visCOS

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Contents

Hello, traveler

This is documentation and code for the R-package **visCOS**. **visCOS** stands for *vis*ual *c*omparison of *o*bservations and *s*imulations. The package is still under (heavy) development and we therefore do not recommended to use the package, yet.

There exist many R-packages dedicated to hydrology.

Among then, several have provide help to the calibration of (conceptual) rainfall-runoff models. As their name suggests, these models relate the a rainfall input to a generated runoff for some given basins They have found a wide array of applications in hydrology. Form the analysis of catchment properties to climate impact studies, so to speak. From the point o view of the R package ecosystem there are to packages, which are of particular interest with regard to **visCOS**: The `hydroGOF` package and the `hydroTSM` package. The former provides the most commonly used (and discussed) objective functions. The latter, helps with the analysis, interpolation and the plotting of hydrological time series.

As an R-package that aim of **visCOS** is to provide summaries - in a visual and numerical sense - to aid a concurrent and comparative parameter estimation for multiple (related) basins or catchments. Topic wise, **visCOS** might therefore be positioned somewhere in-between the two previously mentioned packages. **visCOS** is usable for conceptual rainfall runoff models in general, but almost all of its functionality has been derived from different applications of the COSERO model. COSERO is a HBV-like distributed rainfall-runoff model, developed at the institute for water management, hydrology and hydraulic engineering at BOKU, Vienna. The name is an abbreviation for "**Co**nceptual **Se**mi-Distributed **R**ainfall Run**o**ff Model".

1 Introduction

Within **visCOS** "cooking data" is is used as a synonym for the process of transforming *raw data* into *cooked data*. This process and definitions are, of course, metaphors. We shall explain them in the following.

1.1 Raw Data

Raw-data is data which is not yet in the right format for its use. Raw-data takes on many forms. The ones of interest for **visCOS** are series of observations, *o*, and model simulations, *s*. in the scientific context, raw data is usually served in some simple file format, e.g. *.txt* or *.csv*. In other context more complex formats can be found, but we shall not delve into that now. `R` includes method to read simple formats, e.g. with the different `read.table` functions (simply enter `?read.table` in your `R` terminal to get an overview). However, for larger (unstructured) files we recommend the read functionality of the `data.table` package. In our tests it was fastest and most flexible choice. Lastly, we recommend `readr` package for well structured and large data that has to be read.

1.2 Cooked Data

Cooked data is data that is formatted in a way, that can be used be used by applications. A nice example (or dish if you want to) for cooked data is
tidy-data. Another one might be the storage of data in matrices and vectors. Within the **visCOS** package, cooked data, is data which is in the *cos_data* format. This format is a slightly redundant but flexible representation of hydrological time-series that is derived from the way COSERO produces outputs. All data in *cos_data* format can be used for further exploratory analysis with the package.

...

Currently **visCOS** only allows to compare between *numbered catchments*! The data **must** include an integer number at the end of its name, e.g. `QObs_001` and `QSim_001`).

2 Cooking Data

This chapter defines the basic functions for adapting given (raw) in such a way that it can be used for further use with **visCOS**. In the following we exemplify the usage of these functions and then define their code.

2.1 Examples

The function `get_viscos_example` can be used to get some exemplary data from within **visCOS**:

```
options(width=80)
require(visCOS)
require(magrittr)
#
runoff_example_raw <- get_viscos_example( )
head(runoff_example_raw)
```

```
##   yyyy mm dd hh min QOBS_0001 QOSI_0001 QSIM_0001 QOBS_0002 QOSI_0002 QSIM_0002
## 1 2007  1  1  0   0      2.98      3.48      3.48      2.56      3.11      3.11
## 2 2007  1  1  1   0      2.89      3.48      3.48      2.56      3.11      3.11
## 3 2007  1  1  2   0      2.64      3.48      3.48      2.57      3.11      3.11
## 4 2007  1  1  3   0      2.51      3.48      3.48      2.57      3.11      3.11
## 5 2007  1  1  4   0      2.42      3.48      3.48      2.57      3.11      3.11
## 6 2007  1  1  5   0      2.34      3.49      3.49      2.57      3.11      3.11
```

Usually, one would then need to adapt the (`viscos_options` or name the `data.frame` appropriately. But, in this case the options are already set as in the data:

```
  viscos_options( ) %>% unlist(.)
```

```
##         name_o         name_s        name_lb        name_ub   name_COSyear
##         "qobs"         "qsim"           "lb"           "ub"         "yyyy"
##  name_COSmonth    name_COSday   name_COShour    name_COSmin  name_COSposix
##           "mm"           "dd"           "hh"          "min"    "posixdate"
## name_COSperiod      data_unit   missing_data        color_o        color_s
##       "period"      "(m^3/s)"         "-999"   "dodgerblue"       "orange"
##     of_limits1     of_limits2
##            "0"            "1"
```

A glimpse of the data shows that some columns - `QOSI_0001` and `QOSI_0002` - are not needed for further analysis. We refer to these columns as junk. Another example of junk would be columns where no observations are available. These columns might has a purpose for some application or in the grater scheme of things, but it has no use within **visCOS**. Hence, we need to *throw the data away*.

The package provides a function for doing so. The `remove_junk` function. Here is an example for its use:

```
runoff_example_raw %>%
  remove_junk(.) %>%
  head(.)
```

```
## Loading required package: pasta
```

```
##   yyyy mm dd hh min QOBS_0001 QSIM_0001 QOBS_0002 QSIM_0002
## 1 2007  1  1  0   0      2.98      3.48      2.56      3.11
## 2 2007  1  1  1   0      2.89      3.48      2.56      3.11
## 3 2007  1  1  2   0      2.64      3.48      2.57      3.11
## 4 2007  1  1  3   0      2.51      3.48      2.57      3.11
## 5 2007  1  1  4   0      2.42      3.48      2.57      3.11
## 6 2007  1  1  5   0      2.34      3.49      2.57      3.11
```

Additionally, `cos_data` data.frame needs to have two different definitions for the date of a given row (see: Introduction). One is based on an old way to write dates out in fortran code. In that case each column represents a time-resolution. In concrete, the following columns are used:

- *yyyy* - year,
- *mm* - month,
- *hh* - hour,
- *min* - minute.

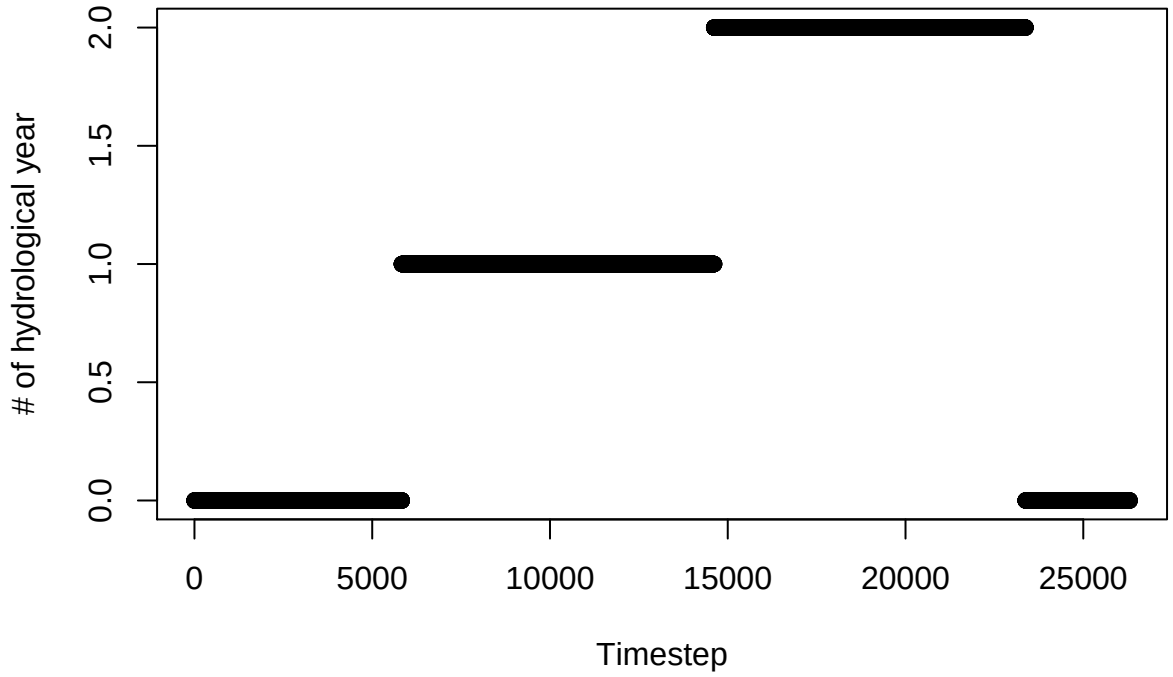
The other format is a more modern way to define time information. That is, the `POSIXct` format (see: link). This format is a standard for `R` and has many usages (e.g. transforming your data frame into a time series). In this format all information is saved in one column. The **visCOS** package has a function that can be used to generate one of the formats if the other one is given. It is called `complete_dates`. Here is an example:

```
runoff_example_raw %>%
  remove_junk(.) %>%
  complete_dates(.) %>%
  head(.)
```

```
##   yyyy mm dd hh min QOBS_0001 QSIM_0001 QOBS_0002 QSIM_0002           posixdate
## 1 2007  1  1  0   0      2.98      3.48      2.56      3.11 2007-01-01 00:00:00
## 2 2007  1  1  1   0      2.89      3.48      2.56      3.11 2007-01-01 01:00:00
## 3 2007  1  1  2   0      2.64      3.48      2.57      3.11 2007-01-01 02:00:00
## 4 2007  1  1  3   0      2.51      3.48      2.57      3.11 2007-01-01 03:00:00
## 5 2007  1  1  4   0      2.42      3.48      2.57      3.11 2007-01-01 04:00:00
## 6 2007  1  1  5   0      2.34      3.49      2.57      3.11 2007-01-01 05:00:00
```

Lastly, **visCOS** can differentiate seasonal information on a monthly resolution. The in- and out-of-period markings are stored in a separate column (defined by `viscos_options("name_COSperiod")`). Here, each season is defined by an number (integer), which starts 1 and is raised for each new season. A 0 indicates the out-of-period rows. The package provides a simple, yet imperfect, helper to get those: The `mark_periods` function. In the following is an example, where the (European) hydrological years, from September till August, are used as seasons. Note, that the example data starts with beginning of September, which is the first hydrological year. The end of the year 2010 is not completely inside a hydrological year, thus the period counter jumps to one:

```
cooked_runoff_example <- runoff_example_raw %>%
  remove_junk(.) %>%
  complete_dates(.) %>%
  mark_periods(start_month = 9, end_month = 8)
# here is an example plot to visualize the periods
plot(cooked_runoff_example$period,
     xlab = "Timestep",
     ylab = "# of hydrological year")
```



2.2 Code

```
# ------------------------------------------------------------------------
# Code for cooking data
# authors: Daniel Klotz, Johannes Wesemann, Mathew Herrnegger
# ########################################################################
```

Currently the following *data cooking* tasks can be performed:

- Provide example data
- Remove junk
- Complete date formats
- Define periods

2.2.1 Get Example Data

The example data is used to test the available functions. It is defined as:

```
# ------------------------------------------------------------------------
#' Get runoff example
#'
#' Get exemplary runoff data to test the different functions of visCOS
#' @export
get_viscos_example <- function( ) {
  path <- system.file("extdata", "runoff_example.csv", package = "visCOS")
  runoff_example <- read.csv(path)
  return(runoff_example)
}
```

2.2.2 Remove not needed columns

The following function removes all columns not specified in the `viscos_options`, as well as basins where no *o* data (observations) are available. One has to be a bit careful with the naming, because **visCOS** is case insensitive. So is this function.

The function first gets an index of the respective column-names. This index is used to filter out the data. Afterwards, the function `only_observed_basins` is applied to sieve out basins where no observation is available (see: next sub chapter).

```
# ------------------------------------------------------------------------
#' removes junk in cos_data
#'
#' Removes all columns which are not foreseen (see: viscos_options) from
#' runoff data
#'
#' @import magrittr
#' @param cos_data The cos_data data.frame (see vignette for info)
#' @return data.frame object without the chunk
#' @export
remove_junk <- function(cos_data) {
  assert_dataframe(cos_data) # see: defensive code
  # determine names of cos_data and get regex:
  names_in_data <- cos_data %>% names(.)
  regex_columns <- get_regex_for_cos_data( ) # see: helpers
  # get idx and clean data: ================================================
  idx <- grep(regex_columns,names_in_data, ignore.case = TRUE)
  clean_cos_data <- only_observed_basins(cos_data[ ,idx])
  return( clean_cos_data )
}
```

2.2.2.1 Get only observed basins

This function removes basins that has no observations (`o_data`). Here, "no observations" means that all the entries of the respective columns are either `NA` or tagged with the value defined with `viscos_options("missing_data")`.

```
# ------------------------------------------------------------------------
# remove basins without observations
#
```

```r
# Removes basins without observation (-999/NA values) from the provided data.frame
#
# @param cos_data A raw cos_data data.frame, which may contains basins
# without observations.
# \strong{Note:} It is assumed that all available basins are simulated!
# @return data.frame without the observation-free basins
#
# @import magrittr
# @import pasta
only_observed_basins <- function(cos_data) {
  # pre: ============================================================
  require("magrittr")
  require("pasta")
  assert_dataframe(cos_data)
  missing_data_marker <- viscos_options("missing_data")
  # check for missing obs: ==========================================
  # set NA values to viscos_options("missing_data") and check if there are
  # cloumns wihtouth observervation:
  chosen_cols <- which( names(cos_data) != viscos_options("name_COSposix") )
  rows_with_na <- is.na(cos_data[ ,chosen_cols])
  data_wihtouth_posix <- cos_data[ ,chosen_cols]
  data_wihtouth_posix[rows_with_na] <- missing_data_marker
  colmax <- sapply(X = data_wihtouth_posix, FUN = max)
  # remove unobserved pairs: ========================================
  if ( any(colmax < 0.0) ){
    name_o <- viscos_options("name_o")
    neg_o_names <- which(colmax < 0.0) %>% names(.)
    neg_s_names <- gsub(name_o,viscos_options("name_s"),
                        neg_o_names,
                        ignore.case = TRUE)
    data_selection <-  paste(neg_o_names,
                             neg_s_names,
                             sep = "|",
                             collapse = "|") %>%
      grepl(names(cos_data), ignore.case = TRUE) %>%
      not(.)
    data_only_observed <- cos_data[ ,data_selection]
  } else {
    data_only_observed <- cos_data
  }
  # bonus: change missing_data to NA (useful for of computation) ============
  idx_NA <- data_only_observed %>% equals(missing_data_marker)
  data_only_observed[idx_NA] <- NA
  return(data_only_observed)
}
```

2.2.3 Complete the date formats

This function is not finished yet! All dates in **viscos** are set to *UTC* and hence to a **fixed time-zone** in order to avoid problems with leaps in time (summer/winter time). These dates have to be provided in two formats (see: introduction):

1. A *five column* format: The needed-columns are year-month-day-hour-minute, with the names as defined

in `viscos_options()`.
2. A *one column* format: `POSIXct` (see: link), and the name as defined in `viscos_options("name_COSposix")`.

