      0     0
3    3272  0       0      0     0
4    3185  1       1      0 -3185
5    3201  1       1     16 -3185
6    3236  1       1     51 -3185
7    3272  1       1     87 -3185
8    3224  1       1     39 -3185
9    3194  1       1      9 -3185
10   3188  1       1      3 -3185
11   3213  1       1     28 -3185
```

We may also prefer to specify `signal` so that it evaluates to a weight; for instance, after a portfolio optimisation. In such a case, you need to set `convert.weights` to `TRUE`. (Make sure to have a meaningful initial wealth: 5 percent of nothing is nothing.)

```
signal <- function()
    0.05

solution <- btest(prices = prices,
                  signal = signal,
                  initial.cash = 100,
                  convert.weights = TRUE)
trade_details(solution, prices)
```

```
   prices      sp asset.1 wealth  cash
1    3182 0.00000 0.00000    100 100.0
2    3205 0.00157 0.00157    100  95.0
3    3272 0.00156 0.00156    100  95.0
4    3185 0.00153 0.00153    100  95.1
5    3201 0.00157 0.00157    100  95.0
6    3236 0.00156 0.00157    100  95.0
7    3272 0.00155 0.00155    100  95.0
8    3224 0.00153 0.00153    100  95.1
9    3194 0.00155 0.00155    100  95.0
10   3188 0.00157 0.00157    100  95.0
11   3213 0.00157 0.00157    100  95.0
```

Note that until now we – potentially – rebalanced in every period. If you do not want that, we need to specify `do.rebalance`.

```
do.rebalance <- function() {
    if (sum(abs(
        SuggestedPortfolio(0) - Portfolio())) > 1e-3)
        TRUE
    else
        FALSE
}

solution <- btest(prices = prices,
                  signal = signal,
                  initial.cash = 100,
                  do.rebalance = do.rebalance,
                  convert.weights = TRUE)

trade_details(solution, prices)
```

```
  price  suggest position  wealth      cash
1  3182 0.000000 0.000000 100.000 100.00000
2  3205 0.031427 0.031427 100.000  -0.72282
```

```
3   3272 0.031201 0.031427 102.106  -0.72282
4   3185 0.031206 0.031427  99.371  -0.72282
5   3201 0.031200 0.031427  99.874  -0.72282
6   3236 0.031201 0.031427 100.974  -0.72282
7   3272 0.031203 0.031427 102.106  -0.72282
8   3224 0.031206 0.031427 100.597  -0.72282
9   3194 0.031203 0.031427  99.654  -0.72282
10  3188 0.031200 0.031427  99.466  -0.72282
11  3213 0.031200 0.031427 100.251  -0.72282
```

`do.rebalance` is called after `signal`. Hence, the suggested position is known and the lag should be zero ('`SuggestedPortfolio(0)`').

The `tol` argument works similarly: it instructs `btest` to only rebalance when the maximum absolute suggested change in any single position is greater than `tol`. Default is 0.00001, which practically means always rebalance.

```
solution <- btest(prices = prices,
                  signal = signal,
                  initial.cash = 100,
                  tol = 2e-5,
                  convert.weights = TRUE)

trade_details(solution, prices)
```

```
   prices      sp asset.1 wealth  cash
1    3182 0.00000 0.00000    100 100.0
2    3205 0.00157 0.00157    100  95.0
3    3272 0.00156 0.00157    100  95.0
4    3185 0.00153 0.00153    100  95.1
5    3201 0.00157 0.00157    100  95.0
6    3236 0.00156 0.00157    100  95.0
7    3272 0.00155 0.00155    100  95.0
8    3224 0.00153 0.00155    100  95.0
9    3194 0.00155 0.00155    100  95.0
10   3188 0.00157 0.00155    100  95.0
11   3213 0.00157 0.00157    100  95.0
```

Passing environments

To keep information persistent, we can use environments. As an example, we store (and update) the most recent entry price.

```
notepad <- new.env()
notepad$entry <- numeric(length(prices))

signal <- function(threshold, notepad) {
```

```
    notepad$entry[Time(0L)] <- notepad$entry[Time(1L)]
    if (Close() < threshold) {
        if (Portfolio() < 1)
            notepad$entry[Time(0L)] <- Close(0L)
        1
    } else {
        0
    }
}

solution <- btest(prices = prices,
                  signal = signal,
                  threshold = 3200,
                  notepad = notepad)

cbind(trade_details(solution, prices), entry = notepad$entry)
```

	price	suggest	position	wealth	cash	entry
1	3182	0	0	0	0	0
2	3205	1	1	0	-3205	3205
3	3272	0	0	67	67	3205
4	3185	0	0	67	67	3205
5	3201	1	1	67	-3134	3201
6	3236	0	0	102	102	3201
7	3272	0	0	102	102	3201
8	3224	0	0	102	102	3201
9	3194	0	0	102	102	3201
10	3188	1	1	102	-3086	3188
11	3213	1	1	127	-3086	3188

Let us check.

```
subset(journal(solution), amount > 0)
```

`btest` provides an environment `Globals` for exactly such purposes.

```
signal <- function(threshold) {
    Globals$entry[Time(0L)] <- Globals$entry[Time(1L)]
    if (Close() < threshold) {
        if (Portfolio() < 1)
            Globals$entry[Time(0L)] <- Close(0L)
        1
    } else {
        0
    }
}

solution <- btest(prices = prices,
                  signal = signal,
```

```
                    threshold = 3200,
                    include.data = TRUE)

cbind(trade_details(solution, prices),
      entry = solution$Globals$entry)
```

```
   price suggest position wealth  cash entry
1   3182       0        0      0     0    NA
2   3205       1        1      0 -3205  3205
3   3272       0        0     67    67  3205
4   3185       0        0     67    67  3205
5   3201       1        1     67 -3134  3201
6   3236       0        0    102   102  3201
7   3272       0        0    102   102  3201
8   3224       0        0    102   102  3201
9   3194       0        0    102   102  3201
10  3188       1        1    102 -3086  3188
11  3213       1        1    127 -3086  3188
```

5.5 Examples: Several assets

It does not really make a difference whether `btest` is called with a single or with several instruments. The pattern in `signal` is still to call `Close()` and friends to obtain data, but now these functions will return matrices with more than one column. For instance, when you have 5 assets, then `Close(n = 250)` would return a matrix of size 250 × 5. When `signal` has finished its computations, it is now expected to return a vector of positions or weights. In the example with 5 assets, it should return a vector of length 5.

5.5.1 A simple example

```
prices1 <- c(100,98, 98, 97, 96, 98,97,98,99,101)
prices2 <- c(100,99,100,102,101,100,96,97,95,82)
prices <- cbind(A = prices1, B = prices2)

signal <- function()
    if (Close()[1L] > Close()[2L])
        c(2, 0) else c(0, 1)

(solution <- btest(prices = list(prices),
                   signal = signal,
                   b=2))
```

```
  trade_details <- function(solution, prices)
      data.frame(price    = prices,
                 suggest  = solution$suggested.position,
                 position = solution$position, ## do not unname
                 wealth   = solution$wealth,
                 cash     = solution$cash)

trade_details(solution, prices)
```

```
   price.A price.B suggest.A suggest.B position.A position.B wealth cash
1      100     100         0         0         NA         NA     NA    0
2       98      99         0         0          0          0      0    0
3       98     100         0         1          0          1      0 -100
4       97     102         0         1          0          1      2 -100
5       96     101         0         1          0          1      1 -100
6       98     100         0         1          0          1      0 -100
7       97      96         0         1          0          1     -4 -100
8       98      97         2         0          2          0     -3 -199
9       99      95         2         0          2          0     -1 -199
10     101      82         2         0          2          0      3 -199
```

```
journal(solution)
```

```
   instrument  timestamp  amount  price
1           B          3       1    100
2           A          8       2     98
3           B          8      -1     97

3 transactions
```

5.6 Miscellaneous

There is more than one way to accomplish a certain task.

5.6.1 Handling missing values

Missing values are everywhere financial time-series. (I do hope the irony is not wasted.) There are holidays on some exchanges but not on others; stocks and bonds become halted or delisted; derivatives and bonds come to life and expire; or databases may simply lack prices for certain dates because of technical glitches.

Backtesting requires careful data preparation, which includes handling missing values. Unfortunately, there is no foolproof way to handle `NA` values, which is why

`btest` does not have an `na.rm` argument. (In an experimental branch, there is an argument `allow.na`; but that branch will probably never be merged into the `master` branch.)

The strategies to handle `NA` values depend on the situation. If only initial price observations are missing, you can set the burnin `b` so that those values are skipped.

Copying forward the last available price is often acceptable for liquid assets when positions need to be valued, or perhaps when indicators such as moving averages are computed. But the backtest should in general not trade on such prices. This is most obvious for illiquid instruments such as options: the last trade may be some time back, and in the meantime market makers may have substantially moved bid/ask.

A more-general approach is to keep track of available assets. It is useful here to keep in mind `btest`'s general mechanism for computing trades: it compares suggested positions with actual ones, and considers the differences to be trades. However, if both suggested and actual positions are zero, nothing needs to be done for those assets. And `btest` takes this literally: those assets will not be included in computations such as the valuation of the portfolio. So a generic strategy is to check whether asset prices exists when the suggested portfolio is computed and to set the positions of missing values to zero.

Two examples follow.

```
prices <- 11:15
prices[4:5] <- NA

signal <- function() {
  if (Time(0) <= 2)
    1 else 0
}
bt <- btest(prices, signal)
position(bt)
journal(bt)
```

```
     [,1]
[1,]    0
[2,]    1
[3,]    0
[4,]    0
[5,]    0

   instrument  timestamp  amount  price
1     asset 1          2       1     12
2     asset 1          3      -1     13

2 transactions
```

```
prices <- cbind(11:15, NA)

signal <- function()
    c(1, 0)

bt <- btest(list(prices), signal)
position(bt)
journal(bt)
```

```
     [,1] [,2]
[1,]    0    0
[2,]    1    0
[3,]    1    0
[4,]    1    0
[5,]    1    0
   instrument  timestamp  amount  price
1     asset 1          2       1     12

1 transaction
```

5.6.2 Distributing backtest computations

`btest` offers functionality to run several backtests, or variations of backtests, automatically. Since such computations are independent from each other, they can also be distributed. `btest` relies on the parallel package to do this.

A simple example.

```
library("PMwR")
signal <- function(h) {
    if (Close() > h)
        1
    else
        0
}

btest(1:10, signal = signal, h = 1)
```

You may now specify variations for each argument.

```
btest(1:10, signal = signal, variations = list(h = 1:5))
```

The default is to process these variations through a loop.

