

Energy Data Analysis with R

Reto Marek

2020-11-25

Contents

1	Introduction	5
1.1	Content	5
1.2	Why R and RStudio?	6
1.3	Other useful sources	6
2	Getting started	7
2.1	Install R and R Studio	7
2.2	Install required packages	8
2.3	Create an R Script	9
2.4	What's next?	10
3	R Basics	11
3.1	Loading Data	11
4	Data Wrangling	13
4.1	Add Metadata for later filtering	13
4.2	Data Frames	15
4.3	Examples	17
5	Explorative Data Analysis	21
5.1	Get overview	21
5.2	Basic plots	23

6 Data Visualizations	25
6.1 Seasonal Plot - Overlapping	25
6.2 Seasonal Plot - Mini Plots	29
6.3 Seasonal Plot - Polar	32
6.4 Seasonal Plot - Before/After	35
6.5 Decomposition - Long term	38
6.6 Decomposition - Short term	40
6.7 Heatmap Median-Weeks	43
6.8 Heatmap Calendar	44
6.9 Daily Profiles - Overview	46
6.10 Daily Profiles - Overlayed	48
6.11 Daily Profiles - Decompose	52
6.12 Daily Profiles - Decomposed	54
6.13 Building Energy Signature	55
6.14 Mollier hx Diagram	58
6.15 SIA 180 Thermal Comfort	59
6.16 Electricity Household	64
6.17 Room Temperature Reduction	72
A Packages in R	75
A.1 Installing a Package	75
A.2 Loading a Package	76
A.3 Upgrading Packages	76

Chapter 1

Introduction

Preface

This book gives you an overview of the statistical software R and its ability to analyze and visualize time series in the context of building energy and comfort.

It is aimed at R beginners as well as experienced R users and is strongly inspired by the R Graphics Cookbook and Engineering Data Analysis in R. The aim of this book is to provide additional specific recipes for energy and comfort related tasks and to make your entry into R smooth and easy.

1.1 Content

The book is independently structured and a beginner gets information on how to install the program environment and gets a quick practical introduction.

The examples in this book will show you how to complete certain specific tasks. Examples are shown so that you can understand the basic principle and reproduce the analysis or visualization with your own data. Simply copy the code into your R-script, replace the sample data files with your own and execute the code.

This book was developed using Yihui Xie's bookdown framework. The book is built using code that combines R code, data, and text to create a book for which R code and examples can be re-executed every time the book is re-built. The online book is hosted using GitHub's free GitHub Pages. All material for this book is available and can be explored at the book's GitHub repository.

1.2 Why R and RStudio?

In a study commissioned by the Swiss Federal Office of Energy, experts from the field were asked how and where they perform energy analyses and create visualizations. The result was that many people today either need Excel or use a building monitoring software to execute analysis and create visualizations. Excel users are pushing the program to its limits with the ever-increasing data sets. Also the interactive ability of the graphics there is limited. The change to an environment like “R” seems to be difficult for many. In the market there are numerous books which make the change to “R” for other disciplines easier. However, experts from the energy and building services engineering industry lack a corresponding work. The present book is intended to close this gap.

The freely available programming language “R” and its graphical user interface “RStudio” offer many more possibilities for data analysis and data visualization.

1.3 Other useful sources

A really good source is R for Data Science by Garrett Grolemund and Hadley Wickham. The entire book is freely available online through the same format of this book.

There are a number of other useful books available, including:

- R Graphics Cookbook
- Introduction to Data Science - Data Analysis and Prediction Algorithms with R
- Hands-On Programming with R
- Engineering Data Analysis in R
- Forecasting: Principles and Practice
- AFIT Data Science Lab R Programming Guide

Chapter 2

Getting started

This chapter gets you up and running with downloading and installing the relevant software. This may seem laborious, but it is necessary and easier than it appears at first glance. components.

2.1 Install R and R Studio

Before we can start the first analysis, we have to install “R” and “RStudio”.

- “R” is a programming language used for statistical computing while “RStudio” provides a graphical user interface
- “R” may be used without “RStudio”, but “RStudio” may not be used without “R”
- Both, “R” and “RStudio” are free of charge and there are no licence fees
- When you later make an analysis and visualizations, you only work in the graphical user interface “RStudio”

2.1.1 Download and Install R

2.1.1.1 Windows

1. Open <https://cran.r-project.org/bin/windows/base/> and press the link “Download R...”
2. Run the downloaded installer file and follow the installation wizard

The wizard will install “R” into your **Program Files** folders and adds a shortcut in your Start menu. Note that you will need to have all necessary administration rights to install new software on your machine.

2.1.1.2 Mac OSX

1. Open <https://cran.r-project.org/bin/macosx/> and download the latest *.pkg file
2. Run the downloaded installer file and follow the installation wizard

The installer allows you to customize your installation. However the default values will be suitable for most users.

2.1.1.3 Linux

“R” is part of many Linux distributions, therefore you should check with your Linux package management system if it’s already installed.

The CRAN website provides files to build “R” from source on Debian, Redhat, SUSE, and Ubuntu systems under the link “Download R for Linux”

- Open <https://cran.r-project.org/bin/linux/> and then follow the directory trail to the version of Linux you wish to install R on top of

The exact installation procedure will vary depending on your Linux operating system. CRAN supports the process by grouping each set of source files with documentation or README files that explain how to install on your system.

2.1.2 Download and Install RStudio

“R Studio” is a development environment for “R”.

1. Open <https://rstudio.com/products/rstudio/download/> and download “RStudio Desktop Open Source”
2. Follow the on-screen instructions
3. Once you have installed “R Studio”, you can run it like any other application by clicking the program icon

2.2 Install required packages

Appendix A gives you an introduction to what a package is and how to install it. Below are the packages used in this book and it is recommended to install them now.

- Open “RStudio” just as you would any program, by clicking on its icon

- Copy the following code and paste it into your console (on the bottom left, right of the symbol >):

```
install.packages("devtools", "tidyverse", "plotly", "lubridate", "r2d3")
install_github("hslu-ige-laes/redutils")
```

- Press **Enter** or **Return**

The installation of the packages is now in progress and this may take a while, please be patient. In the meantime you can read in appendix A what packages are in general and how they can be installed and later loaded into scripts.

2.3 Create an R Script

Finally, you have installed “R” and “RStudio” with the first set of packages on your computer.

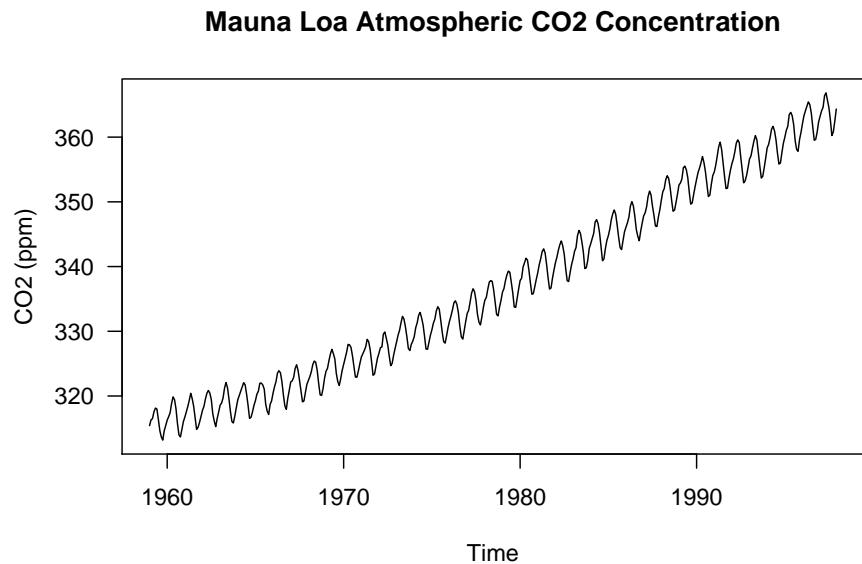
Let’s create the first visualization.

- Open “RStudio” just as you would any program, by clicking on its icon
- Go to the menu on the top left and click to **File / New File / R Script**
- Copy the following code and paste it into your script:

```
library(graphics)
plot(co2, ylab = "CO2 (ppm)", las = 1)
title(main = "Mauna Loa Atmospheric CO2 Concentration")
```

- select all by pressing **Ctrl + A**
- Then run the code by pressing the **Run Button** or **Ctrl + Enter**

You should now get your first visualization:



As you probably noticed, we did not load any data. The basic installation of “R” and some packages come with test data. So that is an easy way to test something. The R Dataset Package provides some preinstalled datasets, including the used “Mauna Loa Atmospheric CO₂ Concentration” dataset.

2.4 What’s next?

Hopefully everything has worked well so far with the installation and your first visualization.

So congratulations!

You have a running R environment, and we can start with more interesting things in the following chapters.

Chapter 3

R Basics

3.1 Loading Data

3.1.1 Csv File

```
df <- read.csv("datafile.csv")
df <- read.csv("datafile.csv", header=FALSE, stringsAsFactors=FALSE)

df <- read.csv("https://github.com/retomarek/r/raw/master/datasets/buildingMonitoringTestDataSet.csv",
              stringsAsFactors=FALSE,
              sep =",",
              na.strings = c("", "NA"))
```

Attention: By default, strings in the data are treated as factors. `read.csv()` is a convenience wrapper function around `read.table()`. If you need more control over the input, see `?read.table`

3.1.2 Excel File

```
# Only need to install once
install.packages("xlsx")

library(xlsx)

df <- read.xlsx("datafile.xlsx", 1)
df <- read.xlsx("datafile.xls", sheetIndex=2)
df <- read.xlsx("datafile.xls", sheetName="Revenues")
```

For reading older Excel files in the .xls format, the gdata package has the function `read.xls()`:

```
# Only need to install once
install.packages("gdata")

library(gdata)
# Read first sheet
df <- read.xls("datafile.xls")
df <- read.xls("datafile.xls", sheet=2)
```

Both the xlsx and gdata packages require other software to be installed on your computer. For xlsx, you need to install Java on your machine. For gdata, you need Perl, which comes as standard on Linux and Mac OS X, but not Windows. On Windows, you'll need ActiveState Perl. The Community Edition can be obtained for free.

Chapter 4

Data Wrangling

4.1 Add Metadata for later filtering

Firstly we have to load a dataset into a dataframe:

```
# load data set
df <- read.csv("https://github.com/hslu-ige-laes/edar/raw/master/sampleData/centralOutsideTemp.csv",
               stringsAsFactors=FALSE,
               sep =";")
```

4.1.1 Year, Month, Day, Day of Week

To group, filter and aggregate data we need to have the date splitted up in day, month and year separately:

```
library(dplyr)
library(lubridate)

df$time <- parse_date_time(df$time, "YmdHMS", tz = "Europe/Zurich")
df$year <- as.Date(cut(df$time, breaks = "year"))
df$month <- as.Date(cut(df$time, breaks = "month"))
df$day <- as.Date(cut(df$time, breaks = "day"))
df$weekday <- wday(df$time,
                     label = TRUE,
                     locale = "English",
                     abbr = TRUE,
                     week_start = getOption("lubridate.week.start", 1))
```

This code first parses the timestamp with a specific timezone. Then three columns are added.

Please note that the month also contains the year and a day. This is useful for a later step where you can group the series afterwards.

```
head(df,2)

##           time centralOutsideTemp
## 1 2018-03-21 11:00:00      5.2
## 2 2018-03-21 12:00:00      6.7

tail(df,2)

##           time centralOutsideTemp
## 21864 2020-09-17 10:00:00     26.65
## 21865 2020-09-17 11:00:00     28.10
```

4.1.2 Season of Year

For some analyses it is useful to color single points of a scatterplot according to the season. For this we need to have the season in a separate column:

```
library(redutils)
# get season from a date
getSeason(as.Date("2019-04-01"))

## [1] "Spring"
```

If you want to change the language, you can give the function dedicated names for the season:

```
getSeason(as.Date("2019-04-01"),
          seasonlab = c("Winter", "Frühling", "Sommer", "Herbst"))

## [1] "Frühling"
```

To apply this function to a whole dataframe we can use the dplyr mutate function. The code below creates a new column named “season”:

```
df <- dplyr::mutate(df, season = getSeason(df$time))

head(df,1)

##           time centralOutsideTemp season
## 1 2018-03-21 11:00:00      5.2 Spring

tail(df,1)

##           time centralOutsideTemp season
## 21865 2020-09-17 11:00:00     28.1 Fall
```

4.2 Data Frames

Firstly we have to load a dataset into a dataframe:

```
# load data set
df <- read.csv("https://github.com/hslu-ige-laes/edar/raw/master/sampleData/flatTempHum.csv",
               stringsAsFactors=FALSE,
               sep =";")
```

4.2.1 Change Row Names

```
# Print the header and the first line
head(df, 1)

##                               time FlatA_Hum FlatA_Temp FlatB_Hum FlatB_Temp FlatC_Hum
## 1 2018-10-03 00:00:00          53      24.43     38.8      22.4      44
##   FlatC_Temp FlatD_Hum FlatD_Temp
## 1      24.5       49      24.43

# rename columns and print the header and the first line
names(df) <- c("timestamp", "Hum_A", "Temp_A", "Hum_B", "Temp_B", "Hum_C", "Temp_C", "Hum_D", "Temp_D")
head(df, 1)

##                               timestamp Hum_A Temp_A Hum_B Temp_B Hum_C Temp_C Hum_D Temp_D
## 1 2018-10-03 00:00:00      53    24.43    38.8    22.4     44    24.5     49    24.43
```