The idea of `complete_dates` is to provide a internal method to get one format out of the other. **However**, currently it is only possible to convert the 5-columns representation into `POSIXct` dates via the internally defined `implode_cosdate` function. So - without further ado - here is the function

```
# ------------------------------------------------------------------------
#' Complete the date-formats with POSIXct or COSdate
#'
#' Complete the data-formats of your data.frame `POSIXct` and/or `COSdate`
#'
#' @param cos_data The data.frame, which contains the runoff information
#' @param name_cosyear string with the name of the `COSdate` year column
#' @param name_posix string with the name of the POSIXct column
#' @return The new runoff data.frame with the added data-format.
#'
#' @import magrittr
#'
#' @export
complete_dates <- function(cos_data) {
  # pre: ==================================================================
  assert_dataframe(cos_data)
  date_names <- unlist(viscos_options("name_COSyear",
                                      "name_COSmonth",
                                      "name_COSmonth",
                                      "name_COShour",
                                      "name_COSmin")
                       )
  # check dates: ==========================================================
  # stop if non-logical expression are obtained
  all_dates_in_cosdata <- any( date_names %in% names(cos_data) )
  posix_cosdata <- any(viscos_options("name_COSposix") == names(cos_data))
  if ( !is.logical(all_dates_in_cosdata) | !is.logical(posix_cosdata) ) {
    stop("Something is wrong :( \n
          Some of the date-columns could not be processed!")
  }
  # execute function for the available format: ============================
  if (!all_dates_in_cosdata & !posix_cosdata) {
    stop("Something is wrong :( \n
         The 5 cosero date columns and the POSIXct colum could not be found")
  } else if (all_dates_in_cosdata & !posix_cosdata) {
    cos_data <- implode_cosdate(cos_data) # see: sub-chapter Implode date
  } else if (!all_dates_in_cosdata & posix_cosdata) {
    stop("POSIXct to COSdates not yet supported :(")
  }
  return(cos_data)
}
```

2.2.3.1 Implode date

This sub-function is used to transform the "old-school" 5 column format into the modern `POSIXct`.

```
# ------------------------------------------------------------------------
implode_cosdate <- function(cos_data) {
```

```
  # pre: ========================================================================
  require("magrittr", quietly = TRUE)
  require("pasta", quietly = TRUE)
  assert_dataframe(cos_data)
  name_string <- cos_data %>% names(.) %>% tolower(.)
  # create posix_date column: ===================================================
  month_digits  <- sprintf("%02d",cos_data[[viscos_options("name_COSmonth")]])
  day_digits    <- sprintf("%02d",cos_data[[viscos_options("name_COSday")]])
  hour_digits   <- sprintf("%02d",cos_data[[viscos_options("name_COShour")]])
  minute_digits <- sprintf("%02d",cos_data[[viscos_options("name_COSmin")]])
  posix_date <- cos_data[[viscos_options("name_COSyear")]] %&%
      month_digits %&%
      day_digits %&%
      hour_digits %&%
      minute_digits %>%
    as.POSIXct(format = "%Y%m%d%H%M",
               origin = .[1],
               scale = "hourly",
               tz = "UTC")
  cos_data[[viscos_options("name_COSposix")]] <- posix_date
  return(cos_data)
}
```

2.2.4 Remove leading zeros in column names

This internal function removes leading zeros from column names of the `cos_data` data.frame. The function has no defensive code but uses `remove_junk` (see: above). It should therefore be used with care!

```
# ------------------------------------------------------------------------------
# remove leading zeros from the names of cos_data (data.frame)
remove_leading_zeros <- function(cos_data) {
  # pre: ========================================================================
  require("magrittr", quietly = TRUE)
  require("pasta", quietly = TRUE)
  cos_data %<>% remove_junk
  name_o <- viscos_options("name_o")
  search_o_or_s <- paste0(name_o,"|", viscos_options("name_s"))
  runoff_names <- cos_data %>% names(.)
  runoff_lowercase_names <- runoff_names %>% tolower(.)
  del_leading_zeros <- function(string) sub("^[0]+", "",string)
  # calc: =======================================================================
  idx_o <- grep(name_o , runoff_lowercase_names)
  separator <- runoff_lowercase_names %>%
    extract( idx_o[1] ) %>%
    gsub(name_o, "", .) %>%
    gsub("\\d", "", .)
  runoff_nums <- runoff_lowercase_names %>%
    gsub(search_o_or_s, "",.) %>%
    gsub(separator, "", .) %>%
    gsub("\\D", "", .)
  search_runoff_nums <- "[" %&% paste(runoff_nums, collapse = "") %&% "]"
  runoff_only_names <- runoff_names %>%
    gsub(search_runoff_nums, "", .) %>%
```

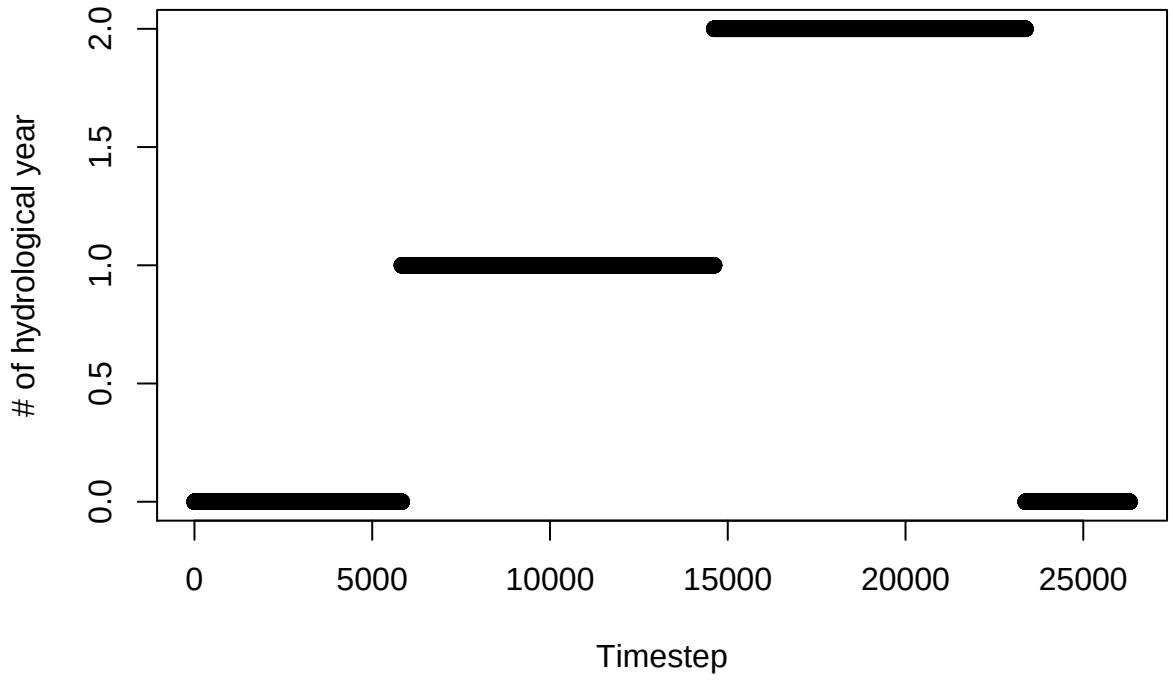
```
    gsub(separator,"",.)
  # clean up: ============================================================
  runoff_new_numbers <- del_leading_zeros(runoff_nums)
  new_names <- runoff_new_numbers %>%
    gsub("\\d+", separator,.) %>%
    paste0(runoff_only_names, ., runoff_new_numbers)
  names(cos_data) <- new_names
  return(cos_data)
}
```

2.2.5 Mark the needed periods

This function creates the period column. The period column consists of increasing integers for each period and zeros, which indicate that a given row is "outside" the period. The name of the column is defined by the option `viscos_options("name_COSperiod")`.

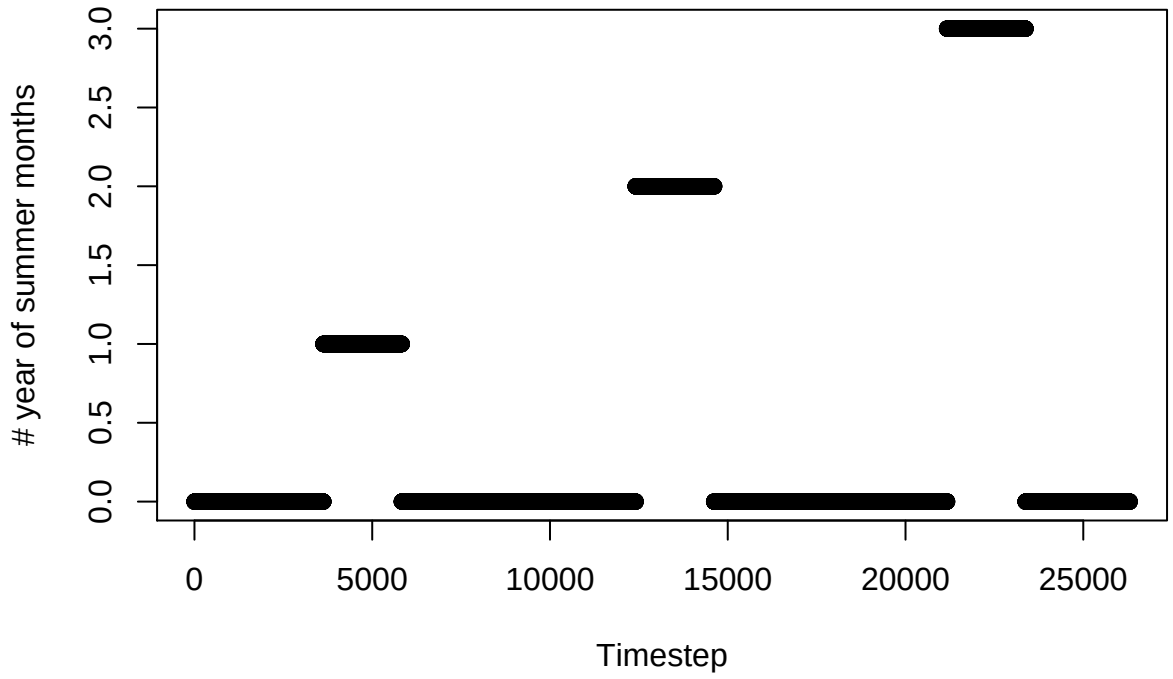
The `mark_periods` funciton takes the `cos_data` and the two integers (`start_month` and `end_month`) as input. The integers define the first and last month of the period respectively. Here, two examples that display the selected periods and the numbering:

```
require(magrittr)
require(visCOS)
# example 1: hydrological years (september till august)
ex1 <- get_viscos_example( ) %>% mark_periods(start_month = 9, end_month = 8)
plot(ex1$period, xlab = "Timestep", ylab = "# of hydrological year")
```




```
# note that the last year is not complete, so the counter jumps back to 0

# example 2: summer months (june till august)
ex2 <- get_viscos_example() %>% mark_periods(start_month = 6, end_month = 8)
plot(ex2$period, xlab = "Timestep", ylab = "# year of summer months")
```



`mark_periods` does currently work as following:

Before starting the acutal computation the variables `period_range` and `out_of_period` are defined. The `period_range` are the months ordered in the given range. The `out_of_period` variable marks all months which are not within the chosen period. With these variables the periods can be "marked" in two steps:

1. All the starting months within cos_data are marked and the cumulative sum is used to count the periods within the data.frame. At the beginning of the first period, the counter is at "1" and becomes "2" with the beginning of the second period and so on.
2. The `out_of_period` of all years is set back to zero again by checking which months of the data are equal to the `out_of_period` entries.

One problem with this solution is that the last year is not extracted properly if the `start_month`is higher than the `end_month`. To compensate this problem the `dplyr` shenanigans are added as an inofficial third step. Another quirk is, that with this solution the the first and last period are included, even if they are not complete.

This solution is not realy satisfying. But, life is short and it at the time it seemed to be the best that the authors could come out with. Suggestions for improvements are welcome!

```
# ------------------------------------------------------------------------
#' Mark Periods
#'
#' Compute/Mark the periods within cos_data. The marking uses a monthly
#' resolution, which are defined by the integers `start_month` and
#' `end_month`.
#'
#' @param cos_data a data.frame that contains the runoff information.
#' @return  `cos_data` with an aditonal column with the marked periods.
#'
#' @import dplyr
#' @import magrittr
#'
#' @export
mark_periods <- function(cos_data, start_month = 10, end_month = 9) {
```

```
  # pre: ================================================================
  assert_dataframe(cos_data)
  name_year <- viscos_options("name_COSyear")
  name_month <- viscos_options("name_COSmonth")
  cos_data %<>% remove_junk %>% complete_dates()
  eval_diff <- function(a) {c( a[1],diff(a) )}
  period_correction <- function(cos_data,period) {
    # tests:
    year_is_max <- cos_data[[name_year]] == max_year
    month_after_end <- cos_data[[name_month]] > end_month
    # assigmnet:
    ifelse((year_is_max & month_after_end), 0, period)
  }
  # calc: ================================================================
  # (I) get labels for the months: ##############################################
  if (start_month <= end_month) {
    period_range <- seq(start_month,end_month)
    out_of_period <- seq(1,12) %>% extract( !(seq(1,12) %in% period_range) )
  } else if (start_month > end_month) {
    range_1 <- seq(start_month,12)
    range_2 <- seq(1,end_month)
    period_range <- c(range_1,range_2)
    out_of_period <- seq(1,12) %>% extract( !(seq(1,12) %in% period_range) )
  }
  # (II) mark periods: ##########################################################
  start_months_in_data <- cos_data[[name_month]] %in% c(start_month)
  cos_data[[viscos_options("name_COSperiod")]] <- start_months_in_data %>%
    eval_diff(.) %>%
    pmax(.,0) %>%
    cumsum(.)
  out_period_in_data <- cos_data[[name_month]] %in% out_of_period
  cos_data$period[out_period_in_data] <- 0
  # (III) corrections for last year #############################################
  max_year <- max(cos_data[[name_year]])
  marked_cos_data <- dplyr::mutate(cos_data,
                            period = period_correction(cos_data, period)
    )
  return(marked_cos_data)
}
```