```
signal <- function(h) {
    Sys.sleep(0.1)
    if (Close() > h)
```

```
        1
    else
        0
}
system.time(btest(1:10, signal = signal, variations = list(h = 1:5)))
system.time(btest(1:10, signal = signal, variations = list(h = 1:5),
                  variations.settings = list(method = "parallel", cores = 5)))

signal1 <- function()
    1

signal2 <- function()
    2

btest(1:10, variations = list(signal = list(signal1, signal2)))
```

5.6.3 Remembering an entry price

In `signal`, assign the current price (with lag 0) to `Globals`. (That is easiest because `do.rebalance` may not be defined.)

5.6.4 Delaying signals

In real life, the information that is used for computing signals may arrive later expected. (This can happen on any time-scale, i.e. for high and low frequency trading.) Or our signal is current, but for some reason we cannot execute a trade.

The first case can usually be handled in `signal`, e.g. by using larger lags. One way to incorporate the second case is to add a random variable to `do.rebalance`:

```
if (runif(1) > prob_of_delay)
    TRUE else FALSE
```

If `TRUE`, rebalancing will take place.

5.6.5 Specifying when to compute a signal and trade

`btest` takes two functions, `do.signal` and `do.rebalance`, that tell the algorithm when to compute a new portfolio and when to rebalance. There are different ways to specify these points in time: as a function that returns `TRUE` or `FALSE` (most general), but also as integers, logicals or actual timestamps (e.g. dates).

Supplying particular timestamps is useful when you know you want to trade on a specific calendar day, say. That is OK because you know in advance when this calendar day is going to be. But be careful when you use other information to specify when to trade. The following examples are not equivalent:

```
btest(prices = prices,
      signal = signal,
      do.signal = prices > 3600)

btest(prices = prices,
      signal = signal,
      do.signal = function() Close() > 3600)
```

Loosely speaking, both variations compute a signal and trade only when `prices` is above 3600. But in the first version, there will be no time lag: if the prices exceeds 3600 at time t_i, we will trade at t_i. In the second example, `Close()` comes with a default lag of 1: if the price exceeds 3600 at t_i, we will trade at t_{i+1}, which is the more realistic case.

When `timestamp` is of a type that can be coerced to `Date`, you can also use the keywords such as `firstofmonth` or `lastofmonth`:

```
btest(prices = prices,
      signal = signal,
      do.signal = "firstofmonth")
```

5.6.6 Writing a log

Specify the function `print.info`. The function is called at the very end of an iteration, so it is best to use no time lag. An example

```
print.info <- function() {
    cat("Time",
        sprintf("%2d", Time(0L)), "...",
        sprintf("%3d", Wealth(0L)), "\n")
    flush.console()
}
```

And since `cat` has a `file` argument, you can have it write such information into a logfile.

5.6.7 Selecting parameters: calling `btest` recursively

Suppose you have a strategy that depends on a parameter vector θ. For a given θ, the signal for the strategy would look like this.

```
signal <- function(theta) {
    ## compute position as a function of theta
}
```

Now suppose we do not know theta. We might want to test several values, and then keep the best one. For this, we need to call btest recursively: at a point in time t, the strategy simulates the results for various values for theta and chooses the best theta, according to some criterion `f`.

A useful idiom is this:

```
signal <- function(theta) {
    if (not defined theta) {
        - run btest with theta_1, ... \theta_n, select best theta
        - theta = argmin_theta f(btest(theta_i))
    }

    compute position as a function of theta
}
```

`btest` will first be invoked without θ (or `NULL`). When the function calls `signal`, θ is not defined and `signal` will call `btest` with a specified θ.

Let us look at an actual example.

```
require("tseries")
require("zoo")
require("runStats")

## tmp <- get.hist.quote("^GSPC",
##                       start = "2010-01-01",
##                       end = "2013-12-31", quote = "Close")

signal <- function(Data) {

    if (is.na(Data$N)) {
        message(Timestamp(0))

        price <- Close(n = 500)
        Ns <- c(10,20)

        Data1 <- list(N = 10, hist = 200)
        res1 <- btest(price, signal, Data = Data1, b = 200)

        Data2 <- list(N = 20, hist = 200)
        res2 <- btest(price, signal, Data = Data2, b = 200)
```

```
        message("N␣10␣:␣", round(tail(res1$wealth, 1), 2))
        message("N␣20␣:␣", round(tail(res2$wealth, 1), 2))

        N <- if (tail(res1$wealth, 1) > tail(res2$wealth, 1))
                 10
             else
                 20
        message("N␣is␣--->␣", N, "\n")
    } else  {
        N <- Data$N
    }

    ##
    price <- Close(n = Data$hist)
    MA <- runStats("mean", price, N = N)
    pos <- 0
    if (Close() > tail(MA, 1))
        pos <- 1
    pos
}

Data <- list(N = NA, hist = 200)
res <- btest(tmp$Close, signal,
             Data = Data,
             b = 500,
             initial.cash = 100,
             convert.weights = TRUE,
             timestamp = index(tmp))

par(mfrow = c(2,1))
plot(index(tmp), res$wealth, type = "s")
plot(tmp)
```

5.6.8 Time-varying asset universes

We'll see how to deal with a particular case of missing values: when certain assets are available only at certain times. We first get some data: time-series of industry portfolios from Kenneth French's website at `https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/` The dataset comprises 30 series of daily data, and we use a subset that starts in January 1990.

```
library("NMOF")
library("zoo")
P <- French(dest.dir = tempdir(),
            "30_Industry_Portfolios_daily_CSV.zip",
            price.series = TRUE,
```

```
                na.rm = TRUE)

  P <- zoo(P, as.Date(row.names(P)))
  P <- window(P, start = as.Date("1990-1-1"))
  str(P)
```

```
''
zoo series from 1990-01-02 to 2021-01-29
  Data: num [1:7831, 1:30] 807 802 796 790 790 ...
 - attr(*, "dimnames")=List of 2
  ..$ : chr [1:7831] "1990-01-02" "1990-01-03" ...
  ..$ : chr [1:30] "Food" "Beer" "Smoke" "Games" ...
  Index:  Date[1:7831], format: "1990-01-02" ...
```

Actually, the data are complete: there are no missing values.

```
any(is.na(P))
```

```
[1] FALSE
```

So let us make them incomplete: in series 16 to 30, we remove all data before January 2000.

```
  window(P[, 16:30], end = as.Date("1999-12-31")) <- NA
```

The key feature of `btest` to handle such data is this: if an asset is not selected (i.e. has a zero position), it is not required for valuing the position, and so it can be missing. Suppose we wanted to to simulate a 50/50 investment in only the first two series (which, we know, are complete). With `btest`, we could do it as follows.

```
  library("PMwR")
  bt <- btest(prices = list(coredata(P)),
              timestamp = index(P),
              signal = function() {
                w <- numeric(ncol(Close()))
                w[1:2] <- c(0.5, 0.5)
                w
              },
              do.signal = "lastofquarter",
              convert.weights = TRUE,
              initial.cash = 100)
  head(journal(bt), n = 10, by = FALSE)
```

As you can see, the function does not complain. If you check the journal, you'll find that all transactions have been in Food and Beer, the first two industries.

```
    instrument   timestamp         amount      price
1         Food  1990-03-30   0.0660393017   758.8663
```

```
2          Beer  1990-03-30   0.0335054119  1481.5517
3          Food  1990-06-29   0.0026905121   842.7345
4          Beer  1990-06-29  -0.0011305346  1775.1047
5          Food  1990-09-28  -0.0014597110   774.9077
6          Beer  1990-09-28   0.0007077629  1575.3859
7          Food  1990-12-31   0.0008250171   881.3539
8          Beer  1990-12-31  -0.0003957095  1824.9844
9          Food  1991-03-28  -0.0004125792  1079.7564
10         Beer  1991-03-28   0.0001984854  2237.6230

10 transactions
```

Now we can start the actual example. The aim in this exercise is to compute a minimum-variance portfolio over all available assets. We begin by defining *when* certain assets were available, and placing this information in a data-frame `active`.

```
active <- data.frame(instrument = colnames(P),
                     start = c(rep(as.Date("1990-1-1"), 15),
                               rep(as.Date("2001-1-1"), 15)),
                     end = tail(index(P), 1))
active
```

```
   instrument      start        end
1        Food 1990-01-01 2021-01-29
2        Beer 1990-01-01 2021-01-29
3       Smoke 1990-01-01 2021-01-29
4       Games 1990-01-01 2021-01-29
5       Books 1990-01-01 2021-01-29
6       Hshld 1990-01-01 2021-01-29
7       Clths 1990-01-01 2021-01-29
8        Hlth 1990-01-01 2021-01-29
9       Chems 1990-01-01 2021-01-29
10      Txtls 1990-01-01 2021-01-29
11      Cnstr 1990-01-01 2021-01-29
12      Steel 1990-01-01 2021-01-29
13      FabPr 1990-01-01 2021-01-29
14      ElcEq 1990-01-01 2021-01-29
15      Autos 1990-01-01 2021-01-29
16      Carry 2001-01-01 2021-01-29
17      Mines 2001-01-01 2021-01-29
18       Coal 2001-01-01 2021-01-29
19        Oil 2001-01-01 2021-01-29
20       Util 2001-01-01 2021-01-29
21      Telcm 2001-01-01 2021-01-29
22      Servs 2001-01-01 2021-01-29
23      BusEq 2001-01-01 2021-01-29
24      Paper 2001-01-01 2021-01-29
25      Trans 2001-01-01 2021-01-29
26      Whlsl 2001-01-01 2021-01-29
```

```
27      Rtail 2001-01-01 2021-01-29
28      Meals 2001-01-01 2021-01-29
29        Fin 2001-01-01 2021-01-29
30      Other 2001-01-01 2021-01-29
```

Note that we did set `start` to 2001, not 2000. You'll see shortly, why.

Now for the `signal` function. It receives `active` as an argument.

```
mv <- function(active) {

  ## find those assets that are active
  ## ==> 'j' is a logical vector that
  ##         indicates the active assets
  j <- Timestamp() >= active[["start"]] &
       Timestamp() <= active[["end"]]


  ## get last 260 prices of active assets and compute
  ## variance--covariance matrix
  P.j <- Close(n = 260)[, j]
  R.j <- returns(P.j)
  S <- cov(R.j)


  ## compute minimum-variance weights
  w.j <- NMOF::minvar(S, wmin = 0, wmax = 0.10)


  ## create a zero-vector with length equal to number
  ## of total assets and assign the weights at
  ## appropriate positions
  w <- numeric(length(j))
  w[j] <- w.j
  w
}
```

Now you see why we used 2001 as the start date for series 16 to 30: we'll use one year of historical data to compute the variance-covariance matrix. (Note that there are better ways to come up with forecasts of the variance-covariance matrix, e.g. methods that apply shrinkage. But the purpose of this note is to show how to handle missing values in `btest`, not to discuss empirical methods.)

We call `btest`.

```
bt.mv <- btest(prices = list(coredata(P)),
               timestamp = index(P),
               signal = mv,
               do.signal = "lastofquarter",
```

```
                convert.weights = TRUE,
                initial.cash = 100,
                active = active,
                b = 260)
bt.mv
```

```
initial wealth 100  =>  final wealth  1779.84
Total return   1679.8%
```

The backtest runs without problems. As an example, let us check trades in industry `Oil`.

```
head(journal(bt.mv)["Oil"], 5)
```

```
  instrument   timestamp          amount     price
1        Oil  2001-03-30   0.0104934366  2656.871
2        Oil  2001-06-29  -0.0003607878  2709.119
3        Oil  2001-09-28   0.0011873853  2383.685
4        Oil  2001-12-31  -0.0043576713  2549.018
5        Oil  2002-03-28  -0.0037902744  2807.207

5 transactions
```

As expected, the first trades occur only in 2001.

A final remark: we would not have needed to prepare `active` upfront. Instead, we could have checked for missing values in the `signal` function.