4.2.2 Wide to Long

```
##           timestamp sensor value
## 1 2018-10-03 00:00:00 Hum_A 53.00
## 2 2018-10-03 00:00:00 Temp_A 24.43
## 3 2018-10-03 00:00:00 Hum_B 38.80
## 4 2018-10-03 00:00:00 Temp_B 22.40
## 5 2018-10-03 00:00:00 Hum_C 44.00
## 6 2018-10-03 00:00:00 Temp_C 24.50
## 7 2018-10-03 00:00:00 Hum_D 49.00
## 8 2018-10-03 00:00:00 Temp_D 24.43
## 9 2018-10-03 01:00:00 Hum_A 53.00
## 10 2018-10-03 01:00:00 Temp_A 24.40
## 11 2018-10-03 01:00:00 Hum_B 38.80
## 12 2018-10-03 01:00:00 Temp_B 22.40
## 13 2018-10-03 01:00:00 Hum_C 44.00
## 14 2018-10-03 01:00:00 Temp_C 24.50
## 15 2018-10-03 01:00:00 Hum_D 49.00
## 16 2018-10-03 01:00:00 Temp_D 24.40
```

4.2.3 Long to Wide

```
# long format
head(df.long)
```

```
##           timestamp sensor value
## 1 2018-10-03 00:00:00 Hum_A 53.00
## 2 2018-10-03 00:00:00 Temp_A 24.43
## 3 2018-10-03 00:00:00 Hum_B 38.80
## 4 2018-10-03 00:00:00 Temp_B 22.40
## 5 2018-10-03 00:00:00 Hum_C 44.00
## 6 2018-10-03 00:00:00 Temp_C 24.50
```

```
# convert long table into wide table
df.wide <- as.data.frame(tidy::pivot_wider(df.long,
                                              names_from = "sensor",
                                              values_from = "value")
                           )
```

```
# wide format
head(df.wide)
```

```
##           timestamp Hum_A Temp_A Hum_B Temp_B Hum_C Temp_C Hum_D Temp_D
## 1 2018-10-03 00:00:00 53.0 24.43 38.8 22.40 44.0 24.50 49.0 24.43
## 2 2018-10-03 01:00:00 53.0 24.40 38.8 22.40 44.0 24.50 49.0 24.40
## 3 2018-10-03 02:00:00 53.0 24.40 39.3 22.40 44.7 24.50 48.3 24.38
## 4 2018-10-03 03:00:00 53.0 24.40 40.3 22.40 45.0 24.50 48.0 24.33
## 5 2018-10-03 04:00:00 53.3 24.40 41.0 22.37 45.2 24.50 47.7 24.30
## 6 2018-10-03 05:00:00 53.7 24.40 41.2 22.30 47.2 24.57 47.2 24.30
```

4.2.4 Merge two Dataframes

```

library(dplyr)
library(lubridate)

# read file one and parse dates
dfOutsideTemp <- read.csv("https://github.com/hslu-ige-laes/edar/raw/master/sampleData/centralOutsideTemp.csv",
                           stringsAsFactors=FALSE,
                           sep =";")

dfOutsideTemp$time <- parse_date_time(dfOutsideTemp$time,
                                         orders = "YmdHMS",
                                         tz = "Europe/Zurich")

# read file two and parse dates
dfFlatTempHum <- read.csv("https://github.com/hslu-ige-laes/edar/raw/master/sampleData/flatTempHum.csv",
                           stringsAsFactors=FALSE, sep =";")

dfFlatTempHum$time <- parse_date_time(dfFlatTempHum$time,
                                         order = "YmdHMS",
                                         tz = "Europe/Zurich")

# merge the two files into a new data frame and keep only rows where all values are available
df <- merge(dfOutsideTemp, dfFlatTempHum, by = "time") %>% na.omit()

```

4.3 Examples

4.3.1 Import csv file from GWF Relay W60 M-Bus Logger

Some data loggers have a cryptic data format which requires some data wrangling ahead before we can use the time series efficiently. Following an example of a M-Bus data logger.

```

library(tidyr)

# load csv file
df <- read.csv("https://github.com/hslu-ige-laes/edar/raw/master/sampleData/flatHeatAndHotWater_GWF_RelayW60Logger.csv",
               stringsAsFactors=FALSE,
               sep =",")
head(df,23)

##      Datum Zeit Adr ID.Nr. HST Nr.          Wert Einheit
## 1 01.01.10 00:00 1     1 GWF  1           729    kWh
## 2 01.01.10 00:00 1     1 GWF  2           80.92   m^3
## 3 01.01.10 00:00 1     1 GWF  3           80.75   m^3
## 4 01.01.10 00:00 1     1 GWF  4             26    °C
## 5 01.01.10 00:00 1     1 GWF  5             25    °C
## 6 01.01.10 00:00 1     1 GWF  6             1.3      K
## 7 01.01.10 00:00 1     1 GWF  7            375  hours
## 8 01.01.10 00:00 1     1 GWF  8            375  hours
## 9 01.01.10 00:00 1     1 GWF  9              0   l/h
## 10 01.01.10 00:00 1     1 GWF 10              0    kW
## 11 01.01.10 00:00 1 11 31.12.09 23:58 Win  V

```



```

# select columns and rearrange
df <- df %>% select(timestamp, Adr, Nr., Wert, Einheit)

# filter out Adr. of interest
df <- df %>% filter(Nr. %in% c(1,12))

# rename columns
df <- df %>% mutate(Nr. = ifelse(Nr. == 1, paste0("Adr",sprintf("%02.0f", Adr), "_energyHeat"), ifelse(Nr. == 12, paste0("Adr",sprintf("%02.0f", Adr), "04_energyHeat"))))

# convert value to numeric
df$Wert <- as.numeric(df$Wert)

# multiply HCA-values by factor 10 to get liters and divide by 1000 to get m3
df <- df %>% mutate(Wert = ifelse(Einheit == "HCA"), Wert * 10/1000, Wert))

df <- df %>% select(-Einheit, -Adr)

# convert long table into wide table
df.wide <- as.data.frame(pivot_wider(df,
                                       names_from = "Nr.",
                                       values_from = Wert,
                                       names_sep = "_"))
)

```

This is the result:

```

head(df.wide)

## # timestamp Adr01_energyHeat Adr01_hotWater Adr02_energyHeat Adr02_hotWater
## # 1 2010-01-01      729       0.87      751       1.16
## # 2 2010-02-01     1850       2.18     2276       7.55
## # 3 2010-03-01     2806       5.84     2826      12.94
## # 4 2010-04-01     3615       9.92     3354      18.51
## # 5 2010-05-01     4150      13.38     3613      24.81
## # 6 2010-06-01     4669      17.50     3640      29.72
## # Adr04_energyHeat Adr04_hotWater Adr03_energyHeat Adr03_hotWater
## # 1          972       1.56      799       0.07
## # 2         2526       8.14     3103       1.32
## # 3         3690      14.83     4786       3.73
## # 4         4700      20.82     6151       6.05
## # 5         5341      27.06     6900       7.74
## # 6         5802      31.61     7702       9.49

```

Finally saving the csv file:

```

write.csv2(df.wide,
           file = "flatHeatAndHotWater.csv",
           row.names = FALSE)

```


Chapter 5

Explorative Data Analysis

5.1 Get overview

Get an overview of the whole data set and specific series of it

5.1.1 Load data

Load test data set in a data frame (e.g. from a csv-file)

```
df <- read.csv("https://github.com/retomarek/r/raw/master/datasets/buildingMonitoringTestDataSet.csv",
               stringsAsFactors=FALSE,
               sep = ",")
```

5.1.2 Names

show the column headers of the data frame

```
names(df)

## [1] "time"                  "WthStnPress"          "WthStnHum"
## [4] "WthStnRain"            "WthStnSolRad"         "WthStnTemp"
## [7] "WthStnWindDir"         "WthStnWindSpd"        "BldgEnergyHotwater"
## [10] "BldgEnergyHeating"     "FlatHum"              "FlatTemp"
## [13] "FlatVolFlowColdwater"  "FlatVolFlowHotwater"
```

5.1.3 Structure

show the structure of the data frame

```
str(df)
```

```
## 'data.frame': 16394 obs. of 14 variables:
## $ time : chr "2018-09-30T22:00:00.000Z" "2018-09-30T23:00:00.000Z" "2018-10-01T00:00:00...
## $ WthStnPress : num 1012 1012 1011 1011 1011 ...
## $ WthStnHum : num 87 87.5 87.5 86.5 88 89 86.5 81 78 80.5 ...
## $ WthStnRain : num 0.8 1.1 0.5 0.5 0.6 0.1 0.2 0 0 0 ...
## $ WthStnSolRad : num 0 0 0 0 0 0 0 3 24.5 ...
## $ WthStnTemp : num 12.8 12.4 11.9 11.9 11.6 ...
## $ WthStnWindDir : num 157.5 11.2 146.2 157.5 146.2 ...
## $ WthStnWindSpd : num 3.2 1.6 2.4 0.8 2.4 0.8 0.8 3.2 4 3.2 ...
## $ BldgEnergyHotwater : num 0 19 0 0 0 ...
## $ BldgEnergyHeating : num 0 0 0 0 0 0 0 0 0 ...
## $ FlatHum : num NA NA NA NA NA NA NA NA NA ...
## $ FlatTemp : num NA NA NA NA NA NA NA NA NA ...
## $ FlatVolFlowColdwater: num 0.006 0 0 0 0.006 ...
## $ FlatVolFlowHotwater : num 0 0 0 0 0 ...
```

5.1.4 Head/Tail

The head and tail functions are generic, so they will work whether your data is stored in a simple data frame, a zoo object, or an xts object.

```
head(df)
```

```
##          time WthStnPress WthStnHum WthStnRain WthStnSolRad
## 1 2018-09-30T22:00:00.000Z     1012.30      87.0      0.8      0
## 2 2018-09-30T23:00:00.000Z     1011.90      87.5      1.1      0
## 3 2018-10-01T00:00:00.000Z     1011.45      87.5      0.5      0
## 4 2018-10-01T01:00:00.000Z     1010.90      86.5      0.5      0
## 5 2018-10-01T02:00:00.000Z     1010.55      88.0      0.6      0
## 6 2018-10-01T03:00:00.000Z     1010.20      89.0      0.1      0
##   WthStnTemp WthStnWindDir WthStnWindSpd BldgEnergyHotwater BldgEnergyHeating
## 1     12.80      157.50        3.2             0             0
## 2     12.35      11.25        1.6           19             0
## 3     11.90      146.25        2.4             0             0
## 4     11.90      157.50        0.8             0             0
## 5     11.60      146.25        2.4             0             0
## 6     11.75      22.50        0.8             0             0
##   FlatHum FlatTemp FlatVolFlowColdwater FlatVolFlowHotwater
## 1     NA       NA         0.006             0
## 2     NA       NA         0.000             0
## 3     NA       NA         0.000             0
## 4     NA       NA         0.000             0
## 5     NA       NA         0.006             0
## 6     NA       NA         0.000             0
```

```
tail(df)
```

```
##          time WthStnPress WthStnHum WthStnRain WthStnSolRad
## 16389 2020-08-13T18:00:00.000Z     1011.650      74.75    2.19964      9
## 16390 2020-08-13T19:00:00.000Z     1012.000      79.00    2.19964      0
```

```

## 16391 2020-08-13T20:00:00.000Z    1011.950    78.25    2.19964    0
## 16392 2020-08-13T21:00:00.000Z    1012.025    76.50    2.19964    0
## 16393 2020-08-13T22:00:00.000Z    1012.250    73.00    0.00000    0
## 16394 2020-08-13T23:00:00.000Z      NA        NA        NA        NA
##           WthStnTemp WthStnWindDir WthStnWindSpd BldgEnergyHotwater
## 16389     22.000     162.00    0.000000        NA
## 16390     20.175     124.25    1.609340        NA
## 16391     19.350     125.00    0.402335        NA
## 16392     19.900     93.00    1.609340        NA
## 16393     20.625     116.25    2.414010        NA
## 16394       NA        NA        NA        NA
##           BldgEnergyHeating FlatHum FlatTemp FlatVolFlowColdwater
## 16389          NA        NA        NA        NA
## 16390          NA        NA        NA        NA
## 16391          NA        NA        NA        NA
## 16392          NA        NA        NA        NA
## 16393          NA        NA        NA        NA
## 16394          NA        NA        NA        NA
##           FlatVolFlowHotwater
## 16389          NA
## 16390          NA
## 16391          NA
## 16392          NA
## 16393          NA
## 16394          NA

```

5.1.5 Five number summary

reveals details of a specific series

```

summary(df$WthStnTemp)

##      Min. 1st Qu. Median      Mean 3rd Qu.      Max.      NA's
## -5.25    5.50   11.25   11.99   17.35   40.30      12

```

5.2 Basic plots

5.2.1 Scatterplot

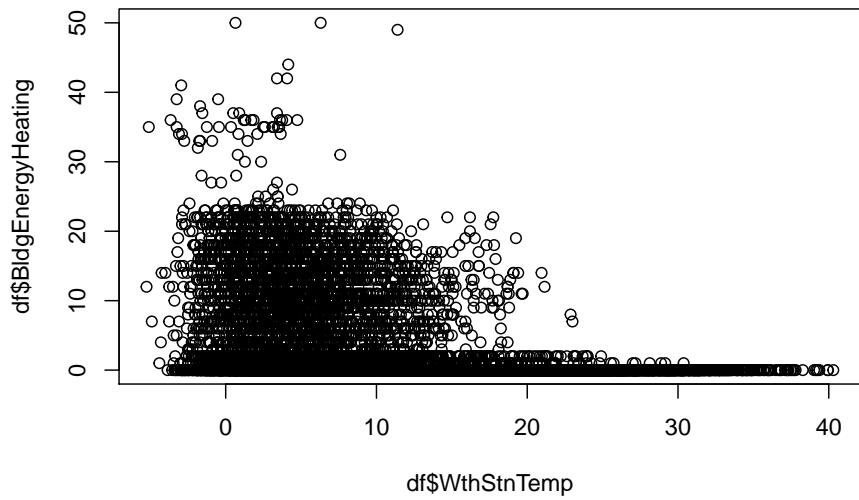
5.2.1.1 plot()

```

# load data set
df <- read.csv("https://github.com/retomarek/r/raw/master/datasets/buildingMonitoringDataSet.csv",
               stringsAsFactors=FALSE,
               sep = ",")

# crate simple scatterplot
plot(df$WthStnTemp, df$BldgEnergyHeating)

```



Chapter 6

Data Visualizations

tbd

6.1 Seasonal Plot - Overlapping

6.1.1 Goal

Plot a seasonal plot as described in Hyndman and Athanasopoulos (2014, chapter 2.4):

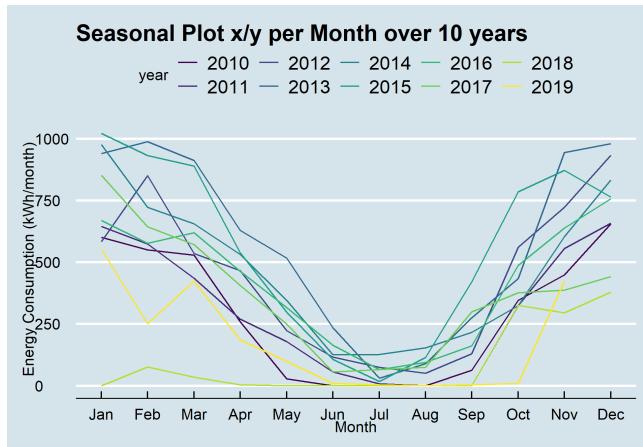


Figure 6.1: Seasonal Plot Overlapping per Month over 10 Years

This is like a standard time series plot except that the data are plotted against the “seasons” for each year and are overlapping. Be aware that seasons in this

context don't correlate with the seasons of the year.