2.2.6 Transform `cos_data` into `xts`

This function is just a small wrapper around the `xts()` function for internal use in **viCOS**. A notable quirk of the function is it puts all column-names to lower cases and removes leading zeros in their enumeration.

```
# ------------------------------------------------------------------------------
#' Convert cos_data to xts-format
#'
#' Converts the cos_data (class: data_frame) into an xts object
#'
#' @return xts object of the cos_data data.frame
#' @import zoo
#' @importFrom xts xts
```

```
#' @import magrittr
cos_data_as_xts <- function(cos_data) {
  # pre: ============================================================
  assert_dataframe(cos_data)
  assert_junk(cos_data)
  assert_complete_date(cos_data)
  # calc: ===========================================================
  # set every- name to lover capitals and generate xts frame
  new_names <- cos_data %>% names(.) %>% tolower(.)
  name_posix <- viscos_options("name_COSposix") %>% tolower(.)
  cos_data <- cos_data %>%
    remove_leading_zeros(.) %>%
    magrittr::set_names(new_names)
  cos_data_as_xts <- xts(x = cos_data[], order.by = cos_data[[name_posix]])
  return(cos_data_as_xts)
}
```

3 Options

visCOS provides a set of global options for controlling the package. They are implemented with the help of the `GlobalOptions` package. This section defines the code for the global options and explains the individual options:

```
#' visCOS global options
#'
#' Get and set the global options of visCOS
#'
#' These are the options you can adapt by executing the function
#' (default values)
#' \preformatted{
#'   viscos_options(
#'    # data.frame column names
#'       name_o = "qobs", # name of the first time-series data, i.e. the observations
#'       name_s = "qsim", # name of the second time-series data, i.e. the simulations
#'       name_lb = "lb", # lower bound information of the simulations
#'       name_ub = "ub", # upper bound information of the simulations
#'       name_COSyear = "yyyy", # name of year-column
#'       name_COSmonth = "mm",  # name of month-column
#'       name_COSday = "dd",  # name of day-column
#'       name_COShour = "hh", # name of hour-column
#'       name_COSmin = "min", # name of minute-column
#'       name_COSposix = "posixdate", # name of the complete-date-column
#'       name_COSperiod = "period", # name of the marked-period column
#'      data_unit = "(m^3/s)", # unit-tag o the simulation and observation data
#'       missing_data = -999, # marker for missing data in the o_columns
#'    # plot options
#'       color_o = "steelblue", # color associated with the first o time-series data
#'       color_s= "orange",  # color associated with the second s time-series data
#'       of_limits = c(0,1) # limits of the plotted objective functions
#'   )
#' }
#'
```

```
#' @examples
#' viscos_options("name_o")
#' viscos_options(name_o = "OtherData")
#' viscos_options("name_o")
#' @export
viscos_options <- GlobalOptions::setGlobalOptions(
  # data.frame column names
  name_o = "qobs",
  name_s = "qsim",
  name_lb = "lb",
  name_ub = "ub",
  name_COSyear = "yyyy",
  name_COSmonth = "mm",
  name_COSday = "dd",
  name_COShour = "hh",
  name_COSmin = "min",
  name_COSposix = "posixdate",
  name_COSperiod = "period",
  data_unit = "(m^3/s)",
  missing_data = -999,
 # plot options
  color_o = "dodgerblue",
  color_s = "orange",
  of_limits = c(0,1)
)
```

4 Ojective Functions

This chapter defines the objective functions that are used in **visCOS**.

Objective functions, in short *of*, are an important part of the hydrological model calibration. Their importance arises from the approximate nature of the models and the large uncertainties of the process. Hydrological models are not only imperfect, in the sense that they simplify nature, but in most cases structurally different than the reality so that different models or their respective parametrisations approximate the hydrograph equally well. Thus, over the time a many objective functions have been developed to either make the model-results better interpretable/comparable or to address specific problems of given objective functions.

4.1 Code

This section defines the code for different objective functions. If possible the calculation is done with the help of the `hydroGOF` package, if not an R-code solution is tried. Currently 4 main objective functions are provided in **visCOS**. They can be directly extracted from the `cos_data` data.frame via the `main_of_` functions. Other objective functions are provided to, but no special extraction and visualisation functions are provided for them.

For the explanation and definition of the objective function it is assumed that o are the observations (defined by `name_o` in visCOS) and s are the simulation(defined by `name_s` in visCOS).

```
#' Objective Functions
#'
#' Different objective Functions, provided by visCOS. A detailed description
#' of each of the provided objective function is provided in the respective
```

```
#' vignette
#'
#' @param o The reference data or observations (o_data)
#' @param s The created data or the simulations (s_data)
#' @name of_overview
NULL
```

4.1.1 The "Main" Objective Functions

Currently the main objective functions are the Nash-Sutcliffe Efficiency, the Kling-Gupta Efficiency, the percentage bias and the correlation.

4.1.1.1 Nash-Sutcliffe Efficiency

The Nash-Sutcliffe Criterion NSE is by far the most used efficiency criterion in hydrology. In the hydrological context o usually represents a set of runoff-observation and s a set of simulations. The NSE is defined in the same way as the general definition of the coefficient of determination R^2:

$$NSE = \frac{\sum_{t=1}^{T} \big(o(t) - s(t)\big)^2}{\sum_{t=1}^{T} \big(o(t) - \bar{o}\big)^2}.$$

The variable $\bar{o}$ represents the average of o. The NSE can be seen as the relational the estimator s and the estimator resulting form the average of the data. It can can have values between minus infinity and 1 with 1 being the perfect fit, 0 when the mean of s is as good as the mean of o and negative values are even worse.

The code for the NSE computation is:

```
#' Nash-Sutcliffe Efficiency
#'
#' @rdname of_overview
#' @import hydroGOF
#' @export
of_nse <- function(o,s) {
  as.numeric( NSE(s,o) )
}
```

4.1.1.2 Kling-Gupta Efficiency

The Kling-Gupta Efficiency KGE was introduced by Gupta et al. (2009) to alleviate some of the shortcomings of the NSE. In their paper they argue why the NSE tends to overate simulations with small variance (note: in the context of the paper simulations = s) and propose their efficiency criterion instead.

The KGE is defined as:

$$KGE = 1 - ED,$$

with

$$ED = \sqrt{\big(corr(o,s) - 1\big)^2 + \big(\alpha(o,s) - 1\big)^2 + \big(\beta(o,s) - 1\big)^2}.$$

In which $\alpha(o,s) = \frac{\sigma_s}{\sigma_o}$ is the standard deviation σ of s divided by the σ of o, $\beta(o,s) = \mu_s/\mu_o$ withμ being the arithmetic mean and $corr(o,s)$ as the Pearson's correlation coefficient (see below). The value range and the quality is similar to the NSE.

The code for the KGE computation is:

```
#' Kling-Gupta Efficiency
#'
#' @rdname of_overview
#' @import hydroGOF
#' @export
of_kge <- function(o,s) {
  as.numeric( KGE(s,o) )
}
```

4.1.1.3 Percentage Bias

The percentage of bias p_{bias} is defined as the sum of the differences between o and s divided by the sum of o:

$$p_{bias} = 100 * \frac{\sum_{t=1}^{T}[o(t) - s(t)]}{\sum_{t=1}^{T} o(t)}.$$

The $100*$ is just a scaling factor applied to express p_{bias} as a percentage.

The code for the p_{bias} computation is:

```
#' Percentage Bias
#'
#' @rdname of_overview
#' @import hydroGOF
#' @export
of_p_bias <- function(o,s) {
  as.numeric( pbias(s,o) )
}
```

4.1.1.4 Pearson's correlation coefficient

Pearson's correlation coefficient, r or $corr(o,s)$, is a measure of the linear relationship between o and s. It is defined as:

$$r \equiv corr(o,s) = \frac{cov(o,s)}{\sigma_s * \sigma_o},$$

where $cov(...)$ denotes the covariance. The correlation coefficient can take on values between -1 and 1. The former corresponds to an inverse and the latter to a direct relationship and the closer the values is to zero the weaker is the implied correlation.

The code for the correlation is:

```
#' Correlation
#'
#' @rdname of_overview
#' @import hydroGOF
#' @export
of_cor <- function(o,s) {
```

```
  diag( cor(o,s) )
}
```

4.1.2 Ohter Objective Functions

Descriptions shall follow

4.1.2.1 Root Mean Sqaured Error

$$\frac{\sum_{t=1}^{T} \left(o(t) - s(t)\right)^2}{T}$$

```
#' Root Mean Sqaured Error
#'
#' @rdname of_overview
#' @import hydroGOF
#' @export
of_rmse <- function(o,s) {
  as.numeric( rmse(s,o) )
}
```

4.1.2.2 Inverted Nash-Sutcliffe Efficiency

$$nse^{-1} = \frac{\sum_{t=1}^{T} \left(s(t) - o(t)\right)^2}{\sum_{t=1}^{T} \left(s(t) - \bar{s}\right)^2}$$

```
#' Inverted Nash-Sutcliffe Efficiency
#'
#' @rdname of_overview
#' @import hydroGOF
#' @export
of_invert_nse <- function(o,s) {
  as.numeric( NSE(o,s) )
}
```

4.1.2.3 Ratio of the Standard Deviations

$$rsd = \frac{\sigma_s}{\sigma_o}$$

```
#' Ratio of Standard Deviations
#'
#' @rdname of_overview
#' @import hydroGOF
#' @export
of_rsd <- function(o,s) {
  as.numeric( rSD(s,o) )
}
```

4.1.2.4 Ratio of the Means

$$rmeans = \mu_s/\mu_o$$

```
#' Ratio of Means
#'
#' @rdname of_overview
#' @export
of_rmeans <- function(o,s) {
  as.numeric( mean(s)/mean(o) )
}
```

4.1.2.5 Volumetric Efficiency

The volumetric efficiency, VE, uses the absolute distance between observation and simulation instead of the quadratic and is bound between 0 to 1.

$$VE = 1 - \frac{\sum_{t=1}^{T} abs\big(s(t) - o(t)\big)}{\sum_{t=1}^{T} o(t)}$$

```
#' Volumetric Efficiency
#'
#' @rdname of_overview
#' @import hydroGOF
#' @export
of_ve <- function(o,s) {
  as.numeric( VE(s,o) )
}
```

4.2 References

- **Percentage Bias:** Yapo P. O., Gupta H. V., Sorooshian S., 1996. Automatic calibration of conceptual rainfall-runoff models: sensitivity to calibration data. Journal of Hydrology. v181 i1-4. 23-48
- **Nash-Sutcliffe Efficiency:** Nash, J. E. and J. V. Sutcliffe (1970), River flow forecasting through conceptual models part I -A discussion of principles, Journal of Hydrology, 10 (3), 282-290
- **Kling-Gupta Efficiency:** Gupta, Hoshin V., Harald Kling, Koray K. Yilmaz, Guillermo F. Martinez. Decomposition of the mean squared error and NSE performance criteria: Implications for improving hydrological modelling. Journal of Hydrology, Volume 377, Issues 1-2, 20 October 2009, Pages 80-91. DOI: 10.1016/j.jhydrol.2009.08.003. ISSN 0022-1694
- **Volumetric Efficiency:** Criss, R. E. and Winston, W. E. (2008), Do Nash values have value? Discussion and alternate proposals. Hydrological Processes, 22: 2723-2725. doi: 10.1002/hyp.7072

5 Time Aggregates

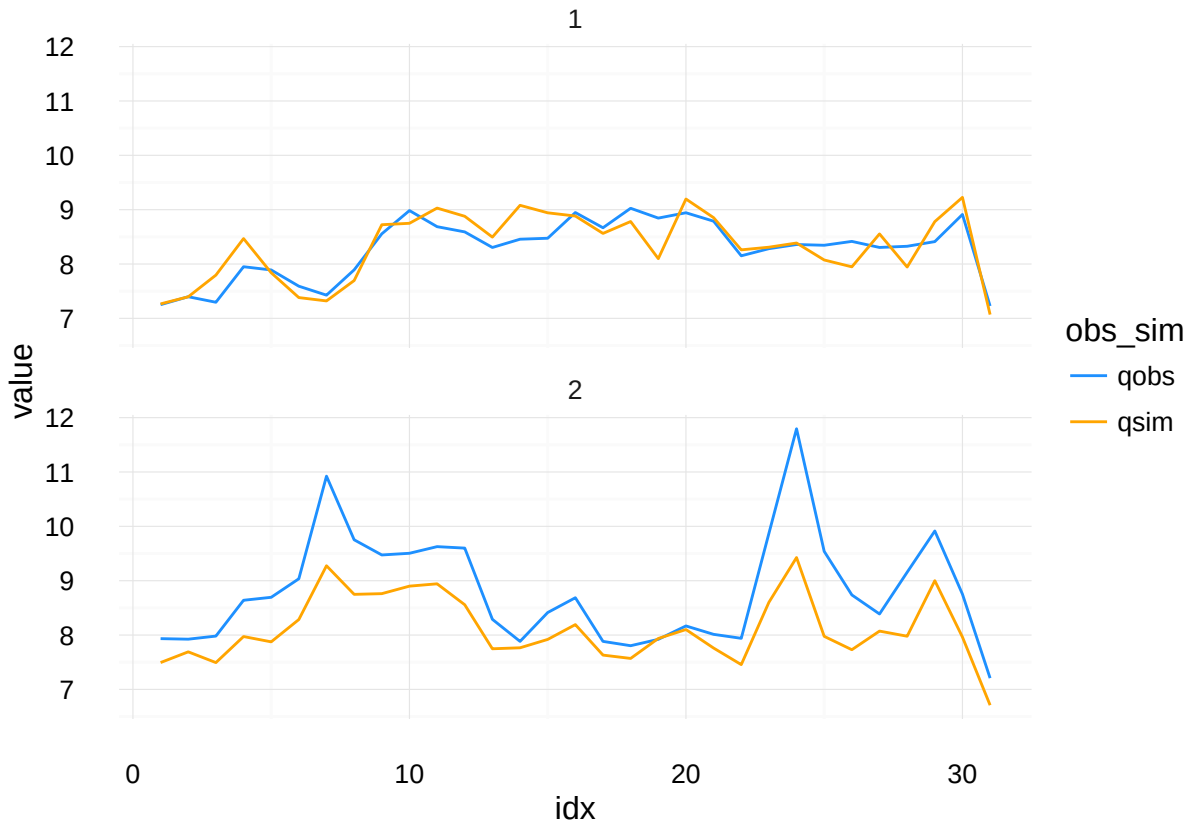
In hydrology it is often useful to summarise the data respect to a given time dimension. In **visCOS** this can be done by using the `aggregate_time` function. The function takes COSERO data.frame and aggregates them according to a chosen time dimension. Note, that the name of the dimension can be specified via the options.