```
mv_with_NA_check <- function() {

  ## fetch data and check for missing values
  P <- Close(n = 260)
  j <- !apply(P, 2, anyNA)

  ## get last 250 prices of active assets and compute
  ## variance--covariance matrix
  P.j <- P[, j]
  R.j <- returns(P.j)
  S <- cov(R.j)

  ## compute minimum-variance weights
  w.j <- NMOF::minvar(S, wmin = 0, wmax = 0.10)

  ## create a zero-vector with length equal to number
  ## of total assets and assign the weights at
  ## appropriate positions
  w <- numeric(length(j))
  w[j] <- w.j
  w
}
```

```
bt.mv2 <- btest(prices = list(coredata(P)),
                timestamp = index(P),
                signal = mv_with_NA_check,
                do.signal = "lastofquarter",
                convert.weights = TRUE,
                initial.cash = 100,
                b = 260)
bt.mv2
head(journal(bt.mv)["Oil"], 5)
```

```
initial wealth 100  => final wealth  1779.84
Total return   1679.8%

   instrument   timestamp         amount     price
1         Oil  2001-03-30   0.0104934366  2656.871
2         Oil  2001-06-29  -0.0003607878  2709.119
3         Oil  2001-09-28   0.0011873853  2383.685
4         Oil  2001-12-31  -0.0043576713  2549.018
5         Oil  2002-03-28  -0.0037902744  2807.207

5 transactions
```

We get the same results. But defining an explicit list is more, well, explicit. Which is often a good thing when analysing data; notably, because it sets an expectation that those active time-series don't have missing values.

6 Backtesting strategies in parallel

6.1 Distributed computing

Distributed computing is straightforward: split a large computation into smaller ones, and distribute these subcomputations to several workers; then, collect the results from the workers and combine them. Perhaps the simplest example is computing the sum of many numbers: Group the numbers into several subsets; give these subsets to workers that then compute the subset-sums; and, finally, add the subset-sums. This example already makes clear a trade-off: we save time because several workers do their job in parallel; but we lose time when we distribute the tasks, and collect and combine the results. The effort required for such 'administrative' operations is called overhead. For computations that take very little time on a modern computer (such as, incidentally, computing a sum of numbers), distributing does not help because the overhead is too large. As a rule: the best way to find out whether a parallel computation actually saves time – and if so, how much – is to run experiments.

Distributed computing has several advantages: it is simple, and often scales well: if the overhead is small compared with the time the actual computation requires, the speedup is roughly linear. Double the number of workers, and the computation time halves.

Cleve Moler called easily-distributable computations 'embarrassingly parallel'. Such computations are everywhere in finance:

- Monte Carlo simulations;
- pricing portfolios in which the positions do not depend on one another;
- optimization with population-based methods;

- running restarts for optimization methods;
- general sensitivity analysis.

6.2 Loops and apply functions

Let us define a simple function, one. It does what its name promises.

```
one <- function(...)
    1
one()
```

```
[1] 1
```

Pretend one did something useful, and you wanted to repeat this computation 1000 times. The reflex is to use a for-loop.

```
runs <- 1000
ones <- numeric(runs)
for (i in seq_len(runs))
    ones[i] <- one()
```

But a for-loop misguides us, in a way. It implies an iterative computation: the first, the second, etc. But we care not about the order in which one is called.

In R, we may use lapply instead (or a higher level variant, such as replicate).

```
ones <- lapply(seq_len(runs), one)
```

It is not merely a change in syntax: lapply does not make a promise about the order in which one is called.

Package parallel offers several parallel equivalents to lapply; one of them is called parLapply. Before we use the function, let us make one slower.

```
one <- function(...) {
    Sys.sleep(1)  ## wait one second
    1
}
```

Running one four times should now take just as many seconds, plus a little overhead.

```
runs <- 4
system.time(
    for (i in seq_len(runs))
        one())
```

The same is true with `lapply`.

```
system.time(
    lapply(seq_len(runs), one))
```

But not when run in parallel, on four cores.

```
library("parallel")
cl <- makeCluster(4)  ## four cores
system.time(parLapply(cl, seq_len(runs), one))
system.time(clusterApply(cl, seq_len(runs), one))
stopCluster(cl)
```

Note that when we call `makeCluster`, we assume that your machine has four cores. You may use function `detectCores` to find out about your machine. But be sure to read the function's help page and its caveats.

6.3 Distributing data

Running a computation in parallel can be split into three parts: distribute data and code to the nodes; have the nodes run the computations; and finally collect the results. R will help us with the second and the third task; in fact, it will do the whole job for us. That means we are left with the task of organizing the computation and distributing it.

Let us create a new function.

```
sum_xy <- function(x, y)
    x + y
```

Suppose we want to evaluate the function for different values of `x` and `y`. These different values are collected in a data frame `df`. Each of `df` thus holds one case that we wish to evaluate.

```
df <- expand.grid(x = 1:2, y = 5:6)
df
```

In a serial computation, i.e. with a loop, we would run through the rows of `df` and call `sum_xy` for each row.

In R we can pack the arguments of a function into a list, and then call the function with this single list as an argument. (In case you do not realize it: this is a very powerful feature.)

```
args <- list(x = 1, y = 5)
do.call("sum_xy", args)
```

```
[1] 6
```

The elements in `args` will be treated and matched as in a standard function call. So for instance `args <- list(1, x = 2)` means that `y` gets the value of `1`.

A simple strategy is the one we described before: put every row of `df` into a list.

```
data <- vector("list", length = nrow(df))
for (i in seq_len(nrow(df)))
    data[[i]] <- list(x = df$x[i], y = df$y[i])
```

Note that in the example here, it would have sufficed to write `\texttt{data[[i]] <- c(df[i, ])}` in the loop. Calling `c` has the (documented) side effect of dropping all attributes, including `class`.

It is easy to memorize this pattern of setting up the data, because it resembles calling the function of interest in a loop, only instead of calling the function, we call `list`.

We could now call `lapply`.

```
lapply(data, function(z) do.call(sum_xy, z))
```

```
[[1]]
[1] 6

[[2]]
[1] 7

[[3]]
[1] 7

[[4]]
[1] 8
```

We are as well ready for the parallel version of `lapply`. Or almost, at least: we have prepared the data. But the nodes that are supposed to do the computations cannot know what `sum_xy` is. So we tell them, by exporting the function `sum_xy` from the main session (i.e. the session that starts the other processes) to the nodes.

```
cl <- makeCluster(4)
clusterExport(cl, "sum_xy")
parLapply(cl, data, function(x) do.call(sum_xy, x))
clusterApply(cl, data, function(x) do.call(sum_xy, x))
stopCluster(cl)
```

```
[[1]]
[1] 6

[[2]]
```

```
[1] 7

[[3]]
[1] 7

[[4]]
[1] 8
[[1]]
[1] 6

[[2]]
[1] 7

[[3]]
[1] 7

[[4]]
[1] 8
```

Alternatively, we could have sent the code of `sum_xy` as an expression and evaluate it on each node.

```
cl <- makeCluster(4)
ignore <- clusterEvalQ(cl,
                       sum_xy <- function(x, y)
                           x + y)
###
parLapply(cl, data, function(x) do.call(sum_xy, x))
stopCluster(cl)
```

6.4 Distributing data, continued

In the example, all arguments to the computation were variable, i.e. they changed in every call. But suppose that y is fixed. In a backtest, think of price data, which may stay the same over different tests. Instead of moving such fixed data around every time, we might as well export it from the master to the nodes.

```
y.value <- 100
x.values <- as.list(1:4)
###
cl <- makeCluster(4)
clusterExport(cl, "y.value")
ignore <- clusterEvalQ(cl,
                       sum_xy <- function(x, y = y.value)
                                          x + y)
###
```

```
parLapply(cl, x.values, function(x) sum_xy(x, y.value))
stopCluster(cl)
```

Let us create two tiny case studies for distributing a backtest. In one, the price data stays unchanged, but we wish to test different parameters. In the other, we wish to run the same strategy on two different data sets.

```
## set up data, functions
prices <- 101:110
signal <- function(threshold) {
    if (Close() > threshold)
        1
    else
        0
}
threshold.values <- as.list(102:105)
###
###
## create cluster and distribute data, functions
cl <- makeCluster(4)
clusterExport(cl,
              c("signal", "prices"))
###
ignore <- clusterEvalQ (cl,
                        library("PMwR"))
###
###
## run btest
parLapply(cl, threshold.values,
          function(x)
              btest(prices = prices,
                    signal = signal,
                    threshold = x))

stopCluster(cl)
```

The second example.

```
## set up data, functions
prices <- list(prices1 = 101:110,
               prices2 = 201:210)
signal <- function() {
    if (Close() > 105)
        1
    else
        0
}
###
###
```

```
cl <- makeCluster(4)  ## create cluster
###
clusterExport(cl,     ## distribute data, functions
              c("signal"))
ignore <- clusterEvalQ (cl,
                        library("PMwR"))
###
###
parLapply(cl, prices, ## run btest
          function(x)
              btest(prices = x,
                    signal = signal))

stopCluster(cl)
```

As the examples have shown, there is typically more than one way to do it. In general, in particular for larger studies, it pays off to take some time to structure the computations and results, and to experiment with different setups.

One useful idea is to store different specifications of backtests in files. If these are `R` code files, we may than use the `parallel` functions directly with `source`. Suppose for each strategy you have an R file in a directory `Backtesting`; then you could evaluate each file with a code snippet as this one.

```
## chunkname: eval-files
files <- dir("~/Backtesting",
             pattern = "^.*\\.R",
             full.names = TRUE)
cl <- makeCluster(4)
clusterApplyLB(cl = cl, files, source)
stopCluster(cl)
```

7 Rebalancing a portfolio

In principle, rebalancing a portfolio is straightforward. You have a current position x_0, and a target position x_1. You take the elementwise difference between these vectors, and you obtain the orders that you need to have executed.

Software can help here in two ways. First, it can make the process of order generation faster, simpler and more reliable, by computing and creating orders, and submitting them automatically. Second, software can help to determine how to rebalance. Institutional investors spend large amounts of time on rebalancing, because here they can measure improvements (notably, saved transaction costs).

7.1 Usage with unnamed vectors

The function `rebalance` computes the transactions necessary for moving from one portfolio to another. The default setting is that the `current` portfolio is in currency units; the `target` portfolio in weights.

To compute the required order sizes, we also need the current prices of the assets. When `current`, `target` and `price` are unnamed, the assets' positions in the vectors need to match.

Suppose we have three stocks A, B and C with prices 1, 2 and 3. The main use case is a situation like this: you hold 50, 30 and 20 shares of these three stocks. However, suppose you have a target weight of 50%, 30% and 20%.

```
prices <- 1:3
current <- c(50, 30, 20)
target <- c(0.5, 0.3, 0.2)
rebalance(current, target, prices, match.names = FALSE)
```

```
  price current value    %       target value    %       order
1     1      50    50 29.4           85    85 50.0          35
2     2      30    60 35.3           26    52 30.6          -4
```

```
3     3      20    60 35.3           11    33 19.4          -9

Notional: 170.  Target net amount : 170.  Turnover (2-way): 70.
```

Or perhaps you prefer an equal weight for every asset. Note that `target` now is a single number.

```
rebalance(current, target = 1/length(current),
          price = prices, match.names = FALSE)
```

```
  price current value    %       target value    %       order
1     1      50    50 29.4           57    57 33.5           7
2     2      30    60 35.3           28    56 32.9          -2
3     3      20    60 35.3           19    57 33.5          -1

Notional: 170.  Target net amount : 170.  Turnover (2-way): 14.
```

Note that the target weights cannot be reached exactly because the function rounds to integers.

`rebalance` also supports a number of special cases. Suppose you want to go into cash and close every position.

```
1 rebalance(current = current, target = 0,
2           price = prices, match.names = FALSE)
```

```
  price current value    %       target value   %       order
1     1      50    50 29.4            0     0 0.0         -50
2     2      30    60 35.3            0     0 0.0         -30
3     3      20    60 35.3            0     0 0.0         -20

Notional: 170.  Target net amount : 0.  Turnover (2-way): 170.
```

Suppose we have no current position and want to give equal weight to each stock. Note first that we need to specify a `notional`. Also, `rebalance` now assumes that you want to invest in every stock for which a price is supplied.