6.1.2 Data Basis

In general, the values of energy meters, as in our example, increase steadily:

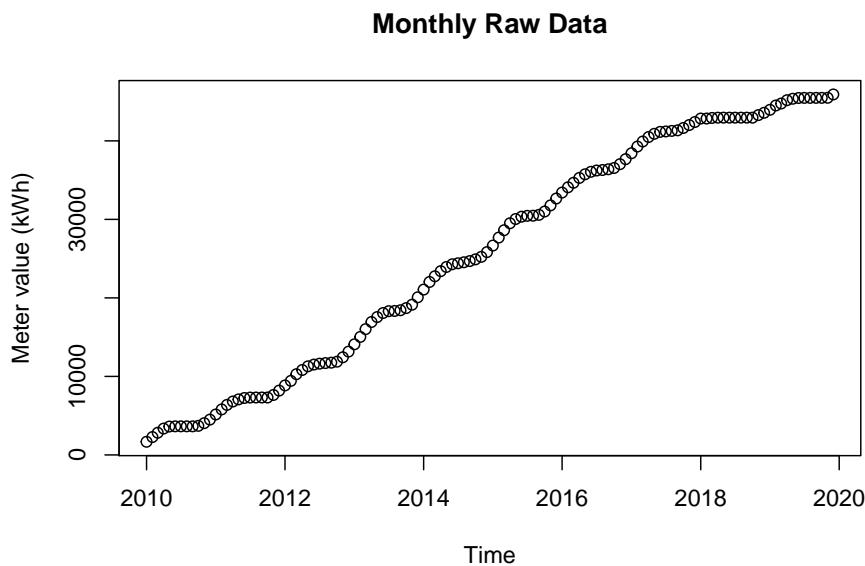


Figure 6.2: Raw Data for Seasonal Plot Overlapping

6.1.3 Solution

Create a new script, copy/paste the following code and run it:

```
library(forecast)
library(dplyr)
library(plotly)
library(htmlwidgets)
library(ggthemes)
library(viridis)
library(lubridate)

# load csv file
df <- read.csv2("https://github.com/hslu-ige-laes/edar/raw/master/sampleData/flatHeatAndHotWater.csv",
                stringsAsFactors=FALSE)

# filter flat
```

```
df <- df %>% select(timestamp, Adr02_energyHeat)

colnames(df) <- c("timestamp", "meterValue")

# calculate consumption value per month
# pay attention, the value of 2010-02-01 00:00:00 represents the meter reading on february first,
# so the consumption for february first is value(march) - value(february) !
df <- df %>% mutate(value = lead(meterValue) - meterValue)

# remove counter value column
df <- df %>% select(-meterValue)

# value correction (outlier because of commissioning)
df[1,2] <- 600

# create time series object for ggseanplot function
df.ts <- ts(df %>% select(value) %>% na.omit(), frequency = 12, start = min(year(df$timestamp)))

# create x/y plot
numYears = length(unique(year(df$timestamp))) # used for colours

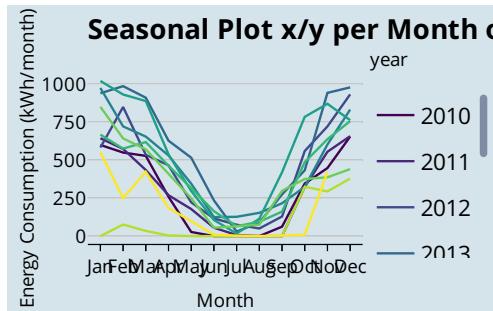
plot <- ggseanplot(df.ts,
                    col = viridis(numYears),
                    main = "Seasonal Plot x/y per Month over 10 years",
                    ylab = "Energy Consumption (kWh/month)"
                    )

# show static plot (uncomment it if you want a static plot)
#plot

# change theme (optional)
plot <- plot + ggthemes::theme_economist()

# make plot interactive (optional)
plotly <- plotly::ggplotly(plot)

# show plot interactive plot (optional)
plotly
```



```
# save static plot as png (optional)
ggsave("images/plotSeasonalXY.png", plot)
```

```
# save interactive plot as html (optional)
library(htmlwidgets)
htmlwidgets::saveWidget(plotly, "plotlySeasonalXY.html")
```

6.1.4 Discussion

A seasonal plot allows the underlying seasonal pattern to be seen more clearly, and is especially useful in identifying years in which the pattern changes.

Hints:

- in the interactive version you can double-click on year in the legend, then only this year is visible
- click once to activate/deactivate a year

6.2 Seasonal Plot - Mini Plots

6.2.1 Goal

Plot a seasonal month plot as described in Hyndman and Athanasopoulos (2014, chapter 2.5):

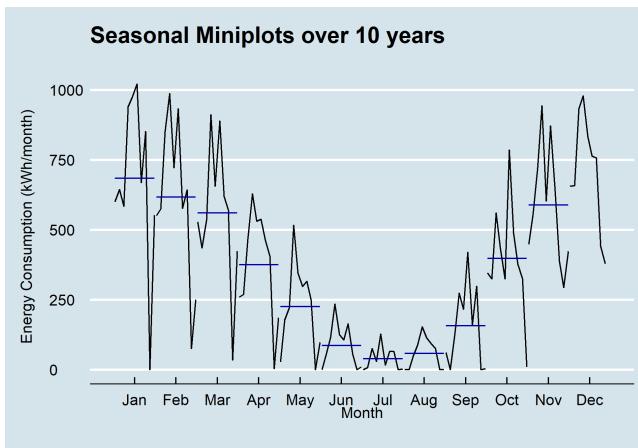


Figure 6.3: Seasonal Plot with mini Time Plots over 10 Years

Here the seasonal patterns for each season are collected together in separate mini time plots. Be aware that seasons in this context don't correlate with the seasons of the year.

6.2.2 Data Basis

In general, the values of energy meters, as in our example, increase steadily:

6.2.3 Solution

Create a new script, copy/paste the following code and run it:

```
library(forecast)
library(dplyr)
library(plotly)
library(htmlwidgets)
library(ggthemes)
library(viridis)
library(lubridate)

# load csv file
df <- read.csv2("https://github.com/hslu-ige-laes/edar/raw/master/sampleData/flatHeatAndHotWater.csv",
```

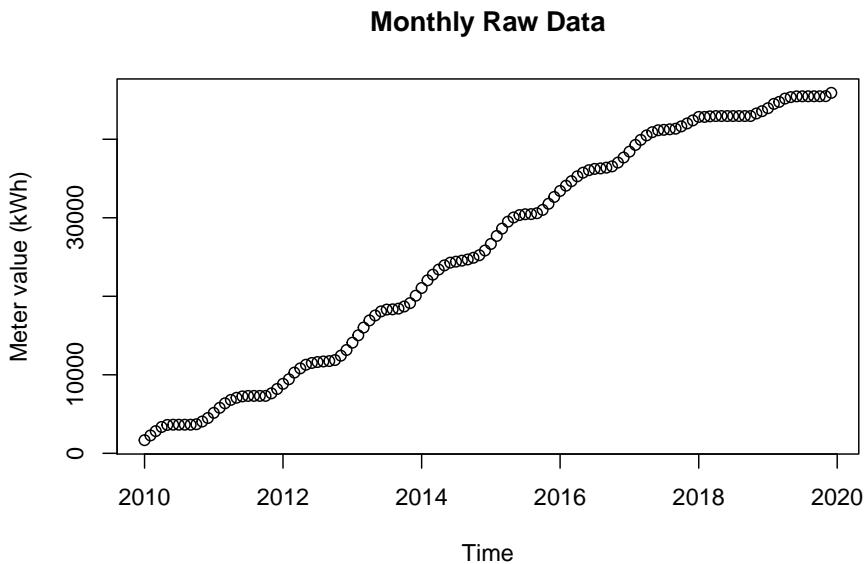


Figure 6.4: Raw Data for Seasonal Miniplots

```

stringsAsFactors=FALSE)

# filter flat
df <- df %>% select(timestamp, Adr02_energyHeat)

colnames(df) <- c("timestamp", "meterValue")

# calculate consumption value per month
# pay attention, the value of 2010-02-01 00:00:00 represents the meter reading on february first,
# so the consumption for february first is value(march) - value(february) !
df <- df %>% mutate(value = lead(meterValue) - meterValue)

# remove counter value column
df <- df %>% select(-meterValue)

# value correction (outlier because of commissioning)
df[1,2] <- 600

# create time series object for ggmonthplot function
df.ts <- ts(df[-1], frequency = 12, start = min(year(df$timestamp)))

# create x/y plot

numYears = length(unique(year(df$timestamp)))

plot <- ggmonthplot(df.ts,
                     col = viridis(numYears),

```

```

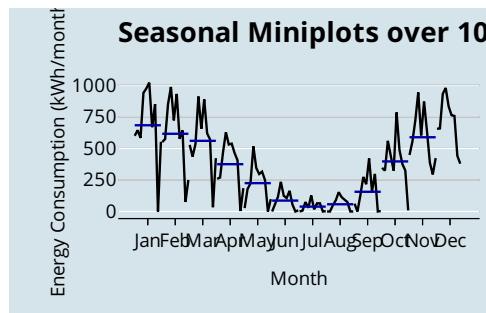
    main = "Seasonal Miniplots over 10 years\n",
    ylab = "Energy Consumption (kWh/month)\n",
    xlab = "Month\n"
  )

# change theme (optional)
plot <- plot + ggthemes::theme_economist()

# make plot interactive (optional)
plotly <- plotly::ggplotly(plot)

# show plot
plotly

```



```

# save static plot as png
ggsave("images/plotSeasonalMiniplots.png", plot)

# save interactive plot as html
library(htmlwidgets)
htmlwidgets::saveWidget(plotly, "plotlySeasonalMiniplots.html")

```

6.2.4 Discussion

- This type of seasonal plot shows the mean value of each month and therefore emphasises on the monthly comparison

- It reveals as well the mean seasonal pattern with the blue lines

6.3 Seasonal Plot - Polar

6.3.1 Goal

Plot a seasonal plot as described in Hyndman and Athanasopoulos (2014, chapter 2.4):

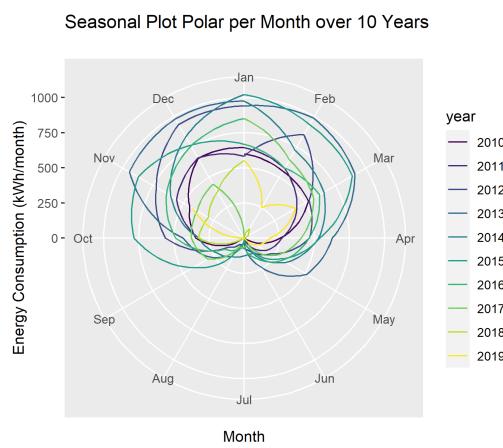


Figure 6.5: Seasonal Plot Polar per Month over 10 Years

This is like an overlapping time series plot which uses polar coordinates. Be aware that seasons in this context don't correlate with the seasons of the year.