5.1 Examples

```
require(ggplot2, quietly = TRUE)
require(visCOS, quietly = TRUE)
```

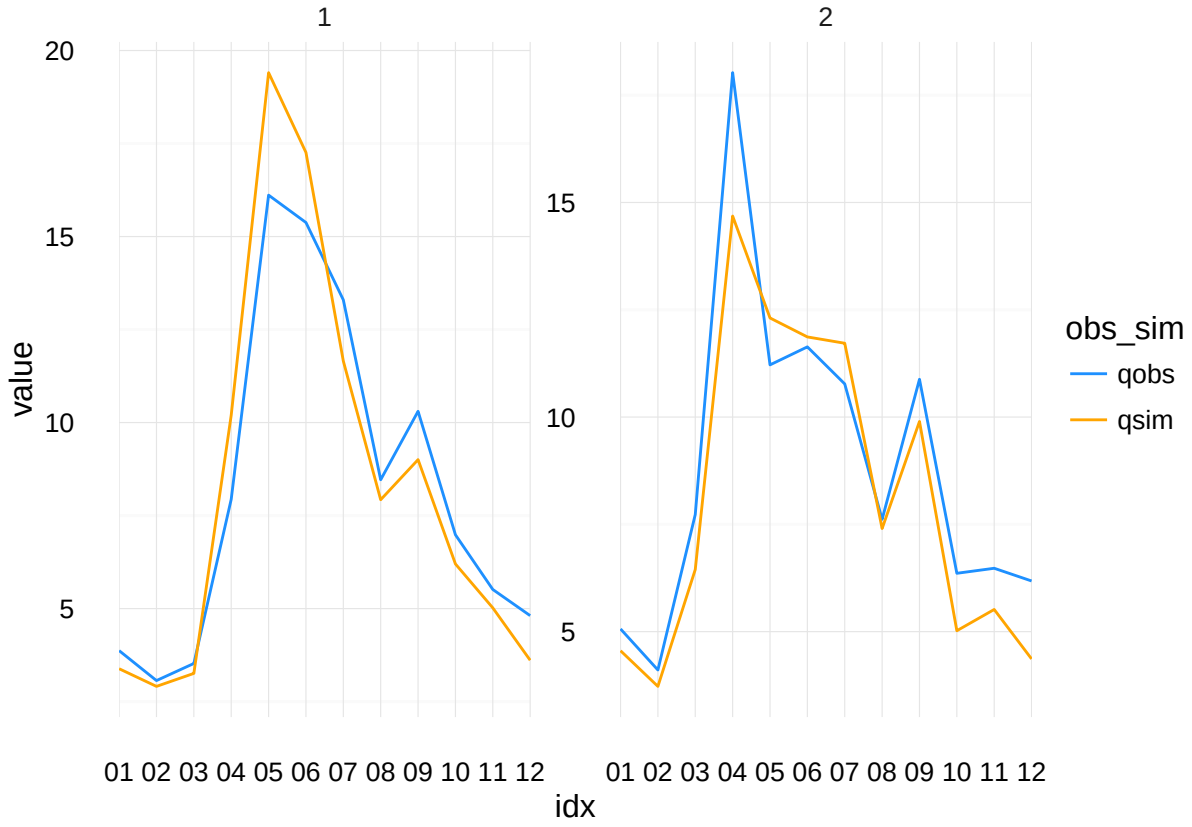
Daily runoff aggregation:

```
cos_data <- visCOS::get_viscos_example()
runoff_aggregate_dd <- aggregate_time(cos_data, "dd")
# plot data:
ggplot(runoff_aggregate_dd) +
    geom_line(aes(x = idx, y = value, col = obs_sim)) +
    scale_colour_manual(values = c(viscos_options("color_o"),
                                   viscos_options("color_s"))) +
    facet_wrap( ~ basin,ncol = 1) +
    theme_minimal()
```



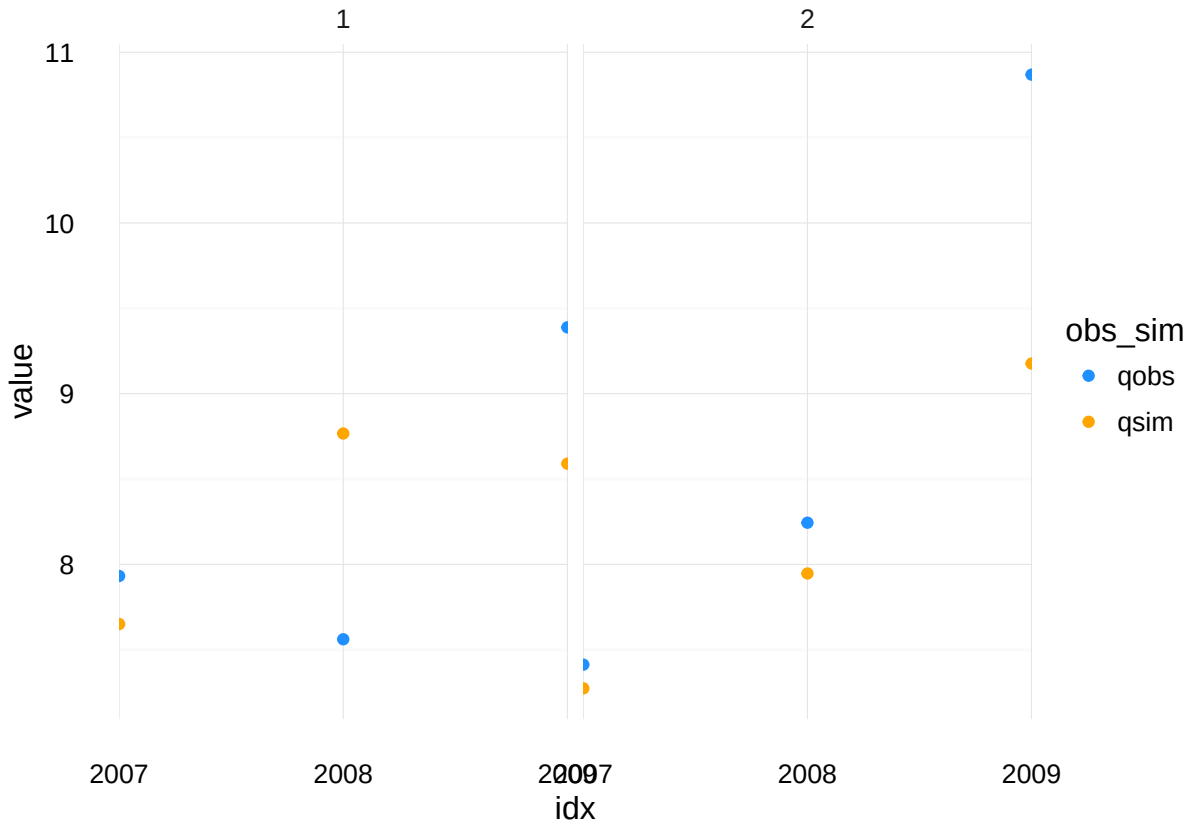
Monthly runoff aggregation:

```
runoff_aggregate_mm <- aggregate_time(cos_data, "mm")
# plot data:
ggplot(runoff_aggregate_mm) +
    geom_line(aes(x = idx, y = value, col = obs_sim)) +
    scale_colour_manual(values = c(viscos_options("color_o"),
                                   viscos_options("color_s"))) +
    scale_x_discrete(limits = runoff_aggregate_mm$time_aggregate) +
    facet_wrap( ~ basin, scales = "free") +
    theme_minimal()
```



Yearly runoff aggregation:

```
runoff_aggregate_yyyy <- aggregate_time(cos_data, "yyyy")
# plot data:
ggplot(runoff_aggregate_yyyy) +
  geom_point(aes(x = idx, y = value, col = obs_sim)) +
  scale_colour_manual(values = c(viscos_options("color_o"),
                                 viscos_options("color_s"))) +
  facet_wrap( ~ basin) +
  scale_x_discrete(limits = runoff_aggregate_yyyy$time_aggregate,
                   labels = abbreviate) +
  theme_minimal()
```



Yearly and monthly runoff aggregation:

```
runoff_aggregate_yyyymm <- aggregate_time(cos_data, "yyyy-mm")
# plot data:
ggplot(runoff_aggregate_yyyymm) +
  geom_line(aes(x = idx, y = value, col = obs_sim)) +
  scale_colour_manual(values = c(viscos_options("color_o"),
                                 viscos_options("color_s"))) +
  scale_x_discrete(limits = runoff_aggregate_yyyymm$time_aggregate,
                   labels = abbreviate) +
  facet_wrap( ~ basin,ncol = 1) +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 90, hjust = 1))
```

5.2 Code

This section defines the code for the `aggregate_time` function. The time aggregation is done by cutting the needed information out of the date-string. This is a rough, but works nicely and seems to be more commonly used than you would expect.

```
#' Time Aggregation
#'
#' Aggregates the COSERO data.frame (\code{cos_data}) according to the
#' timely resolution defined via \code{aggregation}. Possible
#' resolution-choices are \code{'yyyy'} - year, \code{'mm'} - month and
#' \code{'dd'} - day and combinations thereof.
#'
#' @param cos_data the COSERO data.frame as used within visCOS
#' @param aggregation string that defines the resolution of the aggregation.
#' @import magrittr
#' @import ggplot2
#' @import pasta
#' @export
aggregate_time <- function(cos_data, aggregation = "mm") {
  #
  cutting_bounds <- c(Inf,-Inf)
  if (grepl("dd",aggregation)) {
    cutting_bounds[1] <- min(9,cutting_bounds[1])
    cutting_bounds[2] <- max(11,cutting_bounds[2])
  }
  if (grepl("mm",aggregation)) {
```

```
  cutting_bounds[1] <- min(6,cutting_bounds[1])
  cutting_bounds[2] <- max(7,cutting_bounds[2])
}
if (grepl("yyyy",aggregation)) {
  cutting_bounds[1] <- min(1,cutting_bounds[1])
  cutting_bounds[2] <- max(4,cutting_bounds[2])
}
```

```
###### function and string definitions
regex_for_cos_selection <- viscos_options("name_o") %|%  viscos_options("name_s")
# aggregation function:
aggregator_fun <- function(k,data_frame){
  the_aggregation <- aggregate(data_frame[[k]] ~ data_frame$date_selection, FUN = mean)
  return(the_aggregation[ ,2])
}
#####
# If cos_data is not provided fully, the date is completed automatically
# + junk is removed from the data frame
full_cos_data <- cos_data %>%
  visCOS::complete_dates() %>%
  visCOS::remove_junk()
# aggregate:
cos_with_aggreggation <- cbind.data.frame(
  full_cos_data,
  date_selection = substr(full_cos_data$posixdate,
                          cutting_bounds[1],
                          cutting_bounds[2]) %>% as.factor()
  )
names_cos_selection <- grep(
  regex_for_cos_selection,
  names(cos_with_aggreggation) %>% tolower,
  value = TRUE
  )
selected_cos_rows <- grep(regex_for_cos_selection,
                          names(cos_with_aggreggation),
                          ignore.case = TRUE)
time_aggregate <- selected_cos_rows %>%
  sapply(.,function(x) aggregator_fun(x,cos_with_aggreggation)) %>%
  data.frame(idx = 1:nrow(.),
             time_aggregate = unique(cos_with_aggreggation$date_selection),
             .) %>%
  set_names(., c("idx","time_aggregate",names_cos_selection))
# melt the data in a tidy format:
melted_time_aggregate <- time_aggregate %>%
  reshape2::melt(., id.vars = c("idx","time_aggregate")) %>%
  cbind.data.frame(.,
                   basin =  .$variable %>%
                     gsub(regex_for_cos_selection,"",.) %>%
                     gsub("\\D","",.) %>%
                     as.integer,
                   obs_sim = .$variable %>%
                     gsub(viscos_options("name_o") %&% ".*",viscos_options("name_o"),.) %>%
                     gsub(viscos_options("name_s") %&% ".*",viscos_options("name_s"),.))
return(melted_time_aggregate)
```

```
}
```

6 Summaries of important objective functions

This chapter explains the code to calculate the main objective functions *of* used in visCOS. As explained in respective section objective functions are a pivotal part of model calibration. As of now, **visCOS** focuses on 4 main objective function: NSE, KGE, Pearson's Correlation and the Percentage bias (the respective definitions are given here).

The main objective functions for the overall data and the marked periods can be computed through the function `main_of_compute`. In order to run the function the period have to be marked first, e.g. through the `mark_periods` function. Additionally, **visCOS** already provides two different options to create plots for the main objective functions: `main_of_rasterplot` and `main_of_barplot`. Both functions create a list with 4 `ggplot` figures. Each entry in the list corresponds to one of the main objective functions and both lists can be saved to html embedded .jpgs with the `serve` function.