```
1 rebalance(current = 0, target = 1/3, notional = 100,
2           price = prices, match.names = FALSE)
```

```
  price current value   %       target value    %       order
1     1       0     0 0.0           33    33 33.0          33
2     2       0     0 0.0           17    34 34.0          17
3     3       0     0 0.0           11    33 33.0          11

Notional: 100.  Target net amount : 100.  Turnover (2-way): 100.
```

7.2 Usage with named vectors

More usefully, `rebalance` can also use the names of the vectors `current`, `target` and `price`. The argument `match.names` must be set to `TRUE` for this (which is the default, actually).

```
prices  <- c(1,1,1,1)
names(prices) <- letters[1:4]
current <- c(a = 0, b = 10)
target  <- c(a = 0, d = 0.5)
rebalance(current, target, prices)
```

```
  price current value     %       target value    %       order
b     1      10    10 100.0            0     0  0.0         -10
d     1       0     0   0.0            5     5 50.0           5

Notional: 10.  Target net amount : 5.  Turnover (2-way): 15.
```

To also show all instruments, set the argument `drop.zero` to `FALSE`.

```
print(rebalance(current, target, prices), drop.zero = FALSE)
```

```
  price current value     %       target value    %       order
a     1       0     0   0.0            0     0  0.0           0
b     1      10    10 100.0            0     0  0.0         -10
d     1       0     0   0.0            5     5 50.0           5

Notional: 10.  Target net amount : 5.  Turnover (2-way): 15.
```

7.3 Usage with positions

In Section Keeping track of transactions: journals we used the function `position` to compute balances from transactions. The function may also be directly used to set up a position.

```
position(amount = 1)
```

```
1
```

```
position(amount = c(1, 2, 3), instrument = letters[1:3])
```

```
a 1
b 2
c 3
```

Note that with more than one instrument, these instruments need to be named. Otherwise, position would aggregate the positions (as it does for a journal). As a short-cut, you can also pass a named vector. (See `https://enricoschumann.net/notes/computing-positions.html` for more details.)

```
position(amount = c(a = 1, b = 2, c = 3))
```

```
a 1
b 2
c 3
```

Such positions can now be passed as arguments `current` and `target` into function `rebalance`.

7.4 Constructive methods: An example

We want to rebalance, and we have a vector of current weights and a vector of target weights.

The following rules apply:

- new titles (i.e. with current weight zero) are bought and get their target weight
- titles that have a zero target weight are removed from the portfolio
- after the first two rules have been applied, there will probably remain a non-zero cash position. We try to reduce it to zero with the least number of trades: when buying, we start with the assets with the lowest current weights, and vice versa

The function `rebalance1` takes as input the current portfolio (`current`), the target portfolio (`target`) and min max weights (`wmin` und `wmax`). The target portfolio `target` must conform with the weight limits, i.e. all weights must be between `wmin` und `wmax`.

```
rebalance1 <- function(current, target, wmin = 0.025, wmax = 0.075) {
    stopifnot(length(current) == length(target))
    stopifnot(wmax >= wmin)
    zero <- 1e-10

    ans <- numeric(length(current))

    ## new assets
    i <- current < zero & target > zero
    ans[i] <- target[i]
```

```
    # old and new assets
    i <- current > zero & target > zero
    ans[i] <- pmin(pmax(current[i], wmin), wmax)

    cash <- 1 - sum(ans)

    pos <- target > zero
    while (cash > 0) {
        room <- wmax - ans[pos]
        i <- which.max(room)[1]
        eps <- min(room[i], cash)
        ans[pos][i] <- ans[pos][i] + eps
        cash <- cash - eps
    }
    while (cash < 0) {
        room <- ans[pos] - wmin
        i <- which.max(room)[1]
        eps <- min(room[i], -cash)
        ans[pos][i] <- ans[pos][i] - eps
        cash <- cash + eps
    }
    ans
}
```

A test: random portfolios `random_p`

```
random_p <- function(n, wmin = 0.01, wmax = 0.09) {
    .min <- 0
    .max <- 2
    while(.min < wmin || .max > wmax) {
        k <- sample(18:25,1)
        ans <- numeric(n)
        ans[sample(n,k)] <- runif(k)
        ans <- ans/sum(ans)
        .min <- min(ans[ans > 0])
        .max <- max(ans)
    }
    ans
}

current <- random_p(30)
target <- random_p(30)
new <- rebalance1(current, target)

data.frame(
    current = current,
    target = target,
    new = new,
```

```
    weights_differ = current != target,
    do_trade = current != new)
```

7.5 Algorithms

Whenever you need to round positions, you may prefer to do an actual optimisation. The ideal place for this optimisation is the original objective function, not in `rebalance`. And the differences, if there are any at all, are typically small. But here is an example.

```
n <- 10
target <- runif(n)
target <- target/sum(target)
price <- sample(10:200, n, replace = TRUE)
s <- sample(c(1,5,10,100), n, replace = TRUE,
            prob = c(0.4,0.4,0.1,0.1))
data.frame(price = price, lot.size = s)
```

```
   price lot.size
1    178        5
2     37        5
3     62        5
4     93        1
5     81        5
6    111        5
7    146        5
8    154        5
9    187        1
10   138        1
```

Now suppose we have only a limited budget available.

```
budget <- 10000
x <- rebalance(0, target, notional = budget,
               price = price, match.names = FALSE)
x
```

```
   price current value   %       target value    %       order
1    178       0     0 0.0            4   712  7.1           4
2     37       0     0 0.0           40  1480 14.8          40
3     62       0     0 0.0           20  1240 12.4          20
4     93       0     0 0.0           16  1488 14.9          16
5     81       0     0 0.0           13  1053 10.5          13
6    111       0     0 0.0            6   666  6.7           6
7    146       0     0 0.0            4   584  5.8           4
8    154       0     0 0.0            6   924  9.2           6
```

```
9    187       0     0 0.0            5   935  9.3           5
10   138       0     0 0.0            7   966  9.7           7

Notional: 10000.  Amount invested: 10048.  Total (2-way) turnover: 10048.
```

Now we use `TAopt`, from the `NMOF` package, to find the optimal integer portfolio.

```
require("NMOF")
ediff <- function(x) {
    tmp <- x*price/budget - target
    sum(tmp*tmp)
}

neighbour <- function(x) {
    i <- sample.int(length(x), size = 1L)
    x[i] <- x[i] + if (runif(1) > 0.5) - s[i] else s[i]
    x
}

sol <- TAopt(ediff,
             algo = list(x0 = numeric(length(price)),
                         neighbour = neighbour,
                         q = 0.1,
                         nS = 1000,
                         printBar = FALSE))
```

```
Threshold Accepting.

Computing thresholds ... OK.
Estimated remaining running time: 0.23 secs.

Running Threshold Accepting...
Initial solution:  0.109341
Finished.
Best solution overall: 0.001108741
```

```
df <- data.frame(TA = sol$xbest, rounded = s*round(x$target/s))
df[apply(df, 1, function(i) any(i != 0)), ]
```

```
   TA rounded
1   5       5
2  40      40
3  20      20
4  16      16
5  15      15
6   5       5
7   5       5
8   5       5
```

```
9   5        5
10  7        7
```

The difference.

```
ediff(sol$xbest) - ediff(s*round(x$target/s))
```

```
[1] 0
```

7.6 Substituting a basket by its components

If you run tests with baskets of instruments or whole strategies, you often need to substitute the components of the basket for overall basket. PMwR provides a function `replace_weight` that helps with this task. (It is also helpful if you have hierarchies of benchmarks or want to do a 'lookthrough' through a subportfolio within your portfolio.)

Suppose we have this weight vector:

```
w <- c(basket_1 = 0.3,
       basket_2 = 0.5,
       basket_3 = 0.2)
```

We also know what the first two baskets represent.

```
b1 <- c(a = 0.5, b = 0.2, c = 0.3)
b2 <- c(d = 0.1, e = 0.2, a = 0.7)
```

Now we can call `replace_weight`.

```
replace_weight(w,
               basket_1 = b1,
               basket_2 = b2)
```

```
basket_1::a basket_1::b basket_1::c
       0.15        0.06        0.09

basket_2::d basket_2::e basket_2::a
       0.05        0.10        0.35

   basket_3
       0.20
```

If the names of the baskets or of the things in the baskets have spaces or other characters that cause trouble, quote them.

```
replace_weight(c("basket␣1" = 0.3,
                 "basket␣2" = 0.7),
               "basket␣1" = b1,
               "basket␣2" = b2)
```

8 Summarising portfolio time-series

Strategies or portfolios are often analysed purely through their price series (a.k.a. NAV or equity series): more-detailed data may not be available, e.g. for a fund; or it may simply be more convenient to aggregate positions to a single NAV.

To handle such series, PMWR provides an S3 class `NAVseries`. (I will write NAV series for the actual data series and `NAVseries` for the specific implementation.) An NAV series is nothing more than a time-series: a vector of NAVs, together with a vector of timestamps. Then why not simply use an existing time-series class, such as `zoo`? One reason is clarity. A `zoo` or `xts` object is much more general than an NAV series: it may represent more than one series; or it may represent, for instance, returns. An NAV series promises to represent NAVs (i.e. levels, not changes in levels) of a single series, nothing else. Furthermore, defining our own class allows us to define specific methods where appropriate; at the same time we may piggyback on existing time-series methods by defining methods for coercion, e.g. `as.zoo.NAVseries` or `as.xts.NAVseries`.

8.1 Creating NAV series

PMWR comes with a dataset called `DAX`, which stands for *Deutscher Aktienindex* (German Equity Index). The dataset is a data-frame of one column that contains the price for the day, with the timestamps stored as rownames in format `YYYY-MM-DD`.

```
str(DAX)
```

```
'data.frame': 505 obs. of  1 variable:
 $ DAX: num  9400 9435 9428 9506 9498 ...
```

```
head(DAX)
```

```
               DAX
2014-01-02 9400.04
2014-01-03 9435.15
2014-01-06 9428.00
2014-01-07 9506.20
2014-01-08 9497.84
2014-01-09 9421.61
```

We first transform the data-frame into an `NAVseries` by calling the function of the same name.

```
dax <- NAVseries(DAX[[1]],
                 timestamp = as.Date(row.names(DAX)),
                 title = "DAX")
dax
```

A concise summary is printed.

```
DAX
02 Jan 2014 ==> 30 Dec 2015   (505 data points, 0 NAs)
    9400.04           10743
```

There is also a generic function `as.NAVseries`, which can be used, for instance, to coerce `zoo` series to `NAVseries`. Or, after having run a backtest (see Chapter Backtesting), saying

```
as.NAVseries(btest(....))
```

extracts the NAV series from the backtest data.

8.2 Summarising NAV series

Calling `summary` on an NAV series should provide useful statistics of the series. You may notice that the summary does not provide too many statistics. It has been said that the purpose of statistics is to reduce many numbers to only few – not the other way around. Thus, `summary.NAVseries` will confine itself to few statistics that can be computed in a reasonably robust way. By that I mean that a statistic is useful for many types of NAV series.[1] Numbers that are provided should be formatted and presented in a way that is inline with (good) industry practice and makes sense statistically. Returns, for instance, will only be annualised when the NAV series spans

[1] An example of a statistic that cannot be computed in a robust way is a beta coefficient – or, in fact, any other multivariate statistic. Such numbers will depend on a chosen benchmark, and what is more, they typically need careful checking because of asynchronous time-series: A mutual fund's NAV that is published with a delay may show little correlation with a stock-market index (when matched on time-stamps), but that is only because of the 'attenuation bias', which skews the correlation towards zero.

more than one calendar year; volatility will always be annualised and be computed from monthly data (if possible); all numbers are rounded to a meaningful precision (Ehrenberg, 1981).