6.3.2 Data Basis

In general, the values of energy meters, as in our example, increase steadily:

6.3.3 Solution

Create a new script, copy/paste the following code and run it:

```
library(forecast)
library(dplyr)
library(plotly)
library(htmlwidgets)
library(ggthemes)
library(viridis)
library(lubridate)
```

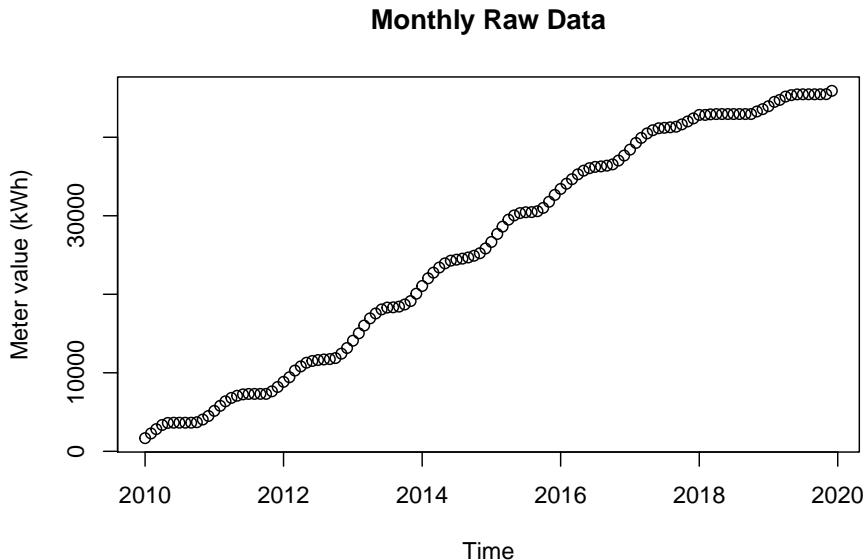


Figure 6.6: Raw Data for Seasonal Plot Polar

```

# load csv file
df <- read.csv2("https://github.com/hslu-ige-laes/edar/raw/master/sampleData/flatHeatAndHotWater.csv",
                stringsAsFactors=FALSE)

# filter flat
df <- df %>% select(timestamp, Adr02_energyHeat)

colnames(df) <- c("timestamp", "meterValue")

# calculate consumption value per month
# pay attention, the value of 2010-02-01 00:00:00 represents the meter reading on february first,
# so the consumption for february first is value(march) - value(february) !
df <- df %>% mutate(value = lead(meterValue) - meterValue)

# remove counter value column
df <- df %>% select(-meterValue)

# value correction (outlier because of commissioning)
df[1,2] <- 600

df.ts <- ts(df %>% select(value) %>% na.omit(), frequency = 12, start = min(year(df$timestamp)))

# create polar plot

numYears = length(unique(year(df$timestamp)))

plot <- ggseasonplot(df.ts,

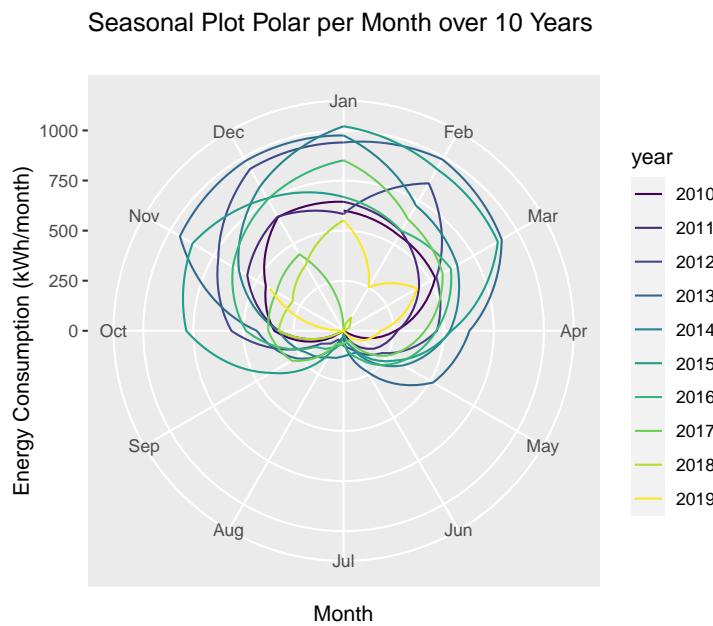
```

```

col = viridis(numYears),
main = "Seasonal Plot Polar per Month over 10 Years\n",
ylab = "Energy Consumption (kWh/month)",
polar = TRUE
)

# show plot (interactive version with plotly unfortunately not possible)
plot

```



```

# save static plot as png (optional)
ggsave("images/plotSeasonalPolar.png", plot)

```

6.3.4 Discussion

This representation emphasizes the high consumption in summer very well, which could undoubtedly be reduced in a residential building. The Years 2018 and 2019 show, that this optimization was done.

To emphasize this optimization please refer to the next chapter 6.4.

6.4 Seasonal Plot - Before/After

6.4.1 Goal

To highlight an energy optimization in a season diagram, we can gray out the seasons before the optimization and only highlight the monthly values after the optimization. To better quantify the success, we can calculate and display the confidence interval of the years before.

In the following we will create the following plot:

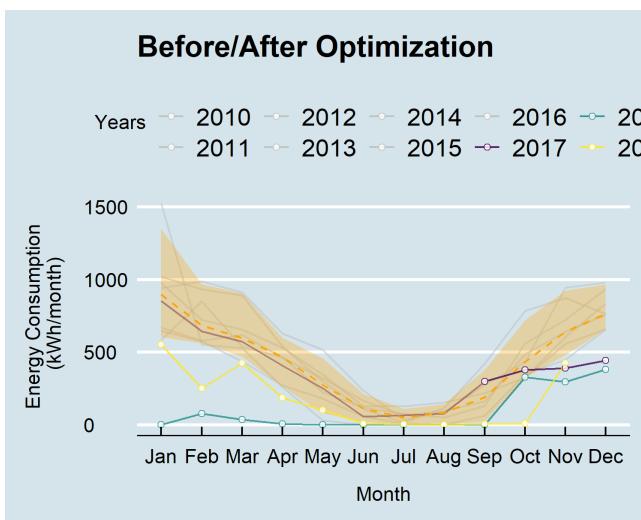


Figure 6.7: Seasonal Plot Overlapping Before/After

6.4.2 Data Basis

In general, the values of energy meters, as in our example, increase steadily:

6.4.3 Solution

Create a new script, copy/paste the following code and run it:

```
library(redutils)
library(dplyr)
library(plotly)
library(htmlwidgets)
library(ggthemes)

# load csv file
```

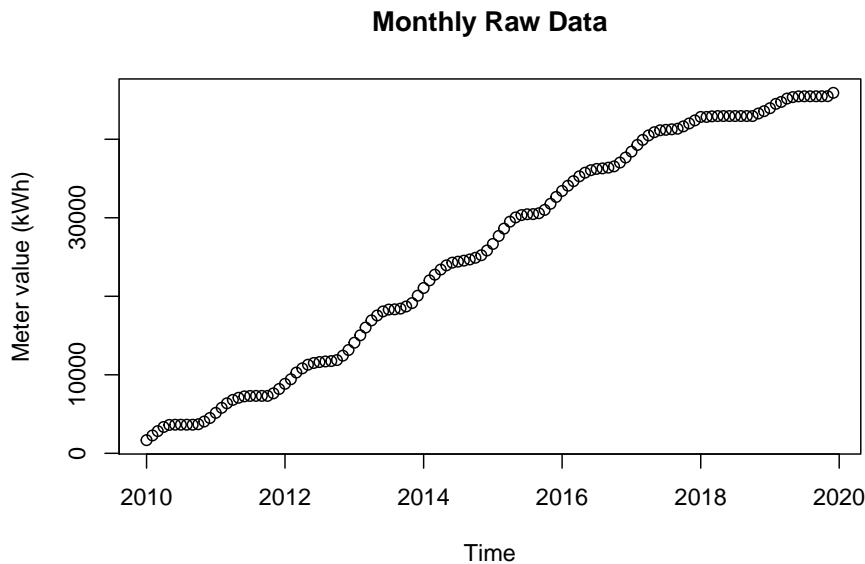


Figure 6.8: Raw Data for Seasonal Plot Overlapping Before/After Optimization

```
df <- read.csv("https://github.com/hslu-ige-laes/edar/raw/master/sampleData/flatHeatAndHotWater.csv",
               stringsAsFactors=FALSE)

# filter flat
df <- df %>% select(timestamp, Adr02_energyHeat)

colnames(df) <- c("timestamp", "meterValue")

# calculate consumption value per month
# pay attention, the value of 2010-02-01 00:00:00 represents the meter reading on february first,
# so the consumption for february first is value(march) - value(february) !
df <- df %>% mutate(value = lead(meterValue) - meterValue)

# remove counter value column
df <- df %>% select(-meterValue)

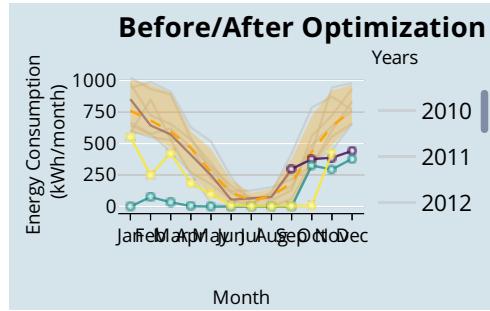
# value correction (outlier because of commissioning)
df[1,2] <- 600

# create plot
plot <- plotSeasonalXYBeforeAfter(df,
                                    dateOptimization = "2017-09-01",
                                    locTimeZone = "Europe/Zurich",
                                    main = "Before/After Optimization",
                                    ylab = "Energy Consumption \n(kWh/month)"
)
```

```
# change theme (optional)
plot <- plot + ggthemes::theme_economist()

# make plot interactive (optional)
plotly <- plotly::ggplotly(plot)

# show plot
plotly
```



```
# save static plot as png (optional)
ggsave("images/plotSeasonalXYBeforeAfter.png", plot)

# save interactive plot as html (optional)
library(htmlwidgets)
htmlwidgets::saveWidget(plotly, "plotlySeasonalXYBeforeAfter.html")
```

6.4.4 Discussion

- One can clearly see the impact of the optimization
- And as well the too low setting of January 2018 where the thermostat of the flat got deactivated
- The confidence band shows as well the year 2013 which had an unusual high consumption from February to June

6.5 Decomposition - Long term

6.5.1 Goal

tbd <https://otexts.com/fpp2/tspatterns.html> Hyndman, R.J., & Athanasopoulos, G. (2018) Forecasting: principles and practice, 2nd edition, OTexts: Melbourne, Australia. OTexts.com/fpp2. Accessed on

6.5.2 Basis

- tbd
- monthly energy consumption meter values over 10 years

6.5.3 Solution

Create a new script, copy/paste the following code and run it:

```
library(dplyr)
library(lubridate)
library(plotly)
library(ggplot2)
library(forecast)

# load csv file
df <- read.csv2("https://github.com/hslu-ige-laes/edar/raw/master/sampleData/flatHeatAndHotWater.csv",
                 stringsAsFactors=FALSE)

# filter flat
df <- df %>% select(timestamp, Adr02_energyHeat)

colnames(df) <- c("Time", "meterValue")

df$Time <- parse_date_time(df$Time,
                           orders = "YmdHMS",
                           tz = "Europe/Zurich")

# calculate consumption value per month
# pay attention, the value of 2010-02-01 00:00:00 represents the meter reading on february first,
# so the consumption for february first is value(march) - value(february) !
df <- df %>% mutate(value = lead(meterValue) - meterValue)

# remove counter value column
df <- df %>% select(-meterValue) %>% na.omit()
df[1,2] <- 600

df.ts <- ts(df %>% select(value) %>% na.omit(), frequency = 12, start = min(year(df$Time)))

df.decompose <- df.ts[,1] %>%
  stl(s.window = 7)
```

```
df.decompose <- df.decompose$time.series

df.decompose <- as.data.frame(df.decompose)

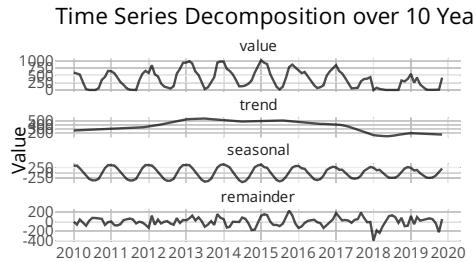
df.decompose <- cbind(df, df.decompose)

data <- as.data.frame(tidyr::pivot_longer(df.decompose,
                                             cols = -Time,
                                             names_to = "Component",
                                             values_to = "Value",
                                             values_drop_na = TRUE)
)
data$component <- as.factor(data$Component)
data$component <- factor(data$Component, c("value",
                                             "trend",
                                             "seasonal",
                                             "remainder"))

data$Value <- round(data$Value, digits = 1)

p <- ggplot(data) +
  geom_path(aes(x = Time,
                y = Value
  ),
  color = "black",
  alpha = 0.7) +
  facet_wrap(~component, ncol = 1, scales = "free_y") +
  scale_x_datetime(date_breaks = "years" , date_labels = "%Y") +
  theme_minimal() +
  theme(panel.spacing = unit(1, "lines"),
        legend.position = "none") +
  labs(x = "") +
  ggtitle("Time Series Decomposition over 10 Years")

ggplotly(p)
```



6.5.4 Discussion

tbd

6.5.5 See Also

tbd

6.6 Decomposition - Short term

6.6.1 Task

tbd <https://otexts.com/fpp2/tspatterns.html> Hyndman, R.J., & Athanasopoulos, G. (2018) Forecasting: principles and practice, 2nd edition, OTexts: Melbourne, Australia. OTexts.com/fpp2. Accessed on