Examples:

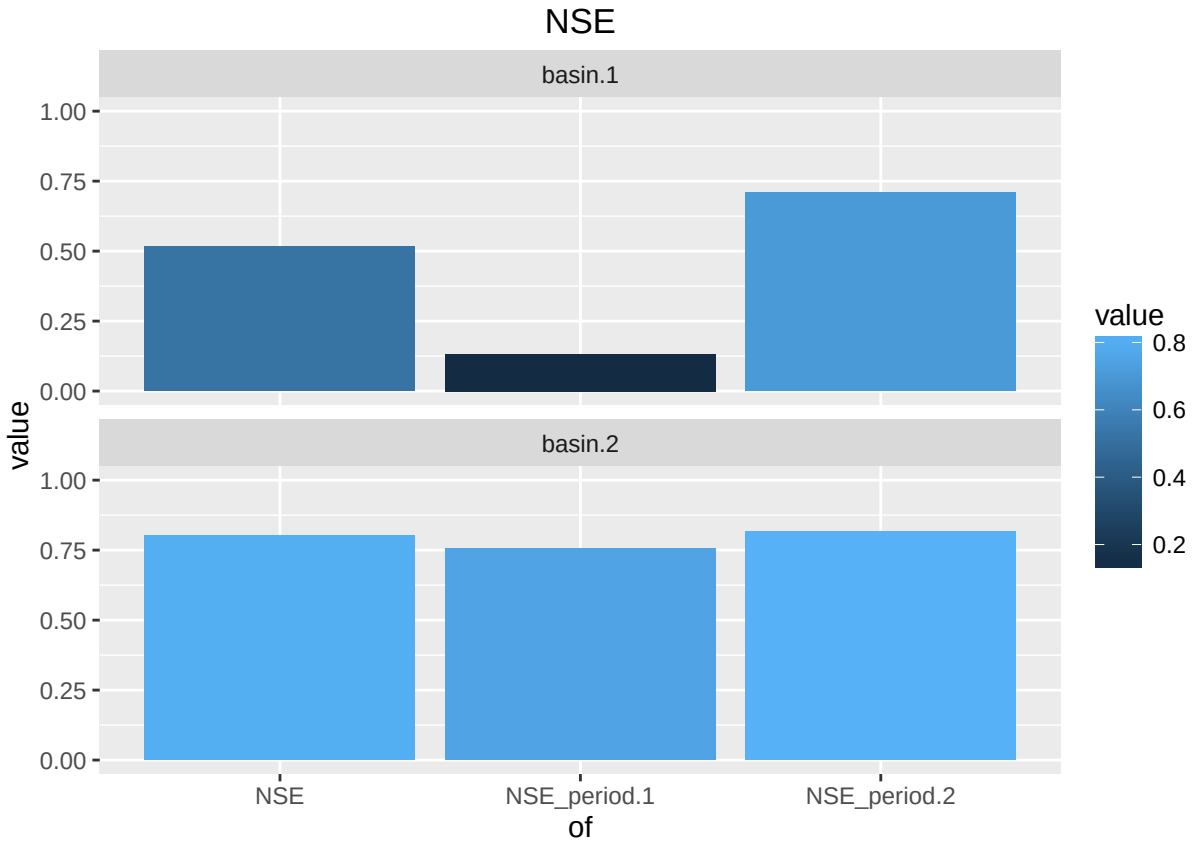
Computing the main objective functions

```
require(visCOS)
require(magrittr)
of_values <- get_viscos_example() %>%
  mark_periods() %>%
  main_of_compute()
of_values
```

```
##                 of    basin.1     basin.2
## 1              NSE  0.5177309   0.8012919
## 2              KGE  0.7246877   0.7489862
## 3           p_bias  0.3000000 -12.5000000
## 4             CORR  0.8177663   0.9107391
## 5     NSE_period.1  0.1326604   0.7566200
## 6     NSE_period.2  0.7096110   0.8168895
## 7     KGE_period.1  0.4138710   0.8487406
## 8     KGE_period.2  0.8419666   0.6820128
## 9  p_bias_period.1  8.8000000  -8.6000000
## 10 p_bias_period.2 -6.9000000 -15.9000000
## 11   CORR_period.1  0.8243198   0.8806770
## 12   CORR_period.2  0.8577983   0.9385221
```

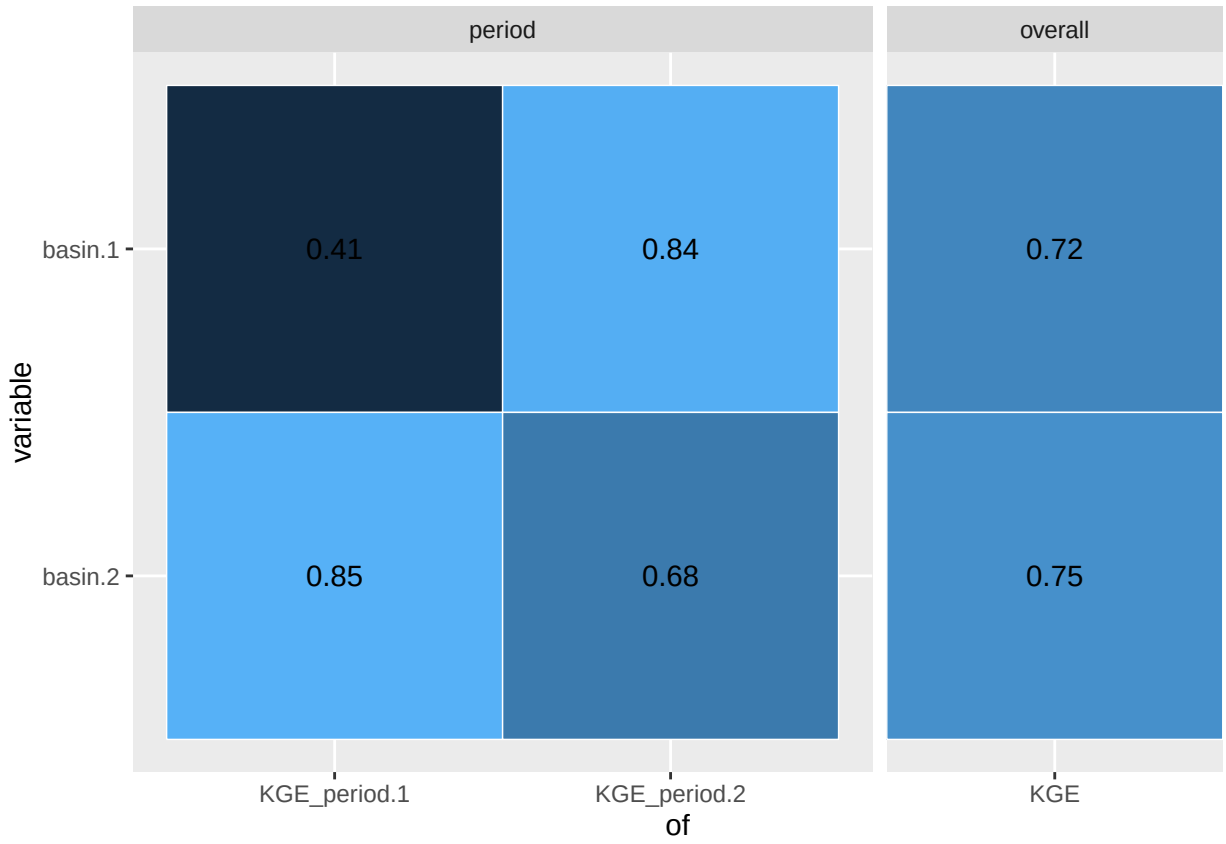
Plotting the results of main objective function with bar plots:

```
of_values <- get_viscos_example() %>%
  mark_periods() %>%
  main_of_barplot() %>%
  extract2(1) %>%
  plot()
```



Plotting the results of main objective function with a raster:

```
of_values <- get_viscos_example() %>%
  mark_periods() %>%
  main_of_rasterplot() %>%
  extract2(2) %>%
  plot()
```



6.1 Code

```
# ------------------------------------------------------------------------
# Code for the Main Objective Functions (main_of)
# authors: Daniel Klotz, Johannes Wesemann, Mathew Herrnegger
# !!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!
```

6.1.1 Compute the Main Objective Functions

The purpose of this function is to extract a the main of objective functions from the `COSERO` data.frame. The objective functions are extracted for each basin separately and computed for the entire length of the data, as well as for each period separately.

The computational part of the function works as follows. In step (I) the non-marked periods of `cos_data` (columns of `viscos_options("name_COSperiod")` which are smaller then 0) are excluded from further calculations. The thereby obtained data.frame is named `evaluation_data`.

```
# ------------------------------------------------------------------------
#' Get basic objective function for cos_data
#'
#' Calculate basic objective functions(NSE, KGE, percentage BIAS, Correlation)
#' for every basin and the chosen periods.
#'
#' @param cos_data cos_data data.frame.
#' @return list of basic objective function evaluated for the different
#' hydrological years and over the whole timespan.
```

```r
#'
#' @import hydroGOF
#' @import dplyr
#'
#' @export
main_of_compute <- function(cos_data) {
  # def: ================================================================
  assert_dataframe(cos_data)
  name_o <- viscos_options("name_o")
  name_s <- viscos_options("name_s")
  name_period <- viscos_options("name_COSperiod")
  if (!exists(name_period, where = cos_data)) {
    stop("Error! Period-Column missing in cos_data, use `mark_periods`")
  }
  evaluation_data <- cos_data[cos_data[[name_period]] > 0, ]
  number_of_basins <- evaluation_data %>%
    names() %>%
    unique() %>%
    grepl(name_o, ., ignore.case = TRUE) %>%
    sum()
  data_periods <- evaluation_data %>%
    magrittr::extract2(name_period) %>%
    unique()
  number_of_periods <- data_periods %>% length
  # compute main-of for entire data: ======================================
  o_pick <- dplyr::select(evaluation_data,starts_with(name_o)) %>% unname()
  s_pick <- dplyr::select(evaluation_data,starts_with(name_s)) %>% unname()
  nse_all <- hydroGOF::NSE(s_pick,o_pick)
  kge_all <- hydroGOF::KGE(s_pick,o_pick)
  p_bias_all <- hydroGOF::pbias(s_pick,o_pick)
  corr_all <- cor(s_pick,o_pick) %>% diag()
  # compute periodwise main-of: ===========================================
  # pre allocations: ######################################################
  NSE_period <- matrix(nrow = number_of_periods,
                       ncol = as.integer(number_of_basins),
                       data = NA)
  KGE_period <- NSE_period
  p_bias_period <- NSE_period
  CORR_period <- NSE_period
  # calculation loop, proabbly slow :( ####################################
  for (k in 1:number_of_periods) {
    o_pick <- dplyr::filter(evaluation_data,period == data_periods[k]) %>%
      dplyr::select(starts_with(name_o)) %>%
      unname()
    s_pick <- dplyr::filter(evaluation_data,period == data_periods[k]) %>%
      dplyr::select(starts_with(name_s)) %>%
      unname()
    NSE_period[k,1:number_of_basins] <- hydroGOF::NSE(s_pick,o_pick)
    KGE_period[k,1:number_of_basins] <- hydroGOF::KGE(s_pick,o_pick)
    p_bias_period[k,1:number_of_basins] <- hydroGOF::pbias(s_pick,o_pick)
    CORR_period[k,1:number_of_basins] <- cor(s_pick,o_pick) %>% diag(.)
  }
  # clean up: =============================================================
```

```
  obj_names <- c("NSE","KGE","p_bias","CORR",
                 paste("NSE_period",1:number_of_periods,sep = "."),
                 paste("KGE_period",1:number_of_periods,sep = "."),
                 paste("p_bias_period",1:number_of_periods,sep = "."),
                 paste("CORR_period",1:number_of_periods,sep = ".")
                 )
  obj_fun <- data.frame(of = obj_names,
                        basin = rbind(nse_all,
                                      kge_all,
                                      p_bias_all,
                                      corr_all,
                                      NSE_period,
                                      KGE_period,
                                      p_bias_period,
                                      CORR_period),
                        row.names = NULL)
  return(obj_fun)
}
```

6.1.2 Plotting

```
# ------------------------------------------------------------------------------
#' Plot main objective function values
#'
#' Currently two options for plotting the main objectives are provided by
#' visCOS: Plotting the different objective functions values as a set of
#' bar plots \code{barplot_of} and plotting a summary table in form of
#' a large raster of all the objective function values \code{rasterplot_of}.
#'
#' @name plot_main_of
NULL
```

6.1.2.1 Bar Plot

```
# ------------------------------------------------------------------------------
#' Bar plot for the Main Objective Function Values
#'
#' @rdname of_overview
#' @export
main_of_barplot <- function(cos_data) {
  # def: ================================================================
  assert_dataframe(cos_data)
  # functions: ==========================================================
  assign_ofgroups <- function(of_melted,mof_names) {
    of_string <- as.character(of_melted$of)
    of_melted$of_group <- of_string %>%
      replace(.,startsWith(of_string,mof_names[1]),mof_names[1]) %>%
      replace(.,startsWith(of_string,mof_names[2]),mof_names[2]) %>%
      replace(.,startsWith(of_string,mof_names[3]),mof_names[3]) %>%
      replace(.,startsWith(of_string,mof_names[4]),mof_names[4])
    return(of_melted)
  }
```

```
  # plot-list function:
  barplot_fun <- function(of_name,of_melted) {
    of_to_plot <- of_melted %>% filter( of_group == of_name)
    if (of_name == "p_bias") {
      gglimits <- c(-viscos_options("of_limits")[2]*100,
                    viscos_options("of_limits")[2]*100)
    } else {
      gglimits <- viscos_options("of_limits")
    }
    plt_out <- ggplot(data = of_to_plot) +
      geom_bar(stat = "identity",
               position = "identity",
               aes(x = of, y = value, fill = value)) +
      facet_wrap(~ variable, ncol = 1) +
      ggtitle(of_name) +
      ylim(gglimits)
    return(plt_out)
  }
  # computations: ============================================================
  mof_names <- c("NSE","KGE","CORR","p_bias")
  of <- main_of_compute(cos_data)
  num_basins <- ncol(of) - 1
  of_melted <- suppressMessages( reshape2::melt(of) ) %>%
    assign_ofgroups(.,mof_names)
  # plotting =================================================================
  plot_list <- lapply(mof_names, function(x) barplot_fun(x,of_melted)) %>%
    magrittr::set_names(mof_names)
  return(plot_list)
}
```

6.1.2.2 Raster-Plot

```
#' Bar plot for the Main Objective Function Values
#'
#' @rdname of_overview
#' @import pasta
#' @export
main_of_rasterplot <- function(cos_data) {
  mof_names <- c("NSE","KGE","CORR","p_bias")
  regex_main_of <- mof_names %.% "*"
  assert_dataframe(cos_data)
  of <- main_of_compute(cos_data)
  #
  plot_list <- lapply(regex_main_of,function(x) plot_fun_raster(x,of)) %>%
    set_names(mof_names)
  return(plot_list)
}

# plot function ----------------------------------------------------------------
plot_fun_raster <- function(regex_single_of,of) {
  # function definitions ===================================================
  extract_single_of <- function(of){
    idx <- grep(regex_single_of,of$of)
```

```
  return(of[idx, ])
}
add_facet_info <- function(of) {
  facet_column <- nrow(of) %>%
    magrittr::subtract(1) %>%
    rep("period",.) %>%
    c("overall",.)
  return( cbind(of,facets = facet_column) )
}
reverse_basin_levels <- function(prepared_data) {
  prepared_data$variable <- factor(prepared_data$variable,
                                   levels = prepared_data$variable %>%
                                     levels() %>%
                                     rev()
                                   )
  return(prepared_data)
}
reverse_facetting_levels <- function(prepared_data) {
  prepared_data$facets <- factor(prepared_data$facets,
                                 levels = prepared_data$facets %>%
                                   levels() %>%
                                   rev()
                                 )
  return(prepared_data)
}
bind_and_round_value <- function(of,gglimits,digits) {
  dplyr::mutate(of,
                value = pmax(value,gglimits[1]) %>%
                  pmin(.,gglimits[2]) %>%
                  round(.,digits)
                )
}
# computation ================================================================
if (regex_single_of == "p_bias.*") {
  # pbias has different limits :(
  gglimits <- c(-viscos_options("of_limits")[2]*100,
                viscos_options("of_limits")[2]*100)
} else {
  gglimits <- viscos_options("of_limits")
}
#
prepared_data <- of %>%
  extract_single_of() %>%
  add_facet_info() %>%
  reshape2::melt(., id.vars = c("of","facets")) %>%
  reverse_basin_levels() %>%
  reverse_facetting_levels() %>%
  bind_and_round_value(.,gglimits,2)
# ggplot =====================================================================
plt_out <- ggplot(prepared_data,
                  aes(of,variable, fill = value),
                  environmnet = environment()) +
  geom_raster(position = "identity") +
```

```
    coord_fixed(ratio = 5)  +
    facet_grid(~ facets,  scales = "free_x", space = "free") +
    theme( legend.position = "none")  +
    geom_tile(color = "white", size = 0.25 ) +
    geom_text(aes(of,variable, label = as.character(value,2)),
              color = "black")
  return(plt_out)
}
```