```
summary(dax)
```

```
-------------------------------------------------------
DAX
02 Jan 2014 ==> 30 Dec 2015  (505 data points, 0 NAs)
    9400.04           10743
-------------------------------------------------------
High               12374.73  (10 Apr 2015)
Low                 8571.95  (15 Oct 2014)
-------------------------------------------------------
Return (%)             6.9  (annualised)
-------------------------------------------------------
Max. drawdown (%)      23.8
_ peak             12374.73  (10 Apr 2015)
_ trough            9427.64  (24 Sep 2015)
_ recovery                   (NA)
_ underwater now (%)   13.2
-------------------------------------------------------
Volatility (%)         18.0  (annualised)
_ upside               14.4
_ downside             10.4
-------------------------------------------------------

Monthly returns

      Jan Feb  Mar  Apr  May  Jun  Jul  Aug  Sep  Oct Nov  Dec YTD
2014 -1.0 4.1 -1.4  0.5  3.5 -1.1 -4.3  0.7  0.0 -1.6 7.0 -1.8 4.3
2015  9.1 6.6  5.0 -4.3 -0.4 -4.1  3.3 -9.3 -5.8 12.3 4.9 -5.6 9.6
```

For summaries of NAV series, a method for `toLatex` can be used to fill LaTeX-templates. The package comes with a vignette that provides examples.

8.3 Drawdowns and Streaks

PMwR offers two functions that may provide insights into NAV series: `drawdowns` and `streaks`. A vignette shows examples.

```
vignette("Drawdowns_streaks", package = "PMwR")
```

8.3.1 Drawdown

Let the symbol v be a time series of portfolio values, with observations indexed at $t = 0, 1, 2 \ldots T$. The drawdown D of this series at time t is defined as

$$D_t = v_t^{\max} - v_t \tag{8.1}$$

in which $v_t^{\max}$ is the running maximum, i.e. $v_t^{\max} = \max\{v_{t'} \,|\, t' \in [0, t]\}$.

Note that D is a vector of length $T + 1$, even though most of the time people care most about its maximum value. Other functions may be computed to capture the information in the drawdown vector, for example, the mean time underwater (i.e. the average time elapsed between two consecutive values in D that are sufficiently close to zero), or the correlation between a portfolio's drawdown and the drawdown of an alternative asset, such as an index. The definition above gives D in currency terms. A percentage drawdown is often preferred, obtained by using the logarithm of v, or by dividing D_t by $v_t^{\max}$.

In pseudocode, drawdown can be computed as follows.

```
set high = P_1
set maxdown = 0
for t = 2 : length(P) do
   if P_t > high then
      high = P_t
   else
      compute underwater = 1 − P_t/high
      if underwater > maxdown then
         maxdown = underwater
      end if
   end if
end for
return maxdown
```

The function `drawdowns` (plural) in PMwR relies on the function `drawdown` (singular) in the NMOF package.

```
NMOF::drawdown
```

```
function(v, relative = TRUE, summary = TRUE) {
    cv <- cummax(v)
    d <- cv - v
    if (relative)
        d <- d/cv
    if (summary) {
        troughTime <- which.max(d)
        peakTime <- which.max(v[seq_len(troughTime)])
        list(maximum       = max(d),
             high          = v[peakTime],
```

```
            high.position = peakTime,
            low           = v[troughTime],
            low.position  = troughTime)
    } else
        d
}
<bytecode: 0x561a349b1ba0>
<environment: namespace:NMOF>
```

Drawdown statistics for a single series, such as starts of drawdowns and recovery times, can be computed in a vectorized way. To illustrate this, start with a vector D of drawdowns. Also, compute a lagged value $\texttt{D}_1$.

```
x <- c(10, 9, 8, 9, 10, 9, 6, 10)
D <- cummax(x) - x
D
```

```
[1] 0 1 2 1 0 1 4 0
```

Note that a drawdown is defined as a positive number; it cannot get negative.

The table illustrates the strategy for computing starts and ends of drawdowns:

time	D	$\texttt{D}_1$		
t_1	0			
t_2	1	0	DD starts	
t_3	2	1		
t_4	1	2		
t_5	0	1		DD ends
t_6	1	0	DD starts	
t_7	4	1		
t_8	0	4		DD ends
		0		

A drawdown starts when $D > 0$ and the previous value was 0. A drawdown can never start in period t_1.

```
D.starts <- c(FALSE, D[-length(D)] == 0 & D[-1] > 0)
which(D.starts)
```

```
[1] 2 6
```

A drawdown ends (is fully recovered) when the current value is~0 and the previous value is > 0. A drawdown can never end in period~t_1.

```
D.ends <- c(FALSE, D[-1] == 0 & D[-length(D)] > 0)
which(D.ends)
```

```
[1] 5 8
```

Remarks:

- If there are more starts than ends, the final drawdown has not been recovered.
- To collect statistics for the drawdowns, simply loop over the starts (with a potential correction for a final, unrecovered drawdown).
- Depending on how the original series was computed, a small tolerance may be more robust that requiring an exact~0 in~D for computing starts and ends.

Let us look at the five worst drawdowns of the DAX series.

```
dd <- drawdowns(dax)
dd[order(dd$max, decreasing = TRUE)[1:5], ]
```

```
         peak     trough    recover        max
18 2015-04-10 2015-09-24       <NA> 0.23815388
9  2014-07-03 2014-10-15 2014-12-05 0.14532032
10 2014-12-05 2014-12-15 2015-01-16 0.07466056
4  2014-01-17 2014-03-13 2014-05-13 0.07443015
17 2015-03-16 2015-03-26 2015-04-10 0.02663112
```

8.3.2 Streaks

The function `streaks` returns a data-frame of uninterrupted up and down movements.

```
streaks(dax, up = 0.1, down = -0.1,
        initial.state = "up")
```

```
       start        end state    return
1 2014-01-02 2014-07-03    up  0.066956
2 2014-07-03 2014-10-15  down -0.145320
3 2014-10-15 2015-04-10    up  0.443631
4 2015-04-10 2015-09-24  down -0.238154
5 2015-09-24 2015-11-30    up  0.207325
6 2015-11-30 2015-12-30  down -0.056159
```

Package plotseries `https://github.com/enricoschumann/plotseries` can be used to plot streaks.

9 Scaling series

Visual comparisons of time-series are ubiquitous in finance.[1] The function `scale1` helps with scaling the levels of time-series so that is becomes easier to compare them. It is a generic function; and `PMwR` provides methods for numeric vectors/matrices, and for `zoo` and `NAVseries` objects.

9.1 Examples

To explain what the function does, we use two very short time-series: the values of the DAX, the German stock-market index, and the REXP, a German government-bond index, from 2 January and 8 January 2014 (just 5 trading days). We also combine them into a matrix drax.

```
dax  <-  DAX[1:5, ]
rexp <- REXP[1:5, ]
drax <- cbind(dax, rexp)
```

Calling `scale1` on `dax` is equivalent to dividing the whole series by its first element.

```
scale1(dax) ==  dax/dax[1]
```

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

Lest you skip the rest of the chapter: `scale1` comes with several additional features.

It is common, too, to scale to a level of 100. We either multiply the whole series by 100, or use the `level` argument.

```
scale1(dax, level = 100)
```

[1] Transformating or scaling data are a key element of exploratory data analysis in general. See Tukey's EDA (1977). TODO: find H. Simon reference on scaling (taking reciprocal value). See also Schumann (2013).

```
[1] 100.00 100.37 100.30 101.13 101.04
attr(,"scale1_origin")
[1] 1
```

(The `scale1_origin` attribute will be explained shortly.)

If we give a matrix to `scale1`, the function scales each column separately.

```
scale1(drax, level = 100)
```

```
        dax   rexp
[1,] 100.00 100.00
[2,] 100.37 100.06
[3,] 100.30 100.23
[4,] 101.13 100.29
[5,] 101.04 100.28
attr(,"scale1_origin")
[1] 1
```

`scale1` is a generic function; it works, for instance, with `zoo` objects.

```
library("zoo")
drax.zoo <- zoo(drax, as.Date(row.names(DAX)[1:5]))
scale1(drax.zoo, level = 100)
```

```
              dax   rexp
2014-01-02 100.00 100.00
2014-01-03 100.37 100.06
2014-01-06 100.30 100.23
2014-01-07 101.13 100.29
2014-01-08 101.04 100.28
attr(,"scale1_origin")
[1] 2014-01-02
```

```
plot(scale1(drax.zoo, level = 100),
     plot.type = "single",
     xlab = "",
     ylab = "",
     col = c("darkblue", "darkgreen"))
```

The argument `when` defines the origin.

```
scale1(drax, when = 3, level = 100)
```

```
         dax    rexp
[1,]  99.703  99.769
[2,] 100.076  99.830
[3,] 100.000 100.000
[4,] 100.829 100.062
```

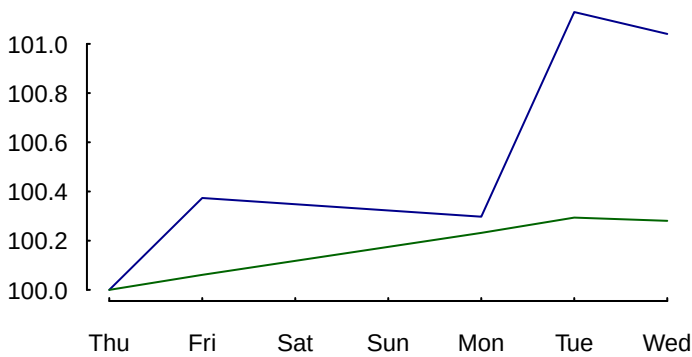


Figure 9.1: Scaled series: Both dax and rexp now start at 100.

```
[5,] 100.741 100.049
attr(,"scale1_origin")
[1] 3
```

This origin is attached to the scaled series as an attribute `scale1_origin`. This is useful if you want mark the start of the scaled series; for instance, in a plot with `abline`.

With a zoo object, `when` should be compatible with the class of the object's index.

```
scale1(drax.zoo, when = as.Date("2014-01-07"), level = 100)
```

```
               dax    rexp
2014-01-02  98.883  99.707
2014-01-03  99.253  99.768
2014-01-06  99.177  99.938
2014-01-07 100.000 100.000
2014-01-08  99.912  99.987
attr(,"scale1_origin")
[1] 2014-01-07
```

`when` also understands the keyword `first.complete`, which is actually the default, and the keywords `first` and `last`. `first.complete` is useful when some series have leading missing values.

```
drax[1:2, 1] <- NA
drax
```

```
        dax   rexp
[1,]     NA 440.53
[2,]     NA 440.79
```

```
[3,] 9428.0 441.55
[4,] 9506.2 441.82
[5,] 9497.8 441.76
```

```
scale1(drax, level = 100)   ## 'first.complete' is the default
```

```
        dax    rexp
[1,]     NA  99.769
[2,]     NA  99.830
[3,] 100.00 100.000
[4,] 100.83 100.062
[5,] 100.74 100.049
attr(,"scale1_origin")
[1] 3
```

When the argument `centre` is `TRUE`, the *mean return* is subtracted from the *returns*.