6.6.2 Basis

- tbd
- 15min energy consumption meter values over five days

6.6.3 Solution

Create a new script, copy/paste the following code and run it:

```

library(dplyr)
library(lubridate)
library(plotly)
library(ggplot2)
library(forecast)

# change language to English, otherwise weekdays are in local language
Sys.setlocale("LC_TIME", "English")

## [1] "English_United States.1252"

# load time series data
df <- read.csv("https://github.com/hslu-ige-laes/edar/raw/master/sampleData/eboBookEleMeter.csv",
               stringsAsFactors=FALSE,
               sep =";")

# rename column names
colnames(df) <- c("time", "meterValue")

df$time <- parse_date_time(df$time,
                           orders = "YmdHMS",
                           tz = "Europe/Zurich")
df$time <- force_tz(df$time, tzzone = "UTC")

# uncomment to filter time range if necessary
#df <- df %>% filter(Time > "2015-03-01 00:00:00", Time < "2015-04-01 00:00:00")

# Fill missing values with NA
grid.df <- data.frame(time = seq(min(df$time, na.rm = TRUE),
                                  max(df$time, na.rm = TRUE),
                                  by = "15 mins"))
df <- merge(df, grid.df, all = TRUE)

# convert steadily counting energy meter value from kWh to power in kW
df <- df %>%
  mutate(value = (meterValue - lag(meterValue))*4) %>%
  select(-meterValue) %>%
  na.omit()

# remove negative values which occur because of change summer/winter time
df <- df %>% filter(value >= 0)

# select time range
df <- df %>% filter(time >= as.POSIXct("2015-01-26 00:00:00", tz = "UTC"),
                      time < as.POSIXct("2015-01-31 00:00:00", tz = "UTC"))

# ===== Start of Code =====
df.ts <- ts(df %>% select(value) %>% na.omit(),
            frequency = 96)

df.decompose <- df.ts[,1] %>%

```

```

stl(s.window = 193)

df.decompose <- df.decompose$time.series

df.decompose <- as.data.frame(df.decompose)

df.decompose <- cbind(df, df.decompose)

data <- as.data.frame(tidy::pivot_longer(df.decompose,
                                         cols = -time,
                                         names_to = "component",
                                         values_to = "value",
                                         values_drop_na = TRUE)
)
data$component <- as.factor(data$component)
data$component <- factor(data$component, c("value",
                                             "trend",
                                             "seasonal",
                                             "remainder"))

# prepare data for plot

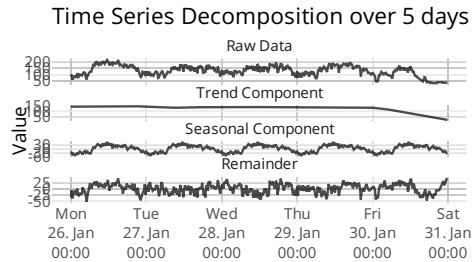
componentTitles = c("Raw Data", "Trend Component", "Seasonal Component", "Remainder")

data <- data %>%
  mutate(component = recode(component,
                            value = componentTitles[1],
                            trend = componentTitles[2],
                            seasonal = componentTitles[3],
                            remainder = componentTitles[4]),
         value = round(data$value, digits = 1)) %>%
  rename(Value = value,
         Time = time)

p <- ggplot(data) +
  geom_path(aes(x = Time,
                y = Value
               ),
            color = "black",
            alpha = 0.7) +
  facet_wrap(~component, ncol = 1, scales = "free_y") +
  scale_x_datetime(date_breaks = "days" , date_labels = "%a\n%d. %b\n%H:%M") +
  theme_minimal() +
  theme(panel.spacing = unit(1, "lines"),
        legend.position = "none") +
  labs(x = "") +
  ggtitle("Time Series Decomposition over 5 days")

ggsave(p)

```



6.6.4 Discussion

- Trend The trend of a time series refers to the general direction in which the time series is moving. Time series can have a positive or a negative trend, but can also have no trend.
- Seasonal Pattern The seasonal component for time series data refers to its tendency to rise and fall at consistent frequencies.
- Remainder The remainder is what's left of the time series data after removing its trend, cycle, and seasonal components. It is the random fluctuation in the time series data that the above components cannot explain.

6.6.5 See Also

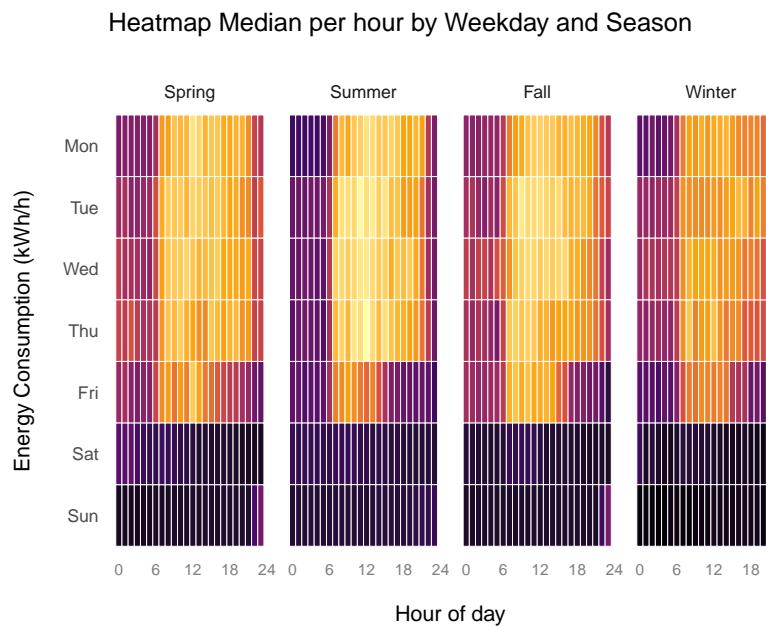
tbd

6.7 Heatmap Median-Weeks

```
library(redutils)
library(plotly)

data <- readRDS(system.file("sampleData/eboBookEleMeter.rds", package = "redutils"))
p <- plotHeatmapMedianWeeks(data, locTimeZone = "Europe/Zurich")

# show the static plot
p
```



```
# create the interactive plot (optional, uncomment line)
#ggplotly(p)
```

6.8 Heatmap Calendar

```
library(ggplot2)
library(ggTimeSeries)
library(plotly)
library(lubridate)
library(dplyr)
library(tidyquant)

data <- readRDS(system.file("sampleData/eboBookEleMeter.rds", package = "redutils"))

data <- data[-nrow(data),]
```

```
data$timestamp <- parse_date_time(data$timestamp,
                                    order = "YmdHMS",
                                    tz = "UTC")

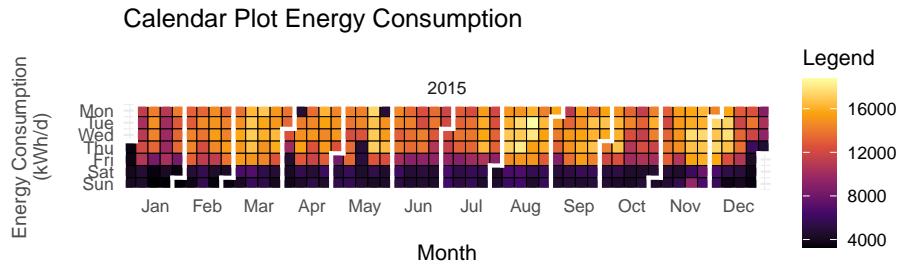
data$day <- as.Date(lubridate::floor_date(data$timestamp, "day"))

data <- data %>%
  select(-timestamp)

data.plot <- data %>%
  dplyr::group_by(day) %>%
  dplyr::mutate(calcVal = sum(value, na.rm = TRUE)) %>%
  ungroup() %>%
  select(-value) %>%
  unique()

p <- ggplot_calendar_heatmap(data.plot,
                               "day",
                               "calcVal",
                               monthBorderSize = 1,
                               monthBorderColour = "white",
                               monthBorderLineEnd = "square") +
  scale_fill_viridis_c(option = "B") +
  theme_minimal() +
  theme(axis.title.y = element_text(colour = "grey30", size = 10, face = "plain"),
        ) +
  labs(x = "\nMonth",
       y = "Energy Consumption\n(kWh/d)\n",
       fill = "Legend") +
  facet_wrap(~Year, ncol = 1) +
  ggtitle("Calendar Plot Energy Consumption\n")

p
```



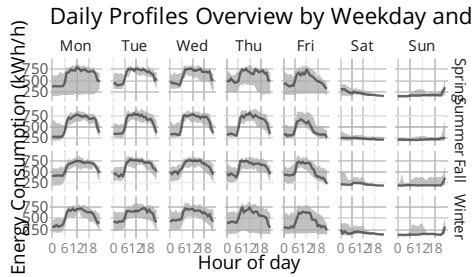
6.8.1 Discussion

Some findings:

- first two days in year minimal consumption
- 6th of April: Easter Monday
- 25th of May: Whitmonday (de: Pfingstmontag)
- More usage in August
- In November one Sunday with unusual high consumption
- On Fridays in general less consumption

6.9 Daily Profiles - Overview

```
library(ggplot2)
library(dplyr)
library(lubridate)
library(reddutils)
library(ggplot2)
library(plotly)
```

6.10 Daily Profiles - Overlaid

```
# change language to English, otherwise weekdays are in local language
Sys.setlocale("LC_TIME", "English")

## [1] "English_United States.1252"

library(plotly)
library(dplyr)
library(lubridate)

# load time series data
df <- read.csv("https://github.com/hslu-ige-laes/edar/raw/master/sampleData/eboBookEleMeter.csv",
               stringsAsFactors=FALSE,
               sep =";")

# rename column names
colnames(df) <- c("timestamp", "meterValue")

df$timestamp <- parse_date_time(df$timestamp,
                                 orders = "YmdHMS",
                                 tz = "Europe/Zurich")
df$timestamp <- force_tz(df$timestamp, tzzone = "UTC")
```

```

# uncomment to filter time range if necessary
#df <- df %>% filter(timestamp > "2015-03-01 00:00:00", timestamp < "2015-04-01 00:00:00")

# Fill missing values with NA
grid.df <- data.frame(timestamp = seq(min(df$timestamp, na.rm = TRUE),
                                         max(df$timestamp, na.rm = TRUE),
                                         by = "15 mins"))
df <- merge(df, grid.df, all = TRUE)

# convert steadily counting energy meter value from kWh to power in kW
df <- df %>%
  mutate(value = (meterValue - lag(meterValue))*4) %>%
  select(-meterValue) %>%
  na.omit()

# remove negative values which occur because of change summer/winter time
df <- df %>% filter(value >= 0)

# add metadata for later grouping and visualization purposes
df$x <- hour(df$timestamp) + minute(df$timestamp)/60 + second(df$timestamp) / 3600
df$weekday <- weekdays(df$timestamp)
df$weekday <- factor(df$weekday, c("Monday", "Tuesday", "Wednesday", "Thursday", "Friday", "Saturday", "Sunday"))
df$day <- as.Date(df$timestamp, format = "%Y-%m-%d %H:%M:%S")

df <- df %>% mutate(value = ifelse(x == 0.00, NA, df$value))

# plot graph with all time series
rangeX <- seq(0, 24, 0.25)
maxValue <- max(df$value, na.rm = TRUE)*1.05

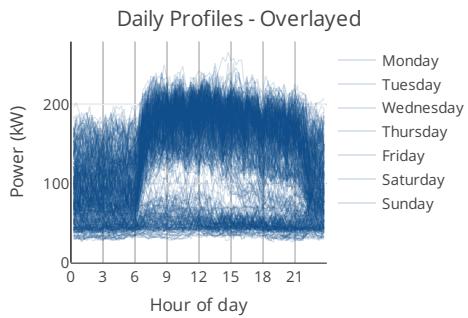
df %>%
  highlight_key(~day) %>%
  plot_ly(x=~x,
          y=~value,
          color=~weekday,
          type="scatter",
          mode="lines",
          line = list(width = 1),
          alpha = 0.15,
          colors = "dodgerblue4",
          text = ~day,
          hovertemplate = paste("Time: ", format(df$timestamp, "%H:%M"),
                                "<br>Date: ", format(df$timestamp, "%Y-%m-%d"),
                                "<br>Value: %{y:.0f}")) %>%
  # workaround with add_trace when having fixed y axis when selecting a dedicated day
  add_trace(x = 0, y = 0, type = "scatter", showlegend = FALSE, opacity=0) %>%
  add_trace(x = 24, y = maxValue, type = "scatter", showlegend = FALSE, opacity=0) %>%
  layout(title = "Daily Profiles - Overlaid",
         showlegend = TRUE,
         xaxis = list(
           title = "Hour of day",
           range = rangeX,
           tickvals = list(0, 3, 6, 9, 12, 15, 18, 21),
           showline=TRUE
         ),
         yaxis = list(
           title = "Power (kW)",

```

```

        range = c(0, maxValue)
    )
) %>%
highlight(on = "plotly_hover",
off = "plotly_doubleclick",
color = "orange",
opacityDim = 1.0,
selected = attrs_selected(showlegend = FALSE)) %>% # this hides elements in the legend
plotly::config(modeBarButtons = list(list("toImage")), displaylogo = FALSE)

```



Next we want to create an overview with the mean values for each 15 minute slot per day.