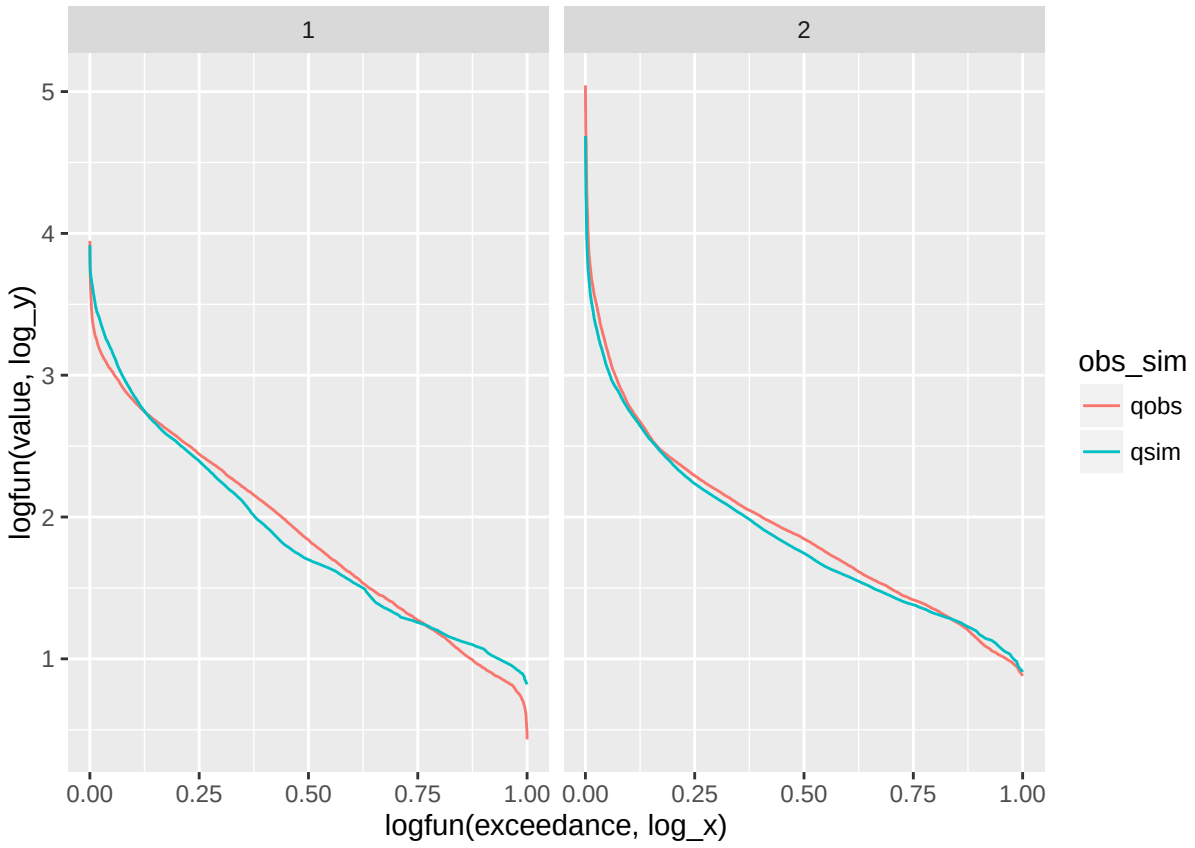
7 Flow Duration Curves

Flow-duration curves represent the relationship between the magnitue and the frequency of a streamflow. They provide an estimate of the percentage of time a given streamflow was exceeded within the evaluated time frame. Foster [1934] attributes the first use of flow duration curves to Clemens Herschel around 1880. Since they have been used for a wide array of applications. **visCOS** provides a function to compute the data for flow-duration curves and a function to plot them directly. The former function is called `fdc_compute`. It computes the flow exceedance properties and returns a data.frame. The calculations are adapted from the method used within the hydroTSM package. It is currently rather slow. The plot-function is called `fdc_plot`. Internally it uses `fdc_compute` for the data preparation and generates a facetted `ggplot` object from it. In the plot each basin is a facet and each sub-plot shows the o-data and s-data (see: Introduction).

7.1 Example

Flow duration curves can be plotted in **visCOS** in the following way:

```
library(visCOS)
cos_data <- get_viscos_example()
fdc_plot(cos_data)
```



7.2 Code

7.2.1 Computing the data for the flow duration curves

```
#' Compute Flow Duration Curves
#'
#' Computes the flow duration curves (fdc) for the `cos_data` data.frame.
#' The calculations are adapted from the method used within the hydroTSM package.
#' @param cos_data A data.frame with columns as used throughout visCOS
#' @import magrittr
#' @import dplyr
#' @importFrom purrr map_df
#' @import pasta
#' @export
fdc_compute <- function(cos_data) {
  # defensive code:
  assert_dataframe(cos_data)
  # def:
  order_bound_data <- function(bound_data) {
    ordred_fdc_data <- bound_data %>%
      mutate(obs_sim = key %>%
             gsub( viscos_options("name_o") %&% ".*",
                   viscos_options("name_o"),
                   .,
                   ignore.case = TRUE ) %>%
```

```
              gsub( viscos_options("name_s") %&% ".*",
                    viscos_options("name_s"),
                    .,
                    ignore.case = TRUE ),
            basin_idx = key %>%
              gsub(viscos_options("name_o"),"",.,ignore.case = TRUE) %>%
              gsub(viscos_options("name_s"),"",.,ignore.case = TRUE) %>%
              gsub("\\D","",.) %>% as.numeric)
    return(ordred_fdc_data)
  }
  # computation:
  cos_data_only <- cos_data %>%
    select(starts_with(viscos_options("name_o")), starts_with(viscos_options("name_s")))
  exceedance_values <- map_df(cos_data_only,calc_percent_exceedance) %>%
                       tidyr::gather() %>%
                       magrittr::extract("value")
  fdc_data <- cos_data_only %>%
    tidyr::gather() %>%
    cbind.data.frame(exceedance = exceedance_values) %>%
    magrittr::set_names(c("key","value","exceedance")) %>%
    order_bound_data(.)
  return(fdc_data)
}
```

```
# function to calculated the percent exceedance (x-axis) for the fdc
calc_percent_exceedance <- function(q) {
  q_sorted <- sort(q)
  q_zero_index <- which(q_sorted == 0)
  nzeros <- length(q_zero_index)
  ind <- match(q, q_sorted)
  n <- length(q)
  percent_exeedence <- rep(NA, n)
  percent_exeedence[1:n] <- sapply(1:n, function(j, y) {percent_exeedence[j] <- length(which(y >= y[j]
                    y = q)
  percent_exeedence <- percent_exeedence/n
  return(percent_exeedence)
}
```

7.2.2 Plotting the Flow duration curves

```
#' Plot Flow Duration Curves
#'
#' Plots the flow duration curves (fdc) for `cos_data`.
#' The function uses `ggplot` to so and facets the different basins into
#' separate subplots. Each subplot shows the fdc of the \eqn{o}-data and
#' the \eqn{s}-data.
#' @export
#' @import ggplot2
fdc_plot <- function(cos_data,
                     log_y = TRUE,
                     log_x = FALSE,
                     ...) {
```

```
  # def:
  # maybe we have to account certain limits for the logs, e.g:
  # if (log_y | log_x & min(ylim) == 0) {
  #   ylim <- range(q, na.rm = TRUE)
  #   tmp <- unlist(q)
  #   tmp[which(tmp == 0)] <- NA
  #   ylim[1] <- min(tmp, na.rm = TRUE)
  # }
  logfun <- function(data,take_log){
    if(take_log){
      return(log(data))
    } else (
      return(data)
    )
  }
  # computation:
  fdc_data <- fdc_compute(cos_data)
  gplot <- ggplot(fdc_data) +
    geom_line(aes(x = logfun(exceedance,log_x), y = logfun(value,log_y), color = obs_sim)) +
    facet_wrap(~ basin_idx)
  return(gplot)
}
```

7.3 References

- Foster, H.A. (1934): Duration curves. ASCE Trans., 99, 1213-1267
- Vogel, R. M.; Fennessy, N. M. (1994): Flow-Duration Curves. I: New Interpretation and Confidence Intervals. JWRMD 120, No. 4

8 Plotting Runoff Peaks Plots

The function `peak_plot` lets users explore the highest events in among the available basins. It provides a list of ggplot2 plots, containing an overview plot (`overview`), a scatter plot (`scatter`) and detail plots of the individual events (`event_plot`). Instead of explaining the properties of each plot in detail it is best to get an intuition of the function by looking at some examples.

8.1 Examples:

For the examples 10 events are extracted from a runoff example

```
require(visCOS)
cos_data <- get_viscos_example()
peakplots <- peak_plot(cos_data, n_events = 10L)
```

The `peakplots` list does now contain plots for each basin within the `cos_data` data.frame:

```
names(peakplots)
```

```
## [1] "basin0001" "basin0002"
```

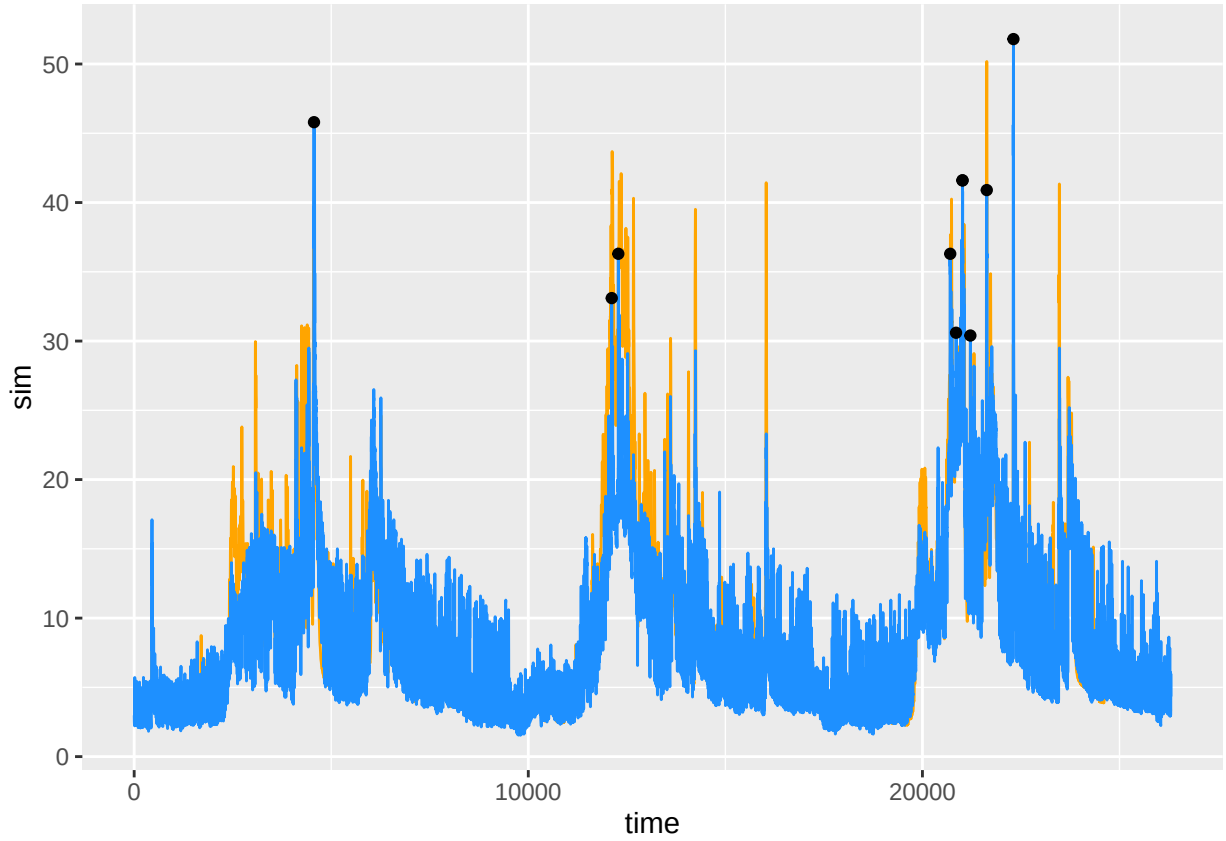
For each basin the a set of plots (`overview`,`scatter`,`event_plot`) are saved within a list for each basin. In the following the plots for basin 1 are shown:

```
names(peakplots$basin0001)
```

```
##  [1] "overview"     "scatter"      "event_plot1"  "event_plot2"  "event_plot3"
##  [6] "event_plot4"  "event_plot5"  "event_plot6"  "event_plot7"  "event_plot8"
## [11] "event_plot9"  "event_plot10"
```