```
scale1(drax.zoo, centre = TRUE)
```

```
               dax    rexp
2014-01-02 1.00000 1.00000
2014-01-03 1.00114 0.99991
2014-01-06 0.99779 1.00091
2014-01-07 1.00348 1.00083
2014-01-08 1.00000 1.00000
attr(,"scale1_origin")
[1] 2014-01-02
```

The default is to subtract the geometric mean: the series will have a growth rate of zero; it will end where it started.

The argument `scale` takes a standard deviation and scales the *returns* to that standard deviation.

```
apply(returns(scale1(drax.zoo, scale = 0.02)), 2, sd)
```

```
 dax rexp
0.02 0.02
```

This may create fairer comparisons, for instance, between fund prices that exhibit very different volatilities. It can also help to visualise correlation.

It should be stressed that `centre` and `scale` change *returns*, but `scale1` expects and evaluates to *levels* (not returns).

The `zoo` method has a further argument that affects returns: `inflate`. To illustrate its use, let us create a constant series.

```
z <- zoo(100,
         seq(from = as.Date("2015-1-1"),
             to   = as.Date("2016-1-1"),
             by   = "1␣day"))
head(z)
tail(z)
```

```
2015-01-01 2015-01-02 2015-01-03 2015-01-04 2015-01-05 2015-01-06
       100        100        100        100        100        100

2015-12-27 2015-12-28 2015-12-29 2015-12-30 2015-12-31 2016-01-01
       100        100        100        100        100        100
```

`inflate` should be a numeric value: the annual growth rate that is added to the time-series's return (or that is subtracted from it, if negative).

```
head(scale1(z, inflate = 0.02))
tail(scale1(z, inflate = 0.02))
```

```
2015-01-01 2015-01-02 2015-01-03 2015-01-04 2015-01-05 2015-01-06
    1.0000     1.0001     1.0001     1.0002     1.0002     1.0003

2015-12-27 2015-12-28 2015-12-29 2015-12-30 2015-12-31 2016-01-01
    1.0197     1.0198     1.0198     1.0199     1.0199     1.0200
```

9.2 Scaling a series: how it works

The previous section provided examples of scaling series. In this section, we are going to see how `scale1` does its computations.

First, a series P passed to `scale1` is transformed into returns, R. The `scale` argument allows you to set a desired **volatility** for the series's returns, defined as their standard deviation. The computation uses the fact that multiplying a random variable by a number b changes its variance to b^2 times its original variance. Hence, `scale1` divides the returns by the actual standard deviation and then multiplies them by the desired one (i.e. the value passed via the `scale` argument).

Changing **total return** (or, equivalently, average return) is slightly more complicated. Suppose we want to scale the total return of the series P such that it equals some target return r_*. Start with writing the total return as the product of single-period returns.

$$\frac{P_1}{P_0}\frac{P_2}{P_1}\cdots\frac{P_T}{P_{T-1}} = \frac{P_T}{P_0} = (1+r_1)(1+r_2)(1+r_3)\cdots = \prod_{t=1}^{T} 1+r_t \tag{9.1}$$

There clearly is an infinity of possible adjustments that would do the trick. We might, for instance, change only P_0 or P_T so that the desired return is achieved.

But that is probably not what we want. A reasonable requirement is that the scaling touches as few other statistical properties as possible. Adding a constant z to the return in every period does that: it does not change the volatility of the returns; neither does it affect linear or rank correlation of the returns with some other series. To compute z, we need to solve the following equation:

$$(1 + r_1 + z)(1 + r_2 + z)(1 + r_3 + z) \cdots = 1 + r_* \tag{9.2}$$

Alternatively, we may use logs.

$$\sum_i \log(1 + r_i + z) = \log(1 + r_*) \tag{9.3}$$

This is an application for root-finding (see chapter 11 of Gilli, Maringer, and Schumann, 2019), for which `scale1` uses `uniroot`.

10 Analysing trades

For some strategies or trading approaches, we may prefer to analyse trades, not equity series. (A case in point are intraday strategies, which have no exposure over night.) That is, we do not evaluate the strategy's performance at pre-defined, usually equally-spaced points in time, but rather split the trading history into separate trades.

10.1 Exposure

We have the following trades and times.

```
amount <- c(1, 3, -3, 1, -3,  1)
time   <- c(0, 1,  3, 4,  7, 12)
```

The holding period (duration) of these trades can be computed so:

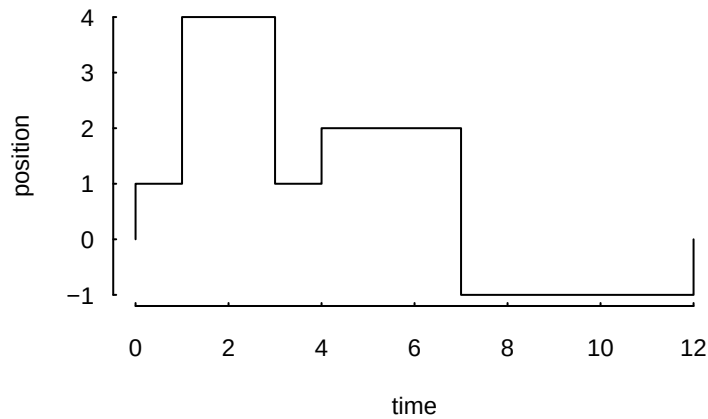
```
data.frame(position = cumsum(amount)[-length(amount)],
           from = time[-length(time)],
           to   = time[-1L],
           duration = diff(time))
```

```
  position from to duration
1        1    0  1        1
2        4    1  3        2
3        1    3  4        1
4        2    4  7        3
5       -1    7 12        5
```

We can plot the exposure. See Figure 10.1.

```
plot(c(time[1], time), cumsum(c(0, amount)),
     type = "s", xlab = "time", ylab = "position")
```

Figure 10.1: Exposure at different times.



Thus, we have had a position from time 0 to time 12 (hours into the trading day, say), but its size varied. The function `tw_exposure` (time-weighted exposure) computes the average *absolute* exposure.

```
tw_exposure(amount, time)
```

```
1.75
```

To give a simpler example: suppose we bought at the open of a trading day and sold at noon. The average exposure for the day is thus half a contract.

```
amount <- c(1,  -1, 0)
time   <- c(0, 0.5, 1)
tw_exposure(amount, time)
```

```
0.5
```

If we bought at the open, went short at noon, and closed the position at the end of the day, the average exposure would be one contract, since *absolute* position size is relevant.

```
amount <- c(1, -2 , 1)
time   <- c(0,0.5,1)
tw_exposure(amount, time)
```

```
1
```

Whether absolute exposure is used is controlled by an argument `abs.value`. Setting it to `FALSE` can be useful to detect long or short biases.

```
tw_exposure(amount, time, abs.value = FALSE)
```

```
0
```

10.2 Splitting and rescaling

We have the following trades.

```
timestamp <- 1:3
amount <- c(-1, 2, -1)
price <- c(100, 99, 101)
```

Calling `split_trades` will return a list of two single trades. Each single trade, in turn, is a list with components `amount`, `price` and `timestamp`.

```
split_trades(amount = amount,
             price = price,
             timestamp = timestamp,
             aggregate = FALSE)
```

```
[[1]]
[[1]]$amount
[1] -1  1

[[1]]$price
[1] 100  99

[[1]]$timestamp
[1] 1 2


[[2]]
[[2]]$amount
[1]  1 -1

[[2]]$price
[1]  99 101

[[2]]$timestamp
[1] 2 3
```

Note that the second transaction (buy 2 @ 99) has been split up: buying one contract closes the first trade; the other contract opens the second trade. This splitting is useful in its own right: there are accounting systems around that cannot handle a trade that switches a position directly from long to short, or vice versa. Instead, the trade needs first be closed (i.e. the net position becomes zero).

With argument `aggregate` set to `TRUE`, the function reconstructs the total series, but with those trades splitted that change the position's sign.

```
split_trades(amount, price, timestamp, aggregate = TRUE)
```

```
$amount
[1] -1  1  1 -1

$price
[1] 100  99  99 101

$timestamp
[1] 1 2 2 3
```

Another example. We have the following trades and impose a limit that the maximum absolute exposure for the trader should only be 2.

```
timestamp <- 1:6
amount <- c(-1,-1,-1,1,1,1)
price <- c(100,99,98,98,99,100)
limit(amount, price, timestamp, lim = 2)
```

```
$amount
[1] -1 -1  1  1

$price
[1] 100  99  99 100

$timestamp
[1] 1 2 5 6
```

Scaling the trades.

```
scale_to_unity(amount)
```

```
[1] -0.333 -0.333 -0.333  0.333  0.333  0.333
```

Closing the trade at once.

```
close_on_first(amount)
```

```
[1] -1 -1 -1  3  0  0
```

11 Plotting irregularly-spaced series during trading hours

11.1 An example

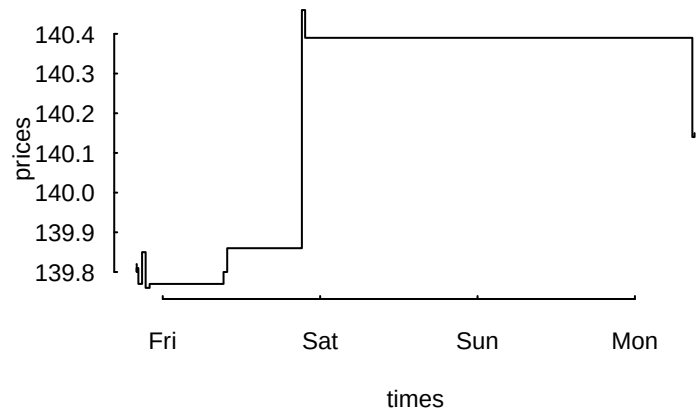
We have the following sample of prices of the Bund future contract, traded at the Eurex in Germany.

times	prices
2012-10-18 20:00:09	139.82
2012-10-18 20:01:11	139.82
2012-10-18 20:01:59	139.8
2012-10-18 20:01:29	139.81
2012-10-18 20:16:49	139.77
2012-10-18 20:50:49	139.85
2012-10-18 21:23:19	139.76
2012-10-18 21:41:39	139.76
2012-10-18 21:59:59	139.77
2012-10-19 09:16:10	139.8
2012-10-19 09:49:31	139.86
2012-10-19 21:12:49	140.46
2012-10-19 21:42:31	140.39
2012-10-22 08:45:15	140.14
2012-10-22 09:05:33	140.15

(You'll find the code to generate those times in the code file for this chapter.)

Note that I have left the time zone to the operating system. Since my computer is typically located in the time zone that the `tz database` (`https://www.iana.org/time-zones`) calls 'Europe/Zurich', the first time should be `2012-10-18 20:00:09`. If, for instance, your computer is in 'America/Chicago' instead and you run the above

Figure 11.1: Price plot on a standard x-axis..



code, the first time would be `2012-10-18 13:00:09`. Which is right: it is the correct time, only translated into Chicago local time.

A `plot` of price against time looks like this.

```
plot(times, prices, type = "s")
```

Such a plot is fine for many purposes. But the contract for which we have prices is only traded from Monday to Friday, not on weekends, and it is traded only from 08:00 to 22:00 Europe/Berlin time. So the plot should omit those times at which no trading takes place. This is what the function `plot_trading_hours` does.