Append the following code at the end of your script:

```

# Calculate Mean value for all 15 minutes for each weekday
df2 <- df %>% group_by(weekday, x) %>% mutate(dayTimeMean = mean(value)) %>% ungroup()

# shrink data frame
df2 <- df2 %>%
  select(x, weekday, timestamp, dayTimeMean) %>%
  unique() %>%
  na.omit() %>%
  arrange(weekday, x)

# plot graph with mean values
maxValMean <- max(df2$dayTimeMean, na.rm = TRUE)*1.05

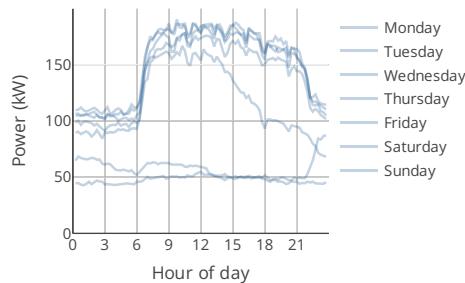
```

```

df2 %>%
  highlight_key(~weekday) %>%
  plot_ly(x=~x,
    y=~dayTimeMean,
    color=~weekday,
    type="scatter",
    mode="lines",
    alpha = 0.25,
    colors = "dodgerblue4",
    text = ~weekday,
    hovertemplate = paste("Time: ", format(df2$timestamp, "%H:%M"),
                          "<br>Mean: %{y:.0f}")) %>%
  # workaround with add_trace to have fixed y axis when selecting a dedicated day
  add_trace(x = 0, y = 0, type = "scatter", showlegend = FALSE, opacity=0) %>%
  add_trace(x = 24, y = maxValMean, type = "scatter", showlegend = FALSE, opacity=0) %>%
  layout(title = "Superimposed Mean Profiles of Power Consumption per 15 min",
         showlegend = TRUE,
         xaxis = list(
           title = "Hour of day",
           tickvals = list(0, 3, 6, 9, 12, 15, 18, 21)
         ),
         yaxis = list(
           title = "Power (kW)",
           range = c(0, maxValMean)
         )
  ) %>%
  highlight(on = "plotly_hover",
            off = "plotly_doubleclick",
            color = "orange",
            opacityDim = 0.7,
            selected = attrs_selected(showlegend = FALSE)) %>% # this hides elements in the legend
  plotly::config(modeBarButtons = list(list("toImage")), displaylogo = FALSE)

```

imposed Mean Profiles of Power Consumption per



6.11 Daily Profiles - Decompose

```
# change language to English, otherwise weekdays are in local language
Sys.setlocale("LC_TIME", "English")

## [1] "English_United States.1252"

library(plotly)
library(dplyr)
library(lubridate)

# load time series data
df <- read.csv("https://github.com/hslu-ige-laes/edar/raw/master/sampleData/eboBookEleMeter.csv",
               stringsAsFactors=FALSE,
               sep =";")

# rename column names
colnames(df) <- c("timestamp", "meterValue")

df$timestamp <- parse_date_time(df$timestamp,
                                 orders = "YmdHMS",
                                 tz = "Europe/Zurich")
df$timestamp <- force_tz(df$timestamp, tzzone = "UTC")
```

```

# uncomment to filter time range if necessary
#df <- df %>% filter(timestamp > "2015-03-01 00:00:00", timestamp < "2015-04-01 00:00:00")

# Fill missing values with NA
grid.df <- data.frame(timestamp = seq(min(df$timestamp, na.rm = TRUE),
                                         max(df$timestamp, na.rm = TRUE),
                                         by = "15 mins"))
df <- merge(df, grid.df, all = TRUE)

# convert steadily counting energy meter value from kWh to power in kW
df <- df %>%
  mutate(value = (meterValue - lag(meterValue))*4) %>%
  select(-meterValue) %>%
  na.omit()

# remove negative values which occur because of change summer/winter time
df <- df %>% filter(value >= 0)

# add metadata for later grouping and visualization purposes
df$x <- hour(df$timestamp) + minute(df$timestamp)/60 + second(df$timestamp) / 3600
df$weekday <- weekdays(df$timestamp)
df$weekday <- factor(df$weekday, c("Monday", "Tuesday", "Wednesday", "Thursday", "Friday", "Saturday", "Sunday"))

df <- df %>% mutate(value = ifelse(x == 0.00, NA, df$value))

# Calculate Mean value for all 15 minutes for each weekday
df <- df %>% group_by(weekday, x) %>% mutate(dayTimeMean = mean(value)) %>% ungroup()

# shrink data frame
df <- df %>%
  select(x, weekday, timestamp, dayTimeMean) %>%
  unique() %>%
  na.omit() %>%
  arrange(weekday, x)

# plot graph with mean values
maxValMean <- max(df$dayTimeMean, na.rm = TRUE)*1.05

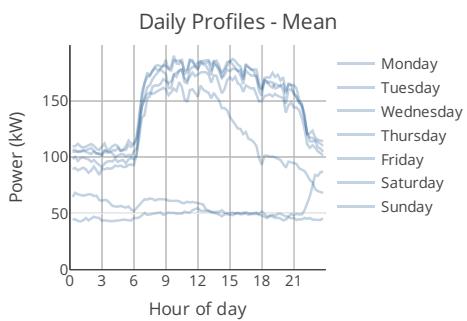
df %>%
  highlight_key(~weekday) %>%
  plot_ly(x=~x,
          y=~dayTimeMean,
          color=~weekday,
          type="scatter",
          mode="lines",
          alpha = 0.25,
          colors = "dodgerblue4",
          text = ~weekday,
          hovertemplate = paste("Time: ", format(df$timestamp, "%H:%M"),
                                "<br>Mean: %{y:.0f}")) %>%
  # workaround with add_trace to have fixed y axis when selecting a dedicated day
  add_trace(x = 0, y = 0, type = "scatter", showlegend = FALSE, opacity=0) %>%
  add_trace(x = 24, y = maxValMean, type = "scatter", showlegend = FALSE, opacity=0) %>%
  layout(title = "Daily Profiles - Mean",
         showlegend = TRUE,
         xaxis = list(
           title = "Hour of day",

```

```

        tickvals = list(0, 3, 6, 9, 12, 15, 18, 21)
    ),
    yaxis = list(
        title = "Power (kW)",
        range = c(0, maxValMean)
    )
) %>%
highlight(on = "plotly_hover",
           off = "plotly_doubleclick",
           color = "orange",
           opacityDim = 0.7,
           selected = attrs_selected(showlegend = FALSE)) %>% # this hides elements in the legend
plotly::config(modeBarButtons = list(list("toImage")), displaylogo = FALSE)

```



6.12 Daily Profiles - Decomposed

```

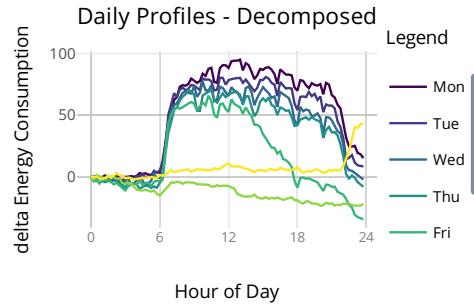
library(plotly)
library(redutils)

data <- readRDS(system.file("sampleData/eboBookEleMeter.rds", package = "redutils"))

p <- plotDailyProfilesDecomposed(data, locTimeZone = "Europe/Zurich")

ggplotly(p)

```



6.13 Building Energy Signature

6.13.1 Task

You want to create a scatter plot with

- the daily mean outside temperature on the x-axis
- the daily energy consumption on the y-axis
- points colored according to season

6.13.2 Basis

- Two separate csv files with time series data from the outside temperature and the energy data with unaligned time intervals
- Energy consumption time series from a energy meter with steadily increasing meter values

6.13.3 Solution

After reading in the two time series the data has to get aggregated per day and then merged. Note that during the aggregation of the energy data you have to calculate the daily consumption from the steadily increasing meter values as well.

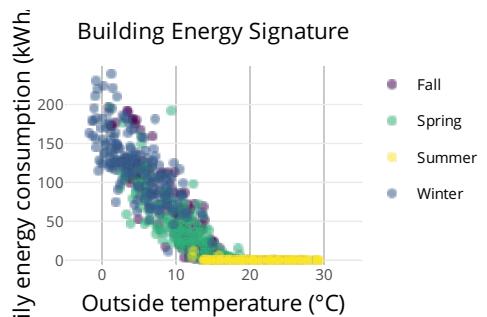
Create a new script, copy/paste the following code and run it:

```
library(ggplot2)
library(plotly)
library(dplyr)
library(reddutils)
library(lubridate)
# load time series data and aggregate daily mean values
dfOutsideTemp <- read.csv("https://github.com/hslu-ige-laes/edar/raw/master/sampleData/centralOutsideTemp.csv",
                           stringsAsFactors=FALSE,
                           sep =";")
dfOutsideTemp$time <- parse_date_time(dfOutsideTemp$time,
                                         order = "YmdHMS",
                                         tz = "Europe/Zurich")
dfOutsideTemp$day <- as.Date(cut(dfOutsideTemp$time, breaks = "day"))
dfOutsideTemp <- dfOutsideTemp %>%
  group_by(day) %>%
  mutate(tempMean = mean(centralOutsideTemp)) %>%
  ungroup()
dfOutsideTemp <- dfOutsideTemp %>%
  select(day, tempMean) %>%
  unique() %>%
  na.omit()
dfHeatEnergy <- read.csv("https://github.com/hslu-ige-laes/edar/raw/master/sampleData/centralHeating.csv",
                         stringsAsFactors=FALSE,
                         sep =";")
dfHeatEnergy <- dfHeatEnergy %>%
  select(time, energyHeatingMeter) %>%
  na.omit()
dfHeatEnergy$time <- parse_date_time(dfHeatEnergy$time,
                                       orders = "YmdHMS",
                                       tz = "Europe/Zurich")
dfHeatEnergy$day <- as.Date(cut(dfHeatEnergy$time, breaks = "day"))
dfHeatEnergy <- dfHeatEnergy %>%
  group_by(day) %>%
  mutate(energyMax = max(energyHeatingMeter)) %>%
  ungroup()
dfHeatEnergy <- dfHeatEnergy %>%
  select(day, energyMax) %>%
  unique() %>%
  na.omit()
dfHeatEnergy <- dfHeatEnergy %>%
  mutate(energyCons = energyMax - lag(energyMax)) %>%
  select(-energyMax) %>%
  na.omit()
# merge the data in a tidy format
df <- merge(dfOutsideTemp, dfHeatEnergy, by = "day")
# calculate season
df <- df %>% mutate(season = reddutils::getSeason(df$day))
```

```

# static chart with ggplot
p <- ggplot2::ggplot(df) +
  ggplot2::geom_point(aes(x = tempMean,
                           y = energyCons,
                           color = season,
                           alpha = 0.1,
                           text = paste("</br>Date: ", as.Date(df$day),
                                       "</br>Temp: ", round(df$tempMean, digits = 1), "\u00b0C",
                                       "</br>Energy: ", round(df$energyCons, digits = 0), "kWh/d",
                                       "</br>Season: ", df$season)))
  ) +
  scale_color_manual(values=c("#440154", "#2db27d", "#fde725", "#365c8d")) +
  ggtitle("Building Energy Signature") +
  theme_minimal() +
  theme(
    legend.position="none",
    plot.title = element_text(hjust = 0.5)
  )
# interactive chart
plotly::ggplotly(p, tooltip = c("text")) %>%
  layout(xaxis = list(title = "Outside temperature (\u00b0C)",
                       range = c(min(-5,min(df$tempMean)), max(35,max(df$tempMean))), zeroline = F),
         yaxis = list(title = "Daily energy consumption (kWh/d)",
                     range = c(-5, max(df$energyCons) + 10)),
         showlegend = TRUE
  ) %>%
plotly::config(displayModeBar = FALSE, displaylogo = FALSE)

```



6.14 Mollier hx Diagram

6.14.1 Task

You want to plot a mollier h-x diagram with

- scatter plot of temperature- and humidity sensor data (mean values per day)
- points colored according to season
- comfort zone

6.14.2 Basis

- A csv file with time series from multiple temperature and humidity sensors in °C and %rH

6.14.3 Solution

The sensor data is not in a constant intervall and not yet aggregated. So after reading in the time series the data has to get filtered and aggregated per day.

Finally use the plot function `mollierHxDiagram` from the `reduutils` package (R Energy Data Utilities). If you have not yet installed this package, proceed as follows:

```
install.packages("devtools")
library(devtools)
install_github("hslu-ige-laes/reduutils")
```

Create a new script, copy/paste the following code and run it:

```
library(reduutils)
library(dplyr)
library(lubridate)

# read and print data
data <- read.csv("https://github.com/hslu-ige-laes/edar/raw/master/sampleData/flatTempHum.csv",
                 stringsAsFactors=FALSE,
                 sep =";")

# select temperature and humidity and remove empty cells
data <- data %>% select(time, FlatA_Temp, FlatA_Hum) %>% na.omit()

# create column with day for later grouping
data$time <- parse_date_time(data$time, "YmdHMS", tz = "Europe/Zurich")
data$day <- as.Date(cut(data$time, breaks = "day"))
```

```
# calculate daily mean of temperature and humidity
data <- data %>%
  group_by(day) %>%
  mutate(tempMean = mean(as.numeric(FlatA_Temp)),
        humMean = mean(as.numeric(FlatA_Hum)))
  ) %>%
ungroup()

# shrink down to daily values and remove rows with empty values
data <- data %>% select(day, tempMean, humMean) %>% unique() %>% na.omit()

# plot mollier hx diagram
plotMollierHx(data)
```

6.15 SIA 180 Thermal Comfort

6.15.1 Task

You want to plot a diagram like the one from the SIA 180:2014 which shows

- scatter plot of indoor- and outdoor temperature sensor data (indoor mean of day, outdoor mean of last 48 hours)
- points colored according to season

- different comfort lines

6.15.2 Basis

- A csv file with time series from multiple temperature and humidity sensors in °C
- A csv file with the outdoor temperature

6.15.3 Solution

The sensor data is not in a constant intervall and not yet aggregated. So after reading in the time series the data has to get filtered, aggregated per day and merged.