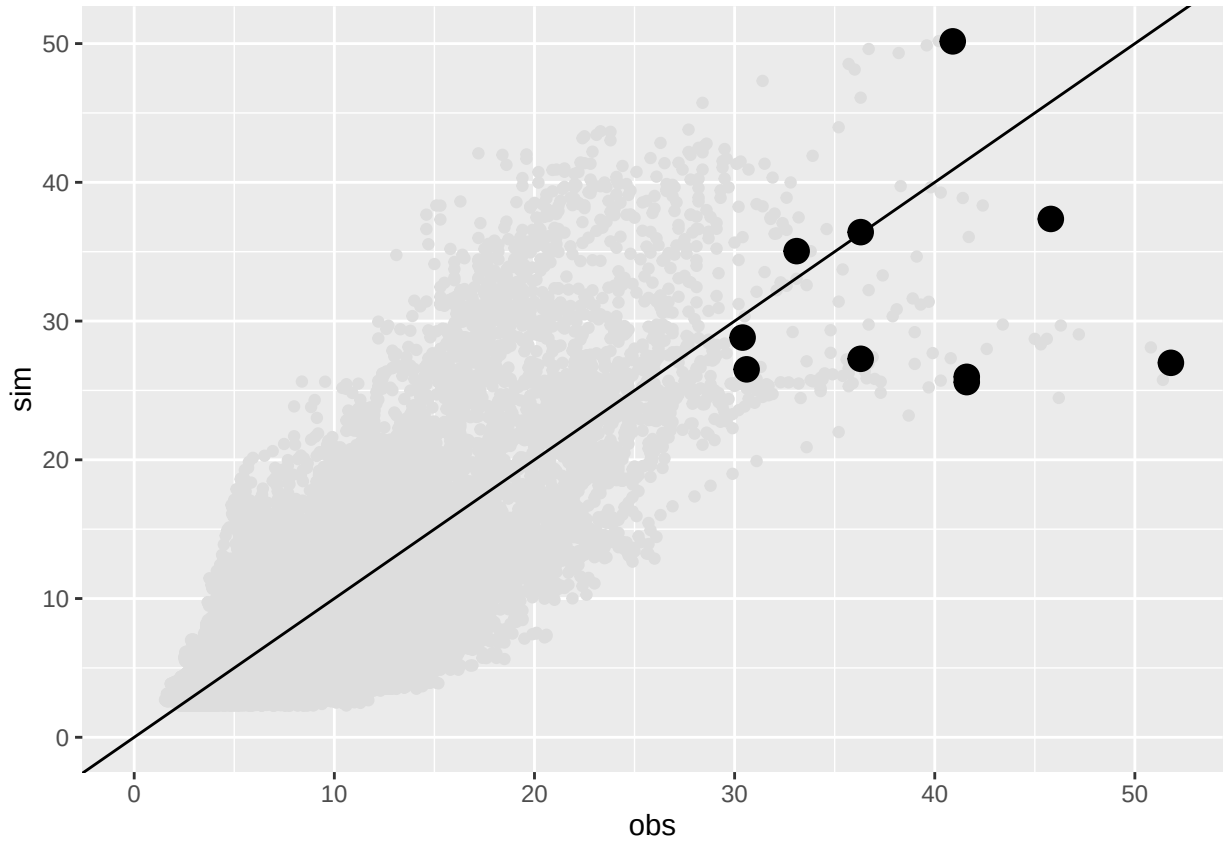
The `overview` plot shows the entire time series of `data1` and `data2` of the basin. The found events are marked with black dots. The `overview` plot for basin 1 is:

```
peakplots$basin0001$overview
```



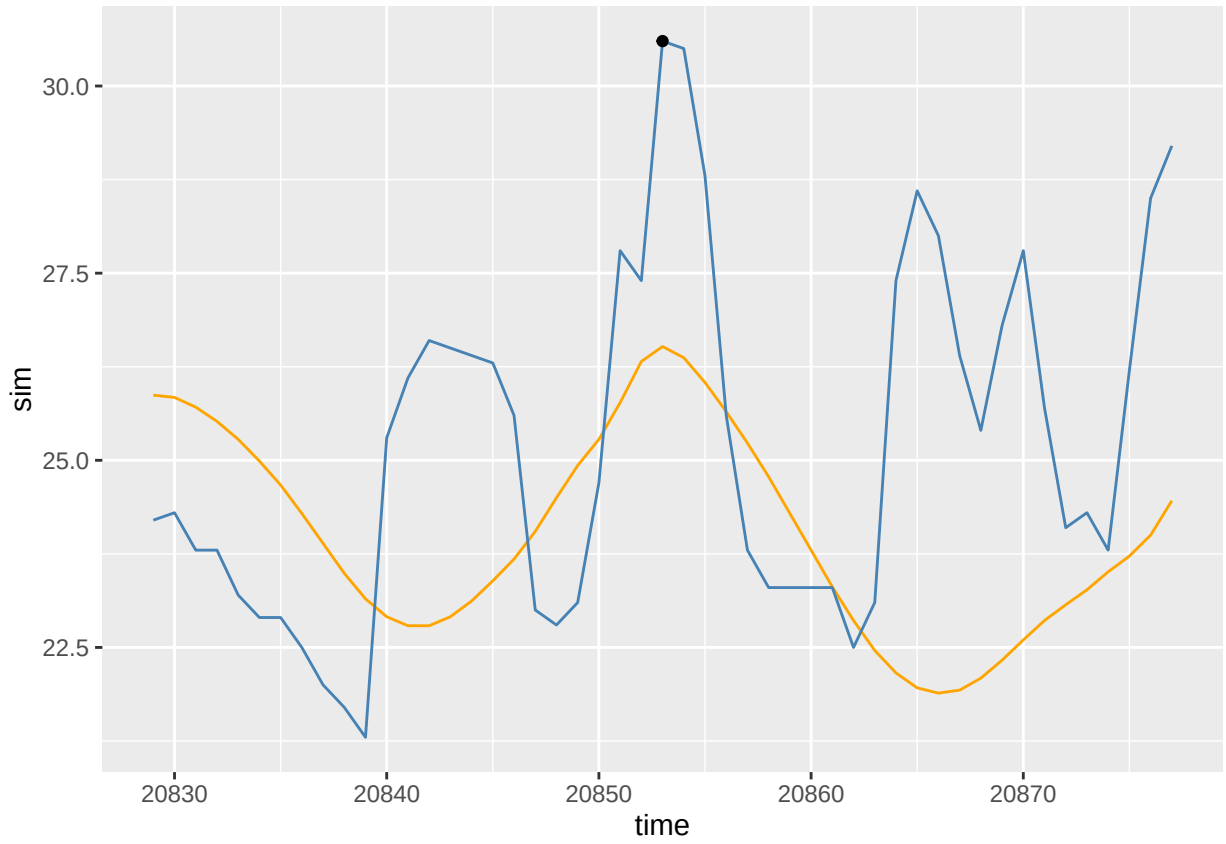
The `scatter` plot shows the found events within a scatter plot, where `data1` is the x-axis and `data2` on the y-axis. In the following an example for basin 1 is given.

```
peakplots$basin0001$scatter
```



Detail plots for each of the found events are given in form of the `event_plot` objects. Here an example:

```
peakplots$basin0001$event_plot5
```



8.2 Code

This part of the document defines the code of `peak_plot`

```
#' Plot List for Runoff Peaks
#' @export
#'
#' @import ggplot2
#' @import dplyr
#' @import magrittr
#' @importFrom tibble tibble
peak_plot <- function(cos_data,n_events= 10L, window_size = 24L) {
  # pre:
  assert_dataframe(cos_data)
  n_events_int <- as.integer(n_events)
  window_size_int <- as.integer(window_size)
  if( is.na(n_events_int)  |
      is.nan(n_events_int) |
      is.infinite(n_events_int) |
      !is.integer(n_events_int) ) {
    stop("n_events is ill defined")
  }
  if( is.na(window_size)  |
      is.nan(window_size) |
      is.infinite(window_size) |
      !is.integer(window_size) ) {
```

```
    stop("window_size is ill defined")
  }
  data1 <- cos_data %>%
     select( starts_with(viscos_options("name_o")) )
  data2 <- cos_data %>%
     select( starts_with(viscos_options("name_s")) )
  data_numbers <- names(data1) %>%
    gsub(viscos_options("name_o"),"",.,ignore.case = TRUE) %>%
    gsub("\\D","",.,ignore.case = TRUE)
  # make plotlist:
  plotlist <- lapply(1:ncol(data1), function(x) plotlist_one_basin(data1[,x],
                                                                   data2[,x],
                                                                   n_events_int,
                                                                   window_size_int)) %>%
    set_names(.,paste("basin", data_numbers, sep =""))
  return(plotlist)
}
```

8.2.1 Generating the Plots for one basin.

This is the function for generating the different plots for one basin. At first the provided time series are grouped into a `tibble`, then the peaks of the observations are obtained via the peak_finder function and organised. Then `ggplot2` is used for plotting.

```
plotlist_one_basin <- function(qobs,qsim,n_events_int,window_size_int) {
  single_data <- tibble::tibble(time = as.integer(1:length(qobs)),
                                obs = as.double(qobs),
                                sim = as.double(qsim))
  #
  peak_idx <- find_peaks(single_data$obs,m = window_size_int)
  peak_organised <- tibble::tibble(idx = as.integer(peak_idx),
                           peak_obs = single_data$obs[peak_idx],
                           peak_sim = single_data$sim[peak_idx])
  highest_peaks_organised <- peak_organised$peak_obs %>%
    sort(decreasing = TRUE) %>%
    .[1:n_events_int] %>%
    '%in%'(peak_organised$peak_obs,.) %>%
    which( . ) %>%
    peak_organised[., ]
  #
  overview_plot <- ggplot() +
    geom_line(data = single_data,aes(x = time, y = sim), col = viscos_options("color_s")) +
    geom_line(data = single_data,aes(x = time, y = obs), col = viscos_options("color_o")) +
    geom_point(data = highest_peaks_organised, aes(idx, peak_obs))
  overview_scatter <- ggplot() +
    geom_point(data = single_data, aes(obs,sim), color = "#DDDDDD") +
    geom_abline() +
    geom_point(data = highest_peaks_organised, aes(peak_obs,peak_sim), size = 4) +
    expand_limits(x = 0, y = 0)
  sub_plots <- lapply(1:nrow(highest_peaks_organised),
                      function(x) sub_peakplot_fun(x,window_size_int,highest_peaks_organised,single_data
    set_names(.,paste("event_plot",1:length(.),sep=""))
  return(overview = append(list(overview = overview_plot,scatter = overview_scatter), sub_plots))
```

```
}
```

8.2.2 Function to find peaks

The function for finding the peaks was proposed and developed by the cross validated user "stas g" in this thread.
This is by far not the only option/possibility to approach the peak finding task. Other nice ideas for finding peaks can be found in this cross validated thread.

```
####
# peak finder function:
find_peaks <- function (x, m = 3){
  shape <- diff(sign(diff(x, na.pad = FALSE)))
  pks <- sapply(which(shape < 0), FUN = function(i){
    z <- i - m + 1
    z <- ifelse(z > 0, z, 1)
    w <- i + m + 1
    w <- ifelse(w < length(x), w, length(x))
    if(all(x[c(z : i, (i + 2) : w)] <= x[i + 1])) return(i + 1) else return(numeric(0))
  })
  pks <- unlist(pks)
  pks
}
```

8.2.3 Subplot Function

This function is a wrapper around `ggplot`, which is used to generate the individual event plots.

```
####
# sub plot function:
sub_peakplot_fun <- function(x, window_size, highest_peaks_organised, peak_data) {
  point <- highest_peaks_organised[x,]
  plot_sub <- ggplot() +
    geom_line(data = peak_data[(point$idx - window_size):(point$idx + window_size),],
              aes(x = time, y = sim),
              col = "orange") +
    geom_line(data = peak_data[(point$idx - window_size):(point$idx + window_size),],
              aes(x = time, y = obs),
              col = "steelblue") +
    geom_point(data = point, aes(idx, peak_obs))
  return(plot_sub)
}
```

8.3 References

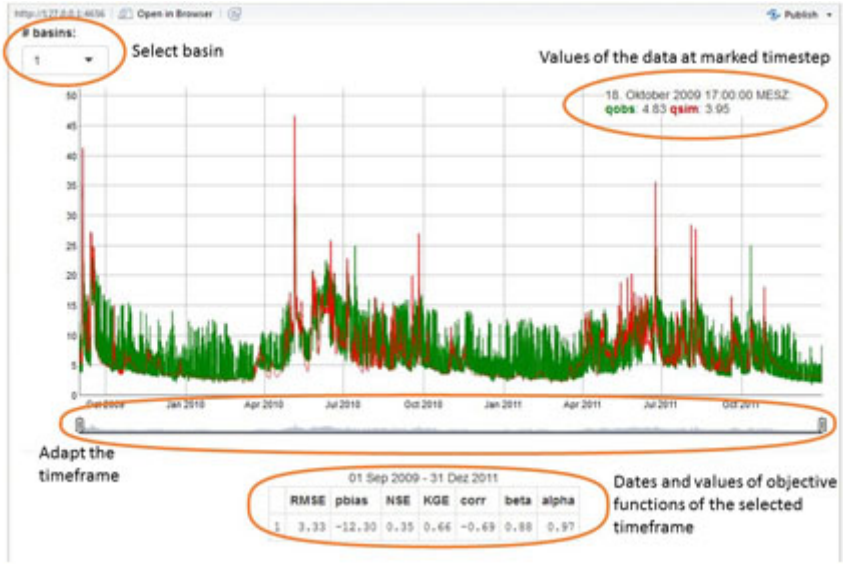
- http://stats.stackexchange.com/questions/22974/how-to-find-local-peaks-valleys-in-a-series-of-data (checked 12/2016)
- http://stats.stackexchange.com/questions/36309/how-do-i-find-peaks-in-a-dataset (checked 12/2016)

9 Exploring Objective Functions

This section defines the code of a shiny gadget. It enables the interactive exploration of (hydro-) graphs for the different basins. The gadget shows always the corresponding objective function for the selected graph. Furthermore, one can get the selected data by clicking on "done" at the end of a session. The following examples provide a good overview of what the function can do.

9.1 Example

This chapter gives examples of `explore_cos_data`. For the pre-requirements take a look at the introduction. Running the `explore_cos_data` function without any options opens a shiny gadget in the viewer:



Information on the *objective functions* can be found here.

```
viscos_options(color_o = "green", color_s = "red")
explore_cos_data(runoff_example)
```

Users can select different basins via the selection box (*# basins:*) on the top-left and interactively zoom and move the graph in the center by clicking on it or moving the date switches below the graph. While doing so the objective functions (presented in the table below) are re-calculated for the chosen time window.

9.2 Code

In the following paragraphs the code of the shiny app is defined. The computations of the app are defined in the `server` part and the appearance in the `ui`.

9.2.1 Explore the data

This function represents the main part of the shiny app. The current solution **forces** users to enumerate their basins with and the shiny app needs some pre-calculation, which need to be calculated before the app is started. These calculations are made before the app as such is defined. They include:

- (I) Defensive code
- (II) Transform data into `xts` (`d_xts`).