```
tmp <- plot_trading_hours(x = prices, t = times,
                          interval = "1␣sec",
                          labels = "day",
                          fromHHMMSS = "080000",
                          toHHMMSS = "220000",
                          type = "s")
```

What we need for such a plot is a function that maps actual time to a point on the x-scale, while the y-scale stays unchanged. If we were talking only about days, not times, we needed something like this:

day	x-position	mapped x-position
Thursday	1	1
Friday	2	2
Saturday	3	<removed>
Sunday	4	<removed>
Monday	5	3

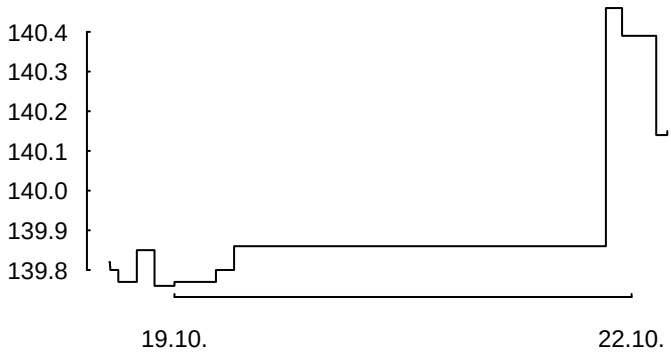


Figure 11.2: Price plot on a standard x-axis..

This mapping is what `plot_trading_hours` provides. And not much more: the design goal of the function is to make it as much as possible an ordinary plot; or more specifically, to make it as similar as possible to the `plot` function. Indeed, `plot_trading_hours` calls `plot` with a small number of default settings:

```
list(type = "l", xaxt = "n", xlab = "", ylab = "")
```

These settings can all be overridden through the `...` argument, which is passed to `plot`. Note that we already set `s` as the plot's `type` in the last code chunk. The only required setting is suppressing the x-axis with setting `xaxt` to 'n', because `plot_trading_hours` will create its own x-axis via a call to `axis(1, ...)`. In case you wish to use your own axis specification, either set `do.plotAxis` to `FALSE` or pass settings to `axis` through the list `axis1.par`.

11.2 More examples

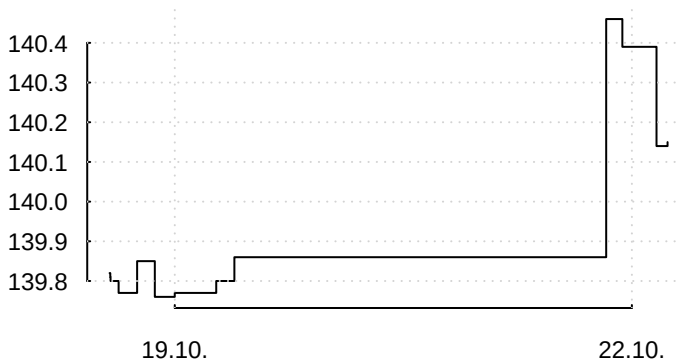
11.2.1 Value of `plot_trading_hours`

Like `plot`, `plot_trading_hours` is typically called for its side effect: creating a plot. But it also returns useful information (invisibly, unless called with `do.plot = FALSE`).

```
str(tmp)
```

```
List of 6
 $ t           : int [1:15] 1 63 81 111 1001 3041 4991 6091 7191 ...
 $ x           : num [1:15] 140 140 140 140 140 ...
```

Figure 11.3:
Grid lines.




```
$ axis.pos    : num [1:2] 7193 57594
$ axis.labels: chr [1:2] "19.10." "22.10."
$ timegrid    : POSIXct[1:61527], format: "2012-10-18 20:00:09" ...
$ map         : function (t)
```

This information can be used to add elements to plots. An example follows.

11.2.2 Adding grid lines

We can add grid lines with `abline`. The y-axis poses no special problem. The positions of the x-axis ticks are returned from `plot_trading_hours`.

```
tmp <- plot_trading_hours(x = prices, t = times,
                          interval = "1␣sec",
                          labels = "day",
                          fromHHMMSS="080000",
                          toHHMMSS = "220000",
                          type = "s")
abline(h = axTicks(2), v = tmp$axis.pos,
       col = "lightgrey", lty = "dotted")
```

If we want to mark a specific time, say 19 October, 13:10:23, we can use the function `map` that the call to `plot_trading_hours` returns. We first create the specific time with, for example, `ISOdatetime` or `strptime`.

```
## Again, I do not specify a time zone since time zones
## depend on the operating system. To reproduce the
## example, you may use this representation:
##
```

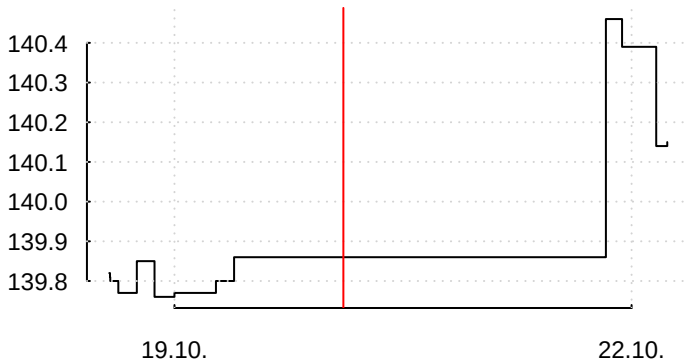


Figure 11.4: Grid lines.

```
## mytime <- structure(1350645023,
##                     class = c("POSIXct", "POSIXt"),
##                     tzone = "")

mytime <- ISOdatetime(2012, 10, 19, 13, 10, 23)
mytime
```

```
[1] "2012-10-19 13:10:23 CEST"
```

Now we use `map` to translate this time into the appropriate x-position.

```
tmp <- plot_trading_hours(x = prices, t = times,
                          interval = "1␣sec", labels = "day",
                          fromHHMMSS="080000",
                          toHHMMSS = "220000",
                          type = "s")
abline(h = axTicks(2), v = tmp$axis.pos,
       col = "lightgrey", lty = "dotted")
abline(v = tmp$map(mytime)$t, col = "red")
```

The function `map` returns a list with two components, `t` and `ix`.

```
tmp$map(mytime)
```

```
$t
[1] 25816

$ix
[1] 1
```

The first component is the appropriate position on the x-axis; since it is a time it is called `t`. The second component gives the subscripts to values that should actually

be plotted. As an example, suppose that we wish to plot points at several prices at 21:00:00 for several days.

```
## moretimes <- structure(c(1350586800, 1350673200, 1350759600),
##                        class = c("POSIXct", "POSIXt"), tzone = "")
##

moretimes <- ISOdatetime(2012, 10, 18:20, 21, 00, 00)
values <- seq(140, 140.20, length.out = length(moretimes))
data.frame(times = moretimes,
           weekday = format(moretimes, "%A"),
           values)
```

```
                times  weekday values
1 2012-10-18 21:00:00 Thursday  140.0
2 2012-10-19 21:00:00   Friday  140.1
3 2012-10-20 21:00:00 Saturday  140.2
```

But 20 October 2012 is a Saturday, and so it does not appear in the plot.

```
tmp$map(moretimes)
```

```
$t
[1]  3592 53993

$ix
[1] 1 2
```

The values that should be plotted can conveniently be found by using `ix`.

```
values[tmp$map(moretimes)$ix]
```

```
[1] 140.0 140.1
```

11.3 Daily data

`plot_trading_hours` also handles data on a daily frequency. The function will assume such a case if the timestamp is of class `Date`; it will then choose sensible defaults for the time-axis. In effect, the function will remove weekends and, if specified, holidays.

As an example, consider the first 10 observations of the `DAX` dataset.

```
x <- DAX[1:10, ]
t <- as.Date(row.names(DAX)[1:10])
data.frame(t, x, weekday = weekdays(t))
```

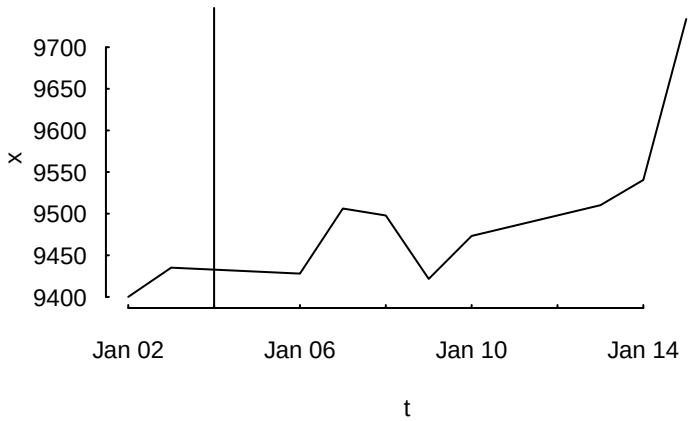


Figure 11.5: daily.

If we plot these data, there will be a value plotted for 2014-01-04, as marked by the vertical line.

```
plot(t, x, type = "l")
abline(v = as.Date("2014-01-04"))
```

That is despite the fact that this is a Saturday.

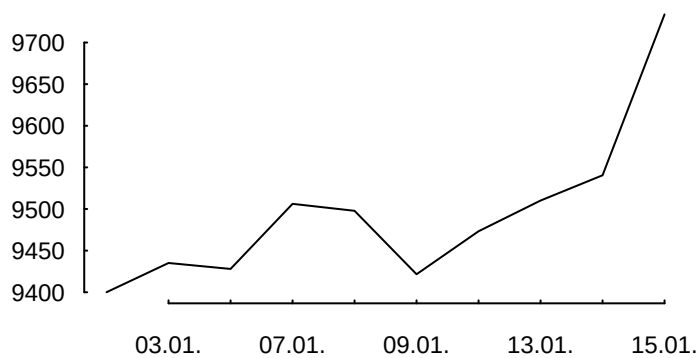
```
format(as.Date("2014-01-04"), "%A")
```

```
Saturday
```

This is not a bug: it is the default behaviour of `plot`. Saturday's value results from an interpolation. `plot_trading_hours` instead ignores such nonexisting dates.

```
plot_trading_hours(x, t)
```

Figure 11.6: daily.



12 Valuation

Computing the value of a position is, in principle, straightforward: multiply the prices of assets by the numbers of contracts you hold and sum the resulting values.

This immediately leads to three questions:

1. What is the price?
2. What is a contract?
3. Are we allowed to sum?

12.1 Prices

Valuing an instrument can mean using either a market price or a theoretical price. In the discussion that follows, I will assume that we already have prices (or net-present values).

13 Other Tools

13.1 Dividend adjustments

The function `div_adjust` corrects price series for dividends. It is meant as a low-level function and is implemented to work on numeric vectors. Consider a hypothetical price series `x`, which goes ex-dividend at time 3.

```
x <- c(9.777, 10.04, 9.207, 9.406)
div <- 0.7
t <- 3
```

The default for `div_adjust` is to match the final price.

```
div_adjust(x, t, div)
```

```
[1] 9.086185 9.330603 9.207000 9.406000
```

If you prefer a correction that matches the first price, set argument `backward` to `FALSE`.

```
div_adjust(x, t, div, backward = FALSE)
```

```
[1]  9.77700 10.04000  9.90700 10.12113
```

13.2 Stocks splits

The function `split_adjust` handles stock splits. It is implemented to work on numeric vectors.

13.3 Treasuries quotes

US treasury bonds are often quoted in 1/32nds of points. For instance, the price `110'030` would mean `110+3/32`.

The function `quote32` lets you parse and 'pretty-print' such prices.

```
quote32(c("110-235", "110-237"))
```

```
[1] 110-23+ 110-23¾
```

Internally, `quote32` will store the prices as numeric values: the fractions are only used for printing.