Create a new script, copy/paste the following code and run it:

```
library(reddutils)
library(dplyr)
library(lubridate)
library(zoo)
library(plotly)

# load time series data and aggregate mean values
dfTemp0a <- read.csv("https://github.com/hslu-ige-laes/edar/raw/master/sampleData/centralOutsideTemp.csv",
                      stringsAsFactors=FALSE,
                      sep =";")

dfTemp0a$time <- parse_date_time(dfTemp0a$time,
                                    order = "YmdHMS",
                                    tz = "UTC")

dfTemp0a$hour <- cut(dfTemp0a$time, breaks = "hour")

dfTemp0a <- dfTemp0a %>%
  group_by(hour) %>%
  mutate(tempMean = mean(centralOutsideTemp)) %>%
  ungroup() %>%
  select(time, tempMean) %>%
  unique()

# Fill missing values with NA
grid.df <- data.frame(time = seq(min(dfTemp0a$time, na.rm = TRUE),
                                   max(dfTemp0a$time, na.rm = TRUE),
                                   by = "hour"))
dfTemp0a <- merge(dfTemp0a, grid.df, all = TRUE)

dfTemp0a <- dfTemp0a %>%
  mutate(temp0a = rollmean(tempMean, 48, fill = NA, align = "right"))

dfTemp0a <- dfTemp0a %>%
  select(time, temp0a) %>%
```

```

unique() %>%
na.omit()

dfTempR <- read.csv("https://github.com/hslu-ige-laes/edar/raw/master/sampleData/flatTempHum.csv",
                     stringsAsFactors=FALSE,
                     sep =";")

dfTempR$time <- parse_date_time(dfTempR$time,
                                 order = "YmdHMS",
                                 tz = "UTC")

# select temperature and humidity and remove empty cells
dfTempR <- dfTempR %>% select(time, FlatA_Temp) %>% na.omit()

dfTempR$hour <- cut(dfTempR$time, breaks = "hour")

dfTempR <- dfTempR %>%
  group_by(hour) %>%
  mutate(tempR = mean(FlatA_Temp)) %>%
  ungroup() %>%
  select(time, tempR) %>%
  unique()

# Fill missing values with NA
grid.df <- data.frame(time = seq(min(dfTempR$time, na.rm = TRUE),
                                   max(dfTempR$time, na.rm = TRUE),
                                   by = "hour"))
dfTempR <- merge(dfTempR, grid.df, all = TRUE)

data <- merge(dfTempR, dfTemp0a, all = TRUE) %>% unique() %>% na.omit()

data$season <- reldutils::getSeason(data$time)

# plot diagram

# axis properties
minx <- floor(min(0, min(data$temp0a)))
maxx <- ceiling(max(28, max(data$temp0a)))

miny <- floor(min(21.0,min(data$tempR))-1)
maxy <- ceiling(max(32.0,max(data$tempR))+1

# line setpoint heat
df.heatSp <- data.frame(temp0a = c(minx, 19, 23.5, maxx), tempR = c(20.5, 20.5, 22, 22))

# line setpoint cool according to SIA 180:2014 Fig. 4
df.coolSp1 <- data.frame(temp0a = c(minx, 12, 17.5, maxx),tempR = c(24.5, 24.5, 26.5, 26.5))

# line setpoint cool according to SIA 180:2014 Fig. 3
df.coolSp2 <- data.frame(temp0a = c(minx, 10, maxx),tempR = c(25, 25, 0.33 * maxx + 21.8))

data %>%
  plot_ly(showlegend = TRUE) %>%
  add_lines(data = df.coolSp2,
            x = ~temp0a,
            y = ~tempR,

```

```

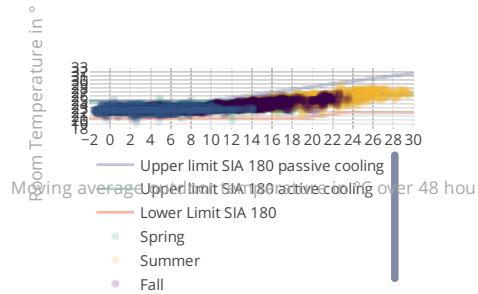
name = "Upper limit SIA 180 passive cooling",
opacity = 0.7,
color = "#FDE725FF",
hoverinfo = "text",
text = ~ paste("Upper limit SIA 180 passive cooling",
              "<br />TempR: ", sprintf("%.1f \u00B0C", tempR),
              "<br />Temp0a: ", sprintf("%.1f \u00B0C", temp0a)
            )
) %>%
add_lines(data = df.coolSp1,
          x = ~temp0a,
          y = ~tempR,
          name = "Upper limit SIA 180 active cooling",
          opacity = 0.7,
          color = "#1E9B8AFF",
          hoverinfo = "text",
          text = ~ paste("Upper limit SIA 180 active cooling",
                        "<br />TempR: ", sprintf("%.1f \u00B0C", tempR),
                        "<br />Temp0a: ", sprintf("%.1f \u00B0C", temp0a)
                      )
            ) %>%
add_lines(data = df.heatSp,
          x = ~temp0a,
          y = ~tempR,
          name = "Lower Limit SIA 180",
          opacity = 0.7,
          color = "#440154FF",
          hoverinfo = "text",
          text = ~ paste("Lower Limit SIA 180",
                        "<br />TempR: ", sprintf("%.1f \u00B0C", tempR),
                        "<br />Temp0a: ", sprintf("%.1f \u00B0C", temp0a)
                      )
            ) %>%
add_markers(data = data %>% filter(season == "Spring"),
            x = ~temp0a,
            y = ~tempR,
            name = "Spring",
            marker = list(color = "#2db27d", opacity = 0.1),
            hoverinfo = "text",
            text = ~ paste("TempR: ", sprintf("%.1f \u00B0C", tempR),
                          "<br />Temp0a: ", sprintf("%.1f \u00B0C", temp0a),
                          "<br />Date:      ", time,
                          "<br />Season:   ", season
            )
)
) %>%
add_markers(data = data %>% filter(season == "Summer"),
            x = ~temp0a,
            y = ~tempR,
            name = "Summer",
            marker = list(color = "#febc2b", opacity = 0.1),
            hoverinfo = "text",
            text = ~ paste("TempR:   ", sprintf("%.1f \u00B0C", tempR),
                          "<br />Temp0a: ", sprintf("%.1f \u00B0C", temp0a),
                          "<br />Date:    ", time,
                          "<br />Season:  ", season
            )
)
) %>%
add_markers(data = data %>% filter(season == "Fall"),
            x = ~temp0a,

```

```

y = ~tempR,
name = "Fall",
marker = list(color = "#440154", opacity = 0.1),
hoverinfo = "text",
text = ~ paste("TempR: ", sprintf("%.1f \u00b0C", tempR),
              "<br />Temp0a: ", sprintf("%.1f \u00b0C", temp0a),
              "<br />Date:      ", time,
              "<br />Season:   ", season
)
) %>%
add_markers(data = data %>% filter(season == "Winter"),
            x = ~temp0a,
            y = ~tempR,
            name = "Winter",
            marker = list(color = "#365c8d", opacity = 0.1),
            hoverinfo = "text",
            text = ~ paste("TempR: ", sprintf("%.1f \u00b0C", tempR),
                          "<br />Temp0a: ", sprintf("%.1f \u00b0C", temp0a),
                          "<br />Date:      ", time,
                          "<br />Season:   ", season
)
) %>%
layout(
  xaxis = list(title = "Moving average outdoor temperature in \u00b0C over 48 hours",
               range = c(minx, maxx),
               zeroline = FALSE,
               tick0 = minx,
               dtick = 2,
               titlefont = list(size = 14, color = "darkgrey")),
  yaxis = list(title = "Room Temperature in \u00b0C",
               range = c(miny, maxy),
               dtick = 1,
               titlefont = list(size = 14, color = "darkgrey")),
  hoverlabel = list(align = "left"),
  margin = list(l = 80, t = 50, r = 50, b = 10),
  legend = list(orientation = 'h',
                x = 0.0,
                y = -0.3)
) %>%
plotly::config(modeBarButtons = list(list("toImage")),
               displaylogo = FALSE,
               toImageButtonOptions = list(
                 format = "svg"
               )
)
)

```



6.15.4 Discussion

tbd

6.15.5 See Also

tbd

6.16 Electricity Household

6.16.1 Task

You want to plot an electricity consumption diagram which shows

- upper plot with daily energy consumption in kWh/day
- lower plot with standby-losses in Watts

Additionaly we would like to see the consumption of an average Swiss household.

6.16.2 Basis

- A csv file with time series of an electric meter in 15 minute interval.

6.16.3 Solution

Create a new script, copy/paste the following code and run it:

```
library(redutils)
library(dplyr)
library(lubridate)
library(zoo)
library(plotly)

# load time series data and aggregate mean values
df <- read.csv("https://github.com/hslu-ige-laes/edar/raw/master/sampleData/flatElectricity.csv",
               stringsAsFactors=FALSE,
               sep =";")

df$time <- parse_date_time(df$time,
                            order = "YmdHMS",
                            tz = "UTC")

# select room
df <- df %>% select(time, FlatC_Ele)

# rename columns
colnames(df) <- c("timestamp", "meterValue")

# filter timerange
df <- df %>% filter(timestamp > "2019-07-01")

# Fill missing values with NA
grid.df <- data.frame(timestamp = seq(min(df$timestamp, na.rm = TRUE),
                                         max(df$timestamp, na.rm = TRUE),
                                         by = "15 mins"))
df <- merge(df, grid.df, all = TRUE)

# convert steadily counting energy meter value from kWh to power in kW
df <- df %>%
  mutate(value = (meterValue - lag(meterValue))) %>%
  select(-meterValue)

# remove negative values which occur because of change summer/winter time
df <- df %>% filter(value >= 0)

# determine date related parameters for later filtering
df$day <- as.Date(df$time, tz = "UTC")
df$week <- lubridate::week(df$time)
df$month <- lubridate::month(df$time)
df$year <- lubridate::year(df$time)

# data cleansing
# tag NA
```

```

df <- df %>% mutate(deleteNA = ifelse(is.na(value),1,0))

# tag values below 0 and higher than 9.2 kW
df <- df %>% mutate(deleteHiLoVal = ifelse(value > 9.2,1, ifelse(value < 0,1,0)))
# Assumption max. fuse 40 ampere (higher fuses for single family houses)
# this results in continuous power 9.2 kW
# this results in an hourly consumption of 9.2kWh
# over 24h = approx. 221 kWh max. consumption per day

# tag whole days which have one or more values to delete, keep only whole valid days
df <- df %>%
  group_by(day) %>%
  mutate(delete = sum(deleteNA, na.rm = TRUE) + sum(deleteHiLoVal, na.rm = TRUE))

df <- df %>% ungroup()

# delete full days with invalid data
df <- df %>%
  filter(delete == 0) %>%
  select(-deleteNA, -deleteHiLoVal, -delete)

# determine season for later filtering
df <- df %>% mutate(season = redutils::getSeason(timestamp))

# calculate sum and min per day
df <- df %>% dplyr::group_by(day) %>% dplyr::mutate(sum = sum(value))
df <- df %>% dplyr::group_by(day) %>% dplyr::mutate(min = min(value)*1000*4)
df <- df %>% ungroup()

df <- df %>% dplyr::select(day, sum, min, season) %>% unique()

df <- df %>% dplyr::mutate(ravgUsage = zoo::rollmean(x=sum, 7, fill = NA))
df <- df %>% dplyr::mutate(rminStandby = -1 * zoo::rollmaxr(x = -1 * min, 7, fill = NA))

typEleConsVal <- redutils::getTypEleConsHousehold(occupants = 2, rooms = 3.5, bldgType = "multi", laundry = 0)

# Plot
main = "Electricity consumption private household"
minY <- 0
maxYUsage <- max(df %>% select(sum), na.rm=TRUE)
maxYUsage <- max(maxYUsage, typEleConsVal/365)
maxYStandby <- max(max(df %>% select(min), na.rm=TRUE), 0.25*maxYUsage/24*1000)
minX <- min(df$day)
maxX <- max(df$day)
averageUsage <- mean(df$sum, na.rm=TRUE)
averageStandby <- mean(df$rminStandby, na.rm=TRUE)
shareStandby <- nrow(df %>% select(sum) %>% na.omit()) * averageStandby * 24 / (1000 * sum(df$sum, na.rm=TRUE))

# legend
l <- list(
  orientation = "h",
  tracegroupgap = "20",
  font = list(size = 8),
  xanchor = "center",
  x = 0.5,
  itemclick = FALSE
)