- (III) Save numeration of basins within the variable `d_nums`.

```
  # ------------------------------------------------------------------------
  #' Explore with Objective Functions
  #'
  #' Runs a Shiny Gadget which can be used to get an overview of a cos_data time
  #' series object.
  #'
  #' @param d_xts cos_data formatted as time series
  #'
  #' @import shiny
  #' @import miniUI
  #' @importFrom xts xts
  #' @import dplyr
  #' @import magrittr
  #' @import dygraphs
  #' @import hydroGOF
  #' @import pasta
  #' @importFrom purrr map_df
  #'
  #' @export
  #'
  #' @examples
  #' # get example data,
  #' # explore the model performance
  #' cos_data <- get_viscos_example()
  #' explore_cos_data(cos_data)
explore_cos_data <- function(cos_data,
                             of_list = list(
                               nse = of_nse,
                               kge = of_kge,
                               p_bias = of_p_bias,
                               r = of_cor
                               ),
                             start_date = NULL,
                             end_date = NULL) {
  # (I) pre-sets: ============================================================
  if (is.null(names(of_list))){
    names(of_list) <- paste("of", 1:length(of_list), sep = "_")
  }
  clean_cos_data <- cos_data %>% remove_leading_zeros
  if ( !viscos_options("name_COSposix") %in% names(clean_cos_data) ) {
    clean_cos_data %<>% complete_dates
  }
  names_data <- names(clean_cos_data) %>% tolower(.)
  number_lb <- grepl(viscos_options("name_lb"),
                     names_data,
                     ignore.case = TRUE) %>% sum(.)
  number_ub <- grepl(viscos_options("name_ub"),
                     names_data,
                     ignore.case = TRUE) %>% sum(.)
  plot_bounds <- FALSE
  if( (number_lb > 0) & (number_ub > 0)) {
    number_obs <- grepl(viscos_options("name_o"),
```

```
                      names_data,
                      ignore.case = TRUE) %>%sum(.)
  number_sim <- grepl(viscos_options("name_s"),
                      names_data,
                      ignore.case = TRUE) %>% sum(.)
  if (number_lb != number_ub) {
    stop("number of available bounds is not the same!" %&&%
           "#lb=" %&% number_lb %&&%
           "#ub=" %&% number_ub)
  } else if ((number_lb != number_obs) | (number_lb != number_sim)) {
    stop("Number of bounds is not the same as the o/s data!" %&&%
          "#bounds=" %&% number_lb %&&%
           "#obs=" %&% number_obs %&&%
           "#sim=" %&% number_sim)
  } else {
    plot_bounds <- TRUE # switch: plot bounds
  }
}
# (II) ================================================================
d_xts <- cos_data_as_xts(clean_cos_data)
# (III) ================================================================
idx_names <- grepl(viscos_options("name_o"),
                   names_data,
                   ignore.case = TRUE)
d_nums <- names_data %>%
    .[idx_names] %>%
    gsub("\\D","",.) %>%
    as.integer(.) %>%
    unique(.)
# (V) Define App: ======================================================
server <- function(input, output, session) {
  # (a) get needed strings: ##############################################
  unique_data_names <- gsub("\\d","",names_data) %>%
    unique(.)
  x_string <- unique_data_names[ grep(viscos_options("name_o"),
                                      unique_data_names) ]
  y_string <- unique_data_names[ grep(viscos_options("name_s"),
                                      unique_data_names) ]
  if (plot_bounds) {
    lb_string <-  unique_data_names[ grep(viscos_options("name_lb"),
                                          unique_data_names) ]
    ub_string <-  unique_data_names[ grep(viscos_options("name_ub"),
                                          unique_data_names) ]
  }
  # (b) select data:
  # note: the regular expressions "$" terminates the searchstring
  selector_x <- reactive({ x_string %&% input$basin_num %&% "$" })
  selector_y <- reactive({ y_string %&% input$basin_num %&% "$" })
  selector_lb <- reactive({
    if(plot_bounds){
      lb_string %&% input$basin_num %&% "$"
    } else {
      NA
```

```
  }
})
selector_ub <- reactive({
  if(plot_bounds){
    ub_string %&% input$basin_num %&% "$"
  } else {
    NA
  }
})
selected_data <- reactive({
  if(plot_bounds) {
    clean_cos_data %>%
      select(matches( selector_x() ),
             matches( selector_y() ),
             matches( selector_lb() ),
             matches( selector_ub() )
             ) %>%
      select(x = matches( selector_x() ),
             y = matches( selector_y() ),
             lb = matches( selector_lb() ),
             ub = matches( selector_ub() ))
  } else {
    clean_cos_data %>%
      select(matches( selector_x() ),
             matches( selector_y() )
             ) %>%
      select(x = matches( selector_x() ),
             y = matches( selector_y() ))
  }
})
# (c) create xts-formated table for use in dygraphs:
xts_selected_data <- reactive ({
  xts(selected_data(),
      order.by = clean_cos_data[[viscos_options("name_COSposix")]])
})
# (d) create plots:
base_graph <- reactive({
  if(plot_bounds) {
    dygraph( xts_selected_data() ) %>%
    dyAxis("y",
           label = visCOS::viscos_options("data_unit")) %>%
    dySeries("x",
             label = visCOS::viscos_options("name_o"),
             color = viscos_options("color_o")) %>%
    dySeries("y",
             label = visCOS::viscos_options("name_s"),
             color = viscos_options("color_s")) %>%
    dySeries("lb",
             label = visCOS::viscos_options("name_lb"),
             color = "grey80") %>%
    dySeries("ub",
             label = visCOS::viscos_options("name_ub"),
             color = "grey80")
```

```
  } else {
    dygraph( xts_selected_data() ) %>%
    dyAxis("y",
           label = visCOS::viscos_options("data_unit")) %>%
    dySeries("x",
             label = visCOS::viscos_options("name_o"),
             color = viscos_options("color_o")) %>%
    dySeries("y",
             label = visCOS::viscos_options("name_s"),
             color = viscos_options("color_s"))
  }
})
output$hydrographs <- renderDygraph({
  base_graph() %>%
    dyRangeSelector(height = 20, strokeColor = "") %>%
    dyCrosshair(direction = "vertical") %>%
    dyOptions(includeZero = TRUE,
              retainDateWindow = TRUE,
              animatedZooms = TRUE)
})
# (e) get dygraph date bounds (switches):
selcted_from <- reactive({
  if (!is.null(start_date)) {
    start_date
  } else if (!is.null(input$hydrographs_date_window)) {
    input$hydrographs_date_window[[1]]
  }
})
selcted_to <- reactive({
  if (!is.null(end_date)) {
    end_date
  } else if (!is.null(input$hydrographs_date_window)) {
    input$hydrographs_date_window[[2]]
  }

})
# (f) extract time_window for the stats header:
output$selected_timewindow <- renderText({
  if (!is.null(input$hydrographs_date_window))
    paste(strftime(selcted_from(), format = "%d %b %Y"),
          "-",
          strftime(selcted_to(), format = "%d %b %Y"),
          sep = " ")
})
# (g) calculate stats:
sub_slctd <- reactive({
  if (!is.null(input$hydrographs_date_window))
    xts_selected_data()[paste(strftime(selcted_from(), format = "%Y-%m-%d-%H-%M"),
                              strftime(selcted_to(), format = "%Y-%m-%d-%H-%M"),
                              sep = "/")]
})
out_of <- reactive({
  if (!is.null(input$hydrographs_date_window)) {
```

```
          map_df(of_list, function(of_,x,y) of_(x,y),
                 x = sub_slctd()$x,
                 y = sub_slctd()$y ) #serve_of( sub_slctd()$x,sub_slctd()$y )
      }
    })

    output$slctd_OF <- renderTable(out_of())
    # (h) exit when user clicks on done
     # When the Done button is clicked, return a value
    observeEvent(input$done, {
      returnValue <- list(
        selected_time = c(strftime(selcted_from(), format = "%Y-%m-%d-%H-%M"),strftime(selcted_to(), fo
        selected_data = data.frame(date = index(sub_slctd()),
                                   coredata(sub_slctd())),
        selected_of = out_of()
      )
      stopApp(returnValue)
    })
  }
```

The `miniUI` is quite spartan. There is an `miniButtonBlock` that allows to select different basin, as as the `dygraph` output (i.e `hydrographs`) for the interactive exploration of the o and s data. The formatted table (`slctd_OF`) displays the different objective functions, that can be given to `explore_cos_data` .

```
  ui <- miniPage(
    miniButtonBlock(selectInput("basin_num",
                                "# basin:",
                                choices = d_nums,
                                selected = 1,
                                selectize = FALSE)),
    miniContentPanel(
      fillCol(
        flex = c(4,1),
        dygraphOutput("hydrographs", width = "100%", height = "100%"),
        fillCol(
          align = "center",
          textOutput("selected_timewindow"),
          tableOutput("slctd_OF")
        )
      )
    ),
    gadgetTitleBar("test")
  )
```

```
dyCrosshair <- function(dygraph,
                        direction = c("both", "horizontal", "vertical")) {
  dyPlugin(
    dygraph = dygraph,
    name = "Crosshair",
    path = system.file("plugins/crosshair.js",
                       package = "dygraphs"),
    options = list(direction = match.arg(direction))
  )
}
```

```
  runGadget(ui,server)
}
```

10 Generate Previews

Possibility to save lists of plots into .jpgs and create a linked html file.

10.1 Code

```
#' Serve is still beta
#'
#' More description shall follow
#' @export
serve <- function(plotlist, path = "", fig_width = 800L, fig_height = 500L) {
  hmtl_filename <- "summary"
  # establish html-file in chosen folder
  '%&%' <- function(a,b) paste(a,b,sep = "") # helper for easier string concatenation
  fileConn <- file(path %&% hmtl_filename %&% ".html" , "w")
  # write html header
  #writeLines(text = '<!DOCTYPE html>',fileConn)
  writeLines(text = "<HEAD>",fileConn)
  writeLines(text = "  <STYLE type='text/css'>",fileConn)
  writeLines(text = "    H1 { text-align: center}",fileConn)
  writeLines(text = "  </STYLE>",fileConn)
 writeLines(text = "</HEAD>",fileConn)
  #writeLines(text = '<html>',fileConn)
  writeLines(text = '<body>',fileConn)
  # check which kind of plotlsit we are dealing with:
  if ( all(names(plotlist) == c("NSE","KGE","p_bias","CORR")) ) {
    list_to_plot <- plotlist

  } else if ( all(grepl("basin",names(plotlist1))) ) {
    list_to_plot <- unlist(plotlist,recursive = FALSE)
  } else {
    stop("plotlist not known!")
  }
  num_plots <- length(list_to_plot)
  figure_names <- names(list_to_plot)
  ## save everything localy & link it within the html file
  jpg_filenames <- "figure"

  for (i in 1:num_plots) {
    writeLines(text = "<H1>" %&% figure_names[i] %&% "</H1>",fileConn)
    plt_name <- jpg_filenames %&% i %&% ".jpg"
    plt_pathANDname <- path %&% plt_name
    plt_hmtlInfos <- "<img src=\"" %&% plt_name %&% '" alt="plotting_failed" style="width:800px;height:5
    #
    writeLines(text = "<H1>" %&% plt_hmtlInfos  %&% "</H1>", fileConn)
    jpeg(file = plt_pathANDname, width = fig_width, height = fig_height, units = "px")
      plot(list_to_plot[[i]])
```

```
    dev.off()
  }
  close(fileConn)
}
```

11 Defensive Code

This section defines the internally used defensive programming part of **visCOS**. This are all functions dedicated to ensure that **visCOS** is working nicely even if it is used wrongly for whatever reason. This often means that a given function has to return an error if certain criteria are not met! Useful examples for such methods can be found in Hadley Wickhams `R` package `assertthat`

11.1 Code

The subsequent functions are defined in this section

function	exported
`assert_junk`	no
`assert_complete_date`	no
`assert_dataframe`	no
`assert_of`	no

11.1.1 Check if `cos_data` is "clean"

Tests if the given data.frame (`cos_data`) contains only the columns defined within `get_regex_for_cos_data` (see: helpers and `viscos_options`). An exception throws an error. **Note** that the check is not case sensitive!

```
#' @import magrittr
assert_junk <- function(cos_data) {
  regEx <- get_regex_for_cos_data( )
  assertChunk <- names(cos_data) %>% grepl(regEx, ., ignore.case = TRUE)
  if (any(assertChunk == FALSE)) {
    stop("there is still unwanted columns in the data. Try: remove_junk")
  }
}
```

11.1.2 Check date completeness

A rough check for the needed date- and/or time-columns within the provided `cos_data`. The function is rahter basic. It only checks if the names of the `viscos_options("name_COSyear")` column and `viscos_options("name_COSposix")` column exist (see: `viscos_options`). An exceptions throws an error.

```
assert_complete_date <- function(cos_data) {
  OK_COSdate <- any(names(cos_data) == viscos_options("name_COSyear"))
  OK_POSIXdates <- any(names(cos_data) == viscos_options("name_COSposix"))
  # choose error messag depending on which columns are missing!
  if (!OK_COSdate & !OK_POSIXdates) {
    stop("No COSdates and no POSIXct-dates in the data!")
  } else if (OK_COSdate & !OK_POSIXdates) {
```

```
    stop("NO POSIXct fomrated column within the cos_data!")
  } else if (!OK_COSdate & OK_POSIXdates) {
    stop("NO COSdate year within the cos_data!")
  }
}
```

11.1.3 Check if the data is a `data.frame`

Tests if `data` is a data.frame and returns an error if not.

```
# uses stop if the input: "data" is not of class "data.frame"
assert_dataframe <- function(data) {
  require("tibble", quietly = TRUE)
  if ( !is.data.frame(data)&!is.tibble(data) ) stop("data needs to be a data_frame!")
}
```

11.2 References

- Wickham, H. (2013). assertthat: Easy pre and post assertions. https://CRAN.R-project.org/package=assertthat

12 Helpers

This section collects small and helpful functions/scripts that are used throughout **visCOS**.

None of the functions is exported!

12.1 Code

The subsequent functions are defined below

function	exported
`get_regex_for_cos_data`	no
`get_basin_numbers`	no
`set_panel_size`	no

12.1.1 Get a Regular Expression String for the needed columns

This function can be called to get the names of the 8 allowed column-names within **visCOS**. `get_regex_for_cos_data` takes no input, as it gets the information directly from the global options (see: *viscos_options section*).

```
get_regex_for_cos_data <- function()
  {
  regex_pattern <- paste("^",viscos_options("name_COSyear"),"$|",
                         "^",viscos_options("name_COSmonth"),"$|",
                         "^",viscos_options("name_COSday"),"$|",
                         "^",viscos_options("name_COShour"),"$|",
                         "^",viscos_options("name_COSmin"),"$|",
```

```
                          viscos_options("name_o"),".*|",
                          viscos_options("name_s"),".*|",
                          viscos_options("name_lb"),".*|",
                          viscos_options("name_ub"),".*|",
                          viscos_options("name_COSposix"),"|",
                          viscos_options("name_COSperiod"),
                          sep = "")
  return(regex_pattern)
}
```

12.1.2 Extract the numeration of the basins

This function fetches the number of basins from the provided data.frame (`cos_data`) by removing all the non-digits characters from the column names.

```
get_basin_numbers <- function(cos_data) {
  require("magrittr", quietly = TRUE)
  assert_dataframe(cos_data)
  assert_junk(cos_data)
  #
  d_names <- names(cos_data)
  d_nums <- d_names  %>% gsub('\\D','',.) %>% unique
  d_nums <- d_nums[!(d_nums == "")] %>% as.integer
  return(d_nums)
}
```