```
as.numeric(quote32(c("110-235", "110-237")))
```

```
[1] 110.73 110.74
```

```
dput(quote32(c("110-235", "110-237")))
```

```
structure(c(110.734375, 110.7421875),
          handle = c(110, 110),
          ticks = c(23, 23),
          fraction = c(2, 3),
          class = "quote32")
```

13.4 Validating security identification numbers

An ISIN, which stands for International Securities Identification Number, uniquely[1] identifies a security.

```
is_valid_ISIN(c("DE0007236101",     ## Siemens
                "DE0007236102"))    ## last digit changed
```

```
[1]  TRUE FALSE
```

There is a function `is_valid_SEDOL` too.

[1] More or less uniquely, depending on the definition of security. ISINs are widely used for equities, in particular in European markets. But note that ISINs do not contain information about the trading venue. Also, for derivatives, an ISIN may not uniquely identify the contract: for instance, Euro-Bund Futures, traded at the Eurex, have a single ISIN for all maturities.

13.5 Price tables

A `pricetable` is a matrix of prices, with some added functionality for subsetting.

13.6 Trees

To *normal people*, a tree consists of a trunc, branches and leaves. To *people who do graph theory*, a tree is a connected graph with only one path between any two nodes.

Trees are useful to represent hierachies – just think of a file tree. For portfolios, a tree can be used to indicate groupings, such as countries or industries. (See argument `account` in function `position`.)

14 FAQ/ FRC (Frequently-required computations)

I have a list of timestamped trades and I need to compute P/L between two points in time, for instance between yesterday's evening close and now (intraday).

Call the points in time t_0 and t_1. The easiest case is if there were no positions at both t_0 and t_1. In that case, create a journal of your trades, and call `pl`.

If there were positions, you will need the valuation prices for all instruments with positions at both points in time. Then, you can use `pl`; see arguments `initial.position` and `vprice`.

Alternatively, you would arrive at the P/L as follows:

1. Compute the position at t_0 and make it a journal J_0. The prices need to be the valuation prices. (That is, pretent you opened the position at their valuation prices at t_0.)
2. Take all transactions at $t > t_0$ and $t \leq t_1$ and put them into a journal J.
3. Compute the position at t_1 make it a journal J_1, and *multiply all amounts by -1*. The prices need to be the valuation prices. (That is, pretent you closed the position at their valuation prices at t_1.)
4. Combine J_0, J, and J_1 and compute the P/L.

How can I compute portfolio returns when I don't have prices, but only returns of the assets?

Compute artificial prices; e.g. using something like

```
P <- cumprod(c(1, 1 + R))
```

Then feed those series to `returns`.

I have a portfolio with constant weights. How to compute its returns when it is rebalanced at specific times?

Compute artificial prices, and then use `returns`: see arguments `weights` and `rebalance.when`. See Section Portfolio returns.

I have a journal of trades and want to compute the number of trades per day?

Use `tapply`. If the timestamp inherits from class `Date` or can be coerced to Date, the following line will compute the number of trades per day.

```
tapply(J, as.Date(J$timestamp), length)
```

Backtesting: How do I access the current weights of the portfolio?

`btest` is based on prices. You can compute returns easily within `signal`:

```
Close()*Portfolio()/Wealth()
```

I have a list of trades: instrument, side (buy/sell), quantity, when and at what price. How to compute the profit and loss for each?

See `pl`.

I have a list of trades in an instrument and want to plot these trades against the price of the traded instrument.

Use `pl`; in particular, pass the prices with `vprice`.

I have a signal series (+1, 0, 0, +1, ...), and need to transform it into a profit-and-loss series.

If these are positions, pass the signals to `btest` and access them with `signals[Time()]`.

I need to determine the month-to-date profit-and-loss.

1. compute position on last day of last month
2. make journal from position (add prices)
3. combine with journal since month start
4. use ~pl on all instruments

`btest`: I want to print my current P/L in every period.

Use `print.info`.

`btest`: I invest in assets that pay accrued interest.

Directly work with the dirty prices. If the signals depend on clean prices, pass them as extra information and access them with `clean_price[Time()]`. Alternatively, work with the clean prices, and use `cashflow` to add the accrued interest to the cash account.

`btest`: Can I rebalance more frequently than I compute a signal?

You can, but it does not make sense in the standard setup. That is, no rebalancing will take place, even if you instruct `btest` to do so. The reason is that a signal computes a suggested position (in units of the instrument); once this position has been built up, no more trading is required. This is even true when using weights: The argument `convert.weights` is a convenience that converts weights into a suggested position; `btest` does not store these weights, only the suggested position.

15 Appendix: Classes and data structures

The following classes are implicitly defined (i.e. they are `S3` classes):

journal keeps transactions. Internally, a object of class `journal` is named list of atomic vectors.

position the numerical positions of different accounts/instruments at specific points in time. Always stored in a numeric matrix with attributes timestamp and instrument; points in time are in rows, instruments in columns.

period returns numeric vector (potentially a matrix) with attributes timestamp and period. The class is called `p_returns`

instrument term sheet (description etc); it does know nothing about market data – not yet implemented

cashflow internal – not yet implemented

NAVseries store a time-series of net asset values

pricetable a matrix of NAVs (or prices); each column corresponds to one asset. Additional attributes instrument and timestamp. Often, pricetables will be created corresponding to positions.

16 Appendix: Notes for developers

16.1 Methods for `returns`

Methods are responsible for 'stripping' the input down do `x` and `t`, calling '`returns.default`' or some other method, and then to re-assemble the original class's structure. When `period` is not specified, methods should keep timestamp information for themselves and not pass it on. That is, `returns.default` should only ever receive a `timestamp` when `period` is specified.

17 Appendix: Date and time in R

17.1 Dates in R

Vectors of class `Date` give the number of days that have passed since 1 January 1970, with dates before that date represented by negative numbers.

```
unclass(as.Date("1970-1-1"))
```

```
[1] 0
```

```
unclass(as.Date("1969-1-1"))
```

```
[1] -365
```

While `Dates` are conceptually integers, their representation does not ensure that they really are: fractions of a day are ignored for printing, but they are not removed. That can give rise to subtle errors. Suppose, for instance, you wanted to select a date that is a little more than one year before another date. You could to this as follows.

```
x0 <- as.Date("2016-11-01") - 365*1.05
x0
```

```
[1] "2015-10-14"
```

But the printed date is not going to match a `Date` created from character.

```
match(as.Date("2015-09-14"), x0)
```

```
[1] NA
```

That is because `x0` will (silently) keep its fractional part.

```
dput(as.Date("2015-09-26"))
dput(x0)
```

```
structure(16704, class = "Date")
structure(16722.75, class = "Date")
```

So, whenever you plan to match or compare `Dates`, make sure that they are integers.

```
match(as.Date("2015-10-14"), trunc(as.Date("2016-11-01") - 365*1.05))
```

```
[1] 1
```

Or coerce to character, which is often safer.

```
match(as.character("2015-10-14"),
      as.character(as.Date("2016-11-01") - 365*1.05))
```

```
[1] 1
```

17.2 From a vector of Dates, extract the last day of each month

```
d <- seq(as.Date("2010-1-1"),
         as.Date("2012-12-15"),
         by = "1␣week")
```

If the Dates are sorted, use `aggregate` with `tail`. (If the Dates come from a `zoo` object, they will always be sorted.)

```
aggregate(d,
          by = list(format(d, "%Y-%m")),
          FUN = tail, 1L)[[2L]]
```

```
[1] "2010-01-29" "2010-02-26" "2010-03-26" "2010-04-30"
[5] "2010-05-28" "2010-06-25" "2010-07-30" "2010-08-27"
[9] "2010-09-24" "2010-10-29"
[ reached getOption("max.print") -- omitted 26 entries ]
```

If the Dates are not sorted, either `sort` them

```
if (is.unsorted(d))
    d <- sort(d)
```

or use `max`.

```
d <- sample(d, size = length(d))
aggregate(d, by = list(format(d, "%Y-%m")), FUN = max)[[2L]]
```

```
[1] "2010-01-29" "2010-02-26" "2010-03-26" "2010-04-30"
[5] "2010-05-28" "2010-06-25" "2010-07-30" "2010-08-27"
[9] "2010-09-24" "2010-10-29"
[ reached getOption("max.print") -- omitted 26 entries ]
```

The code also works when dates are duplicated.

17.3 From a vector of Dates, extract the first day of each month

As before, but sort in descending order or use `min`.

17.4 Compute the week number and start/end of week

From R-help.

```
iso_start_end <- function(d) {
    d <- as.Date(d)
    wday <- as.POSIXlt(d)$wday
    wday[wday == 0] <- 7
    data.frame(date = d,
               week = format(d, "%V"),
               starts = d - wday + 1,
               ends = d + 7 - wday)
}

d <- c("2010-08-21", "2010-08-22",
       "2010-08-23", "2010-08-24")
iso_start_end(d)
```

```
        date week     starts       ends
1 2010-08-21   33 2010-08-16 2010-08-22
2 2010-08-22   33 2010-08-16 2010-08-22
3 2010-08-23   34 2010-08-23 2010-08-29
4 2010-08-24   34 2010-08-23 2010-08-29
```

17.5 Dates in JavaScript

```
console.log(Date(2016, 0, 18, 10, 11, 12));
```

```
Fri Jan 20 2017 10:48:26 GMT+0100 (CET)
```

17.6 Time

Unix time, the number of seconds since 1970-01-01 00:00:00 UTC. Traditionally, represented as a 4-byte integer.

17.7 Unix timestamps in the Bourne shell

```
date         ## current time
date +%s
```

```
Tue 12 Mar 14:56:56 CET 2024
1710251816
```

Convert back to human-readable time.

```
date --date='1710251816'
```

```
Tue 12 Mar 14:56:56 CET 2024
```

17.8 Unix timestamps in R

R represents the timestamp as doubles.

```
    (tmp <- unclass(Sys.time()))
```

```
1473428055.30705
```

Convert back to human-readable time.

```
    .POSIXct(tmp)
```

```
2016-09-09 15:34:15
```

18 Appendix: R and package versions used

```
R version 4.2.2 Patched (2022-11-10 r83330)
Platform: x86_64-pc-linux-gnu (64-bit)
Running under: Ubuntu 22.10

Matrix products: default
BLAS:   /usr/lib/x86_64-linux-gnu/openblas-openmp/libblas.so.3
LAPACK: /usr/lib/x86_64-linux-gnu/openblas-openmp/libopenblasp-r0.3.20.so

locale:
 [1] LC_CTYPE=en_US.UTF-8       LC_NUMERIC=C
 [3] LC_TIME=en_GB.UTF-8        LC_COLLATE=en_US.UTF-8
 [5] LC_MONETARY=en_GB.UTF-8    LC_MESSAGES=en_US.UTF-8
 [7] LC_PAPER=en_GB.UTF-8       LC_NAME=C
 [9] LC_ADDRESS=C               LC_TELEPHONE=C
[11] LC_MEASUREMENT=en_GB.UTF-8 LC_IDENTIFICATION=C

attached base packages:
[1] stats     graphics  grDevices utils     datasets  methods
[7] base

other attached packages:
[1] rbenchmark_1.0.0 orgutils_0.5-0   NMOF_2.8-0
[4] zoo_1.8-11       PMwR_0.19-0

loaded via a namespace (and not attached):
[1] datetimeutils_0.6-0 compiler_4.2.2      tools_4.2.2
[4] parallel_4.2.2      fastmatch_1.1-3     grid_4.2.2
[7] textutils_0.3-1     lattice_0.20-45
```

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Index