```

```

)
fig1 <- df %>%
  plot_ly(x = ~day, showlegend = TRUE) %>%
  add_trace(data = df %>% filter(season == "Spring"),
             type = "bar",
             y = ~sum,
             name = "Spring",
             legendgroup = "group1",
             marker = list(color = "#2db27d", opacity = 0.2),
             hoverinfo = "text",
             text = ~ paste("<br />daily usage:           ", sprintf("%.1f kWh/d", sum),
                           "<br />rolling average:      ", sprintf("%.1f kWh/d", ravgUsage),
                           "<br />Average vis. points: ", sprintf("%.1f kWh/d", averageUsage),
                           "<br />Date:                  ", day,
                           "<br />Season:                ", season
             )
  ) %>%
  add_trace(data = df %>% filter(season == "Summer"),
             type = "bar",
             y = ~sum,
             name = "Summer",
             legendgroup = "group1",
             marker = list(color = "#febc2b", opacity = 0.2),
             hoverinfo = "text",
             text = ~ paste("<br />rolling average:      ", sprintf("%.1f kWh/d", ravgUsage),
                           "<br />Average vis. points: ", sprintf("%.1f kWh/d", averageUsage),
                           "<br />Date:                  ", day,
                           "<br />Season:                ", season
             )
  ) %>%
  add_trace(data = df %>% filter(season == "Fall"),
             type = "bar",
             y = ~sum,
             name = "Fall",
             legendgroup = "group1",
             marker = list(color = "#440154", opacity = 0.2),
             hoverinfo = "text",
             text = ~ paste("<br />rolling average:      ", sprintf("%.1f kWh/d", ravgUsage),
                           "<br />Average vis. points: ", sprintf("%.1f kWh/d", averageUsage),
                           "<br />Date:                  ", day,
                           "<br />Season:                ", season
             )
  ) %>%
  add_trace(data = df %>% filter(season == "Winter"),
             type = "bar",
             y = ~sum,
             name = "Winter",
             legendgroup = "group1",
             marker = list(color = "#365c8d", opacity = 0.2),
             hoverinfo = "text",
             text = ~ paste("<br />rolling average:      ", sprintf("%.1f kWh/d", ravgUsage),
                           "<br />Average vis. points: ", sprintf("%.1f kWh/d", averageUsage),
                           "<br />Date:                  ", day,
                           "<br />Season:                ", season
             )
  )
)
```

```

add_trace(data = df,
          type = "scatter",
          mode = "markers",
          y = ~ravgUsage,
          name = "Average Cons. (7 days)",
          legendgroup = "group2",
          marker = list(color = "orange", opacity = 0.4, symbol = "circle"),
          hoverinfo = "text",
          text = ~ paste("<br />rolling average:      ", sprintf("%.1f kWh/d", ravgUsage),
                        "<br />Average vis. points: ", sprintf("%.1f kWh/d", averageUsage),
                        "<br />Date:                  ", day,
                        "<br />Season:                ", season
                      )
        )
) %>%
add_segments(x = ~minX,
             xend = ~maxX,
             y = ~averageUsage,
             yend = ~averageUsage,
             name = "Average Cons. Total",
             legendgroup = "group2",
             line = list(color = "orange", opacity = 1.0, dash = "dot"),
             hoverinfo = "text",
             text = ~ paste("<br />rolling average:      ", sprintf("%.1f kWh/d", ravgUsage),
                           "<br />Average vis. points: ", sprintf("%.1f kWh/d", averageUsage),
                           "<br />Date:                  ", day,
                           "<br />Season:                ", season
                         )
           )
) %>%
add_segments(x = ~minX,
             xend = ~maxX,
             y = ~averageStandby*24/1000,
             yend = ~averageStandby*24/1000,
             name = "Average Standby Total",
             legendgroup = "group3",
             showlegend = FALSE,
             line = list(color = "black", opacity = 1.0, dash = "dot"),
             hoverinfo = "text",
             text = ~ paste("<br />Average standby power:    ", sprintf("%.Of W", averageStandby),
                           "<br />equals to daily energy: ", sprintf("%.1f kWh", averageStandby*24/1000),
                           "<br />Standby percent of total cons.: ", sprintf("%.Of %%", shareStandby)
                         )
           )
) %>%
add_segments(x = ~minX,
             xend = ~maxX,
             y = ~typEleConsVal,
             yend = ~typEleConsVal,
             name = "typical household",
             legendgroup = "group4",
             line = list(color = "#481567FF", opacity = 1.0, dash = "dot"),
             hoverinfo = "text",
             text = ~ paste("<br />typical household:      ", sprintf("%.Of kWh/year", typEleConsVal),
                           "<br />equals to daily energy: ", sprintf("%.1f kWh/day", typEleConsVal),
                           "<br />consumption of current flat: ", sprintf("%.1f kWh/day", averageUsage)
                         )
           )
) %>%
add_annotations(
  x = minX,

```

```

y = typEleConsVal,
text = paste0("typical comparable household ", sprintf("%.1f kWh/d", typEleConsVal)),
xref = "x",
yref = "y",
showarrow = TRUE,
arrowhead = 7,
ax = 100,
ay = -20,
font = list(color = "#481567FF")
) %>%
add_annotations(
  x = maxX,
  y = averageUsage,
  text = paste0("Average consumption ", sprintf("%.1f kWh/d", averageUsage)),
  xref = "x",
  yref = "y",
  showarrow = TRUE,
  arrowhead = 7,
  ax = -100,
  ay = -60,
  font = list(color = "orange")
) %>%
add_annotations(
  x = maxX,
  y = averageStandby*24/1000,
  text = paste0(sprintf("%.1f %%", shareStandby), " of the consumption are standby-losses"),
  xref = "x",
  yref = "y",
  showarrow = TRUE,
  arrowhead = 7,
  ax = -160,
  ay = -15,
  font = list(color = "black")
) %>%
layout(
  title = main,
  xaxis = list(
    title = ""
  ),
  yaxis = list(title = "Consumption<br>(kWh/d)",
    range = c(minY, maxYUsage),
    titlefont = list(size = 14, color = "darkgrey")),
  hoverlabel = list(align = "left"),
  margin = list(l = 80, t = 50, r = 50, b = 10),
  legend = 1
)

fig2 <- df %>%
  plot_ly(x = ~day, showlegend = TRUE) %>%
  add_trace(data = df,
            type = "bar",
            y = ~min,
            name = "Daily standby-losses",
            legendgroup = "group3",
            marker = list(color = "darkgrey", opacity = 0.2),
            hoverinfo = "text",
            text = ~ paste("<br />daily standby:           ", sprintf("%.0f W", min),

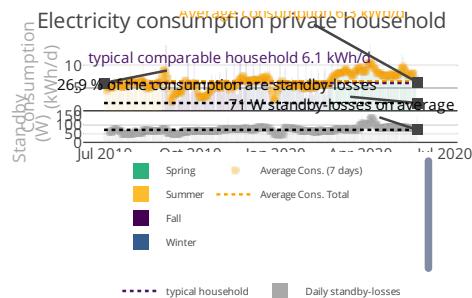
```

```

        "<br />rolling average:      ", sprintf("%.0f W", rminStandby),
        "<br />Average vis. points: ", sprintf("%.0f W", averageStandby),
        "<br />Date:                  ", day,
        "<br />Season:                ", season
    )
)
) %>%
add_trace(data = df,
           type = "scatter",
           mode = "markers",
           y = ~rminStandby,
           name = "Average Standby (7 days)",
           legendgroup = "group3",
           marker = list(color = "darkgrey", opacity = 0.5, symbol = "circle"),
           hoverinfo = "text",
           text = ~ paste("<br />daily standby:      ", sprintf("%.0f W", min),
                         "<br />rolling average:      ", sprintf("%.0f W", rminStandby),
                         "<br />Average vis. points: ", sprintf("%.0f W", averageStandby),
                         "<br />Date:                  ", day,
                         "<br />Season:                ", season
           )
)
) %>%
add_segments(x = ~minX,
              xend = ~maxX,
              y = ~averageStandby,
              yend = ~averageStandby,
              name = "Average Standby Total",
              legendgroup = "group3",
              line = list(color = "black", opacity = 1.0, dash = "dot"),
              hoverinfo = "text",
              text = ~ paste("<br />Average standby power:      ", sprintf("%.0f W", averageStandby),
                            "<br />equals to daily energy:      ", sprintf("%.1f kWh", averageStandby),
                            "<br />Standby percent of total cons.: ", sprintf("%.0f %%", shareStandby)
              )
)
) %>%
add_annotations(
  x = maxX,
  y = averageStandby,
  text = paste0(sprintf("%.0f W", averageStandby), " standby-losses on average"),
  xref = "x",
  yref = "y",
  showarrow = TRUE,
  arrowhead = 7,
  ax = -60,
  ay = -20,
  font = list(color = "black")
)
) %>%
layout(
  xaxis = list(
    title = ""
  ),
  yaxis = list(title = " Standby<br>(W)",
               range = c(minY, maxYStandby),
               titlefont = list(size = 14, color = "darkgrey"),
               legend = list(orientation = 'h')),
  legend = 1
)

```

```
# calculate ratio which is visual representative for comparison
# ratio <- 1/maxYUsage * maxYStandby * 24 / 1000
ratio <- 0.3
fig <- subplot(fig1, fig2, nrows = 2, shareX = TRUE, heights = c(1-ratio, ratio), titleY = TRUE) %>%
  plotly::config(modeBarButtons = list(list("toImage")),
                 displaylogo = FALSE,
                 toImageButtonOptions = list(
                   format = "svg"
                 )
  )
fig
```



6.16.4 Discussion

tbd

6.16.5 See Also

tbd

6.17 Room Temperature Reduction

6.17.1 Task

As part of an energy optimization, you lower the room temperatures in a room and would now like to show the reduction effect using the time series of the room temperature sensor. In the example below you make two optimizations at different dates.

You want to create a time series plot with

- the daily median, min and max value
- the overall median of each period
- the desired setpoint

6.17.2 Basis

- Time series data from e.g. a temperature sensor with unaligned time intervals

6.17.3 Solution

```
library(dplyr)
library(lubridate)
library(dygraphs)
library(xts)
library(redutils)
library(RColorBrewer)

# Settings
tempSetpoint = 22.0

startDate = "2018-11-01"
endDate = "2019-02-01"

optiDate1 = "2018-12-17"
optiLabel1 = "Optimization I"

optiDate2 = "2019-01-03"
optiLabel2 = "Optimization II"

optiDelayDays = 5

# read and print data
df <- read.csv("https://github.com/hslu-ige-laes/edar/raw/master/sampleData/flatTempHum.csv",
               stringsAsFactors=FALSE,
```

```

sep =";")

# select temperature and remove empty cells
df <- df %>% select(time, FlatA_Temp) %>% na.omit()

# create column with day for later grouping
df$time <- parse_date_time(df$time, "YmdHMS", tz = "Europe/Zurich")
df$day <- as.Date(cut(df$time, breaks = "day"))
df$day <- as.Date(as.character(df$day, "%Y-%m-%d"))

# filter time range
df <- df %>% filter(day > startDate, day < endDate)

# calculate daily median, min and max of temperature
df <- df %>%
  group_by(day) %>%
  mutate(minDay = min(as.numeric(FlatA_Temp)),
         medianDay = median(as.numeric(FlatA_Temp)),
         maxDay = max(as.numeric(FlatA_Temp)))
  ) %>%
ungroup()

# shrink down to daily values and remove rows with empty values
df <- df %>% select(day, medianDay, minDay, maxDay) %>% unique() %>% na.omit()

# calculate medians for time ranges
df <- df %>%
  mutate(period = ifelse(day >= startDate & day <= optiDate1,
                         "Baseline",
                         ifelse((day >= (as.Date(optiDate1) + optiDelayDays))
                               & (day <= optiDate2),
                               "Opti1",
                               ifelse((day >= (as.Date(optiDate2) + optiDelayDays))
                                     & (day <= endDate),
                                     "Opti2",
                                     NA)
                           )))
))

df <- df %>%
  group_by(period) %>%
  mutate(medianPeriod = ifelse(is.na(period), NA, median(medianDay))) %>%
ungroup() %>%
select(-period)

# create xts object for plotting
plotdata <- xts( x=df[,-1], order.by=df$day)

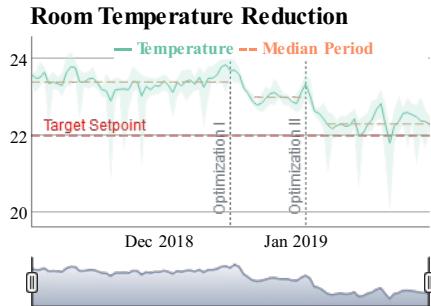
# plot graph
dygraph(plotdata, main = "Room Temperature Reduction") %>%
  dyAxis("x", drawGrid = FALSE) %>%
  dySeries(c("minDay", "medianDay", "maxDay"),
           label = "Temperature") %>%
  dySeries(c("medianPeriod"),
           label = "Median Period",
           strokePattern = "dashed") %>%
  dyOptions(colors = RColorBrewer::brewer.pal(3, "Set2")) %>%
  dyEvent(x = optiDate1,

```

```

label = optiLabel1,
labelLoc = "bottom",
color = "slategray",
strokePattern = "dotted") %>%
dyEvent(x = optiDate2,
        label = optiLabel2,
        labelLoc = "bottom",
        color = "slategray",
        strokePattern = "dotted") %>%
dyLimit(tempSetpoint,
        color = "red",
        label = "Target Setpoint") %>%
dyRangeSelector() %>%
dyLegend(show = "always")

```



6.17.4 Discussion

In this example we used the dygraph package to create the graph. This package is fast and allows to show a rangeslider on the bottom of the graph. The exact same graph but without a slider is as well possible with ggplot.

Please note that the calculation of the periodic median after optimization I and II starts delayed because it takes time until the building has cooled down.

Appendix A

Packages in R

Many functions of R are not pre-installed and must be loaded manually. R packages are similar to libraries in C, Python etc. An R package bundles useful functions, help files and data sets. You can use these functions within your own R code once you load the package.

The following chapters describe how to install, load, update and use packages.

A.1 Installing a Package

The easiest way to install an R Package is to use the RStudio tab “Packages”:

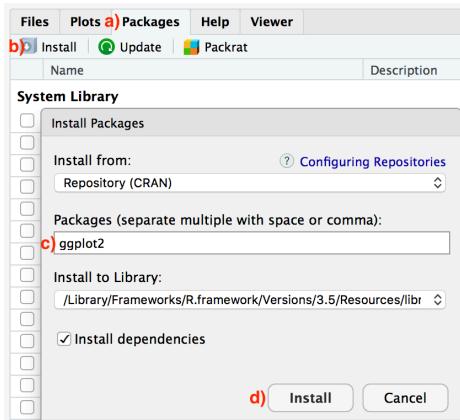


Figure A.1: Install packages via RStudio GUI

- Click on the “Packages” tab

- b) Click on “Install” next to Update
- c) Type the name of the package under “Packages, in this case type ggplot2
- d) Click “Install”

This will search for the package “ggplot” specified on a server (the so-called CRAN website). If the package exists, it will be downloaded to a library folder on your computer. Here R can access the package in future R sessions without having to reinstall it.

An other way is to use the `install.packages` function. Open R (if already opened please close all projects) and type the following at the command line:

```
install.packages("ggplot2")
```

If you want to install a package directly from github, the package “devtools” must be installed first:

```
install.packages("devtools")
library(devtools)
install_github("hslu-ige-laes/redutils")
```

A.2 Loading a Package

If you have installed a package, its functions are not yet available in your R project. To use an R package in your script, you must load it with the following command:

```
install.packages("ggplot2")
```

A.3 Upgrading Packages

R packages are often constantly updated on CRAN or GitHub, so you may want to update them once in a while with:

```
update.packages(ask = FALSE)
```