R packages around JDemetra+ - Part 1

A versatile toolbox for time series analysis

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Section 1

rjd3 ecosystem overview

JDemetra+: a library of algorithms for time series analysis

JDemetra+ a library of algorithms (written in Java) on:

- Seasonal Adjustment (Historical domain)
- Trend and cycle estimation
- Benchmarking and temporal disaggregation
- Revision Analysis
- Nowcasting

They can be accessed via Graphical user-interface (GUI) and/or R packages.

JDemetra+ is an open source software, officially recommended by Eurostat since 2015 for Seasonal Adjustment to Eurosystem members.

JDemetra + on Github

- Repository dedicated to Java algorithms and Graphical User interface (+ extensions) : https://github.com/jdemetra
- Repository dedicated to R packages: https://github.com/rjdverse

For each R package:

- README files
- Documentation of (almost) all functions in (almost) all R packages
- GitHub pages (linked in JD+ on-line documentation, https://jdemetra-new-documentation.netlify.app/)

JDemetra+ algorithms in R (1/3)

By domain of use:

- Seasonal adjustment of low frequency data
  - **{rjd3x13}** (Reg-Arima + x11 based decomposition)
  - **{rjd3tramoseats}** (Tramo+ AMB decomposition)
  - **{rjd3sts}** (Basic structural models, SA)
  - **{rjd3stl}** (SA with Local regression)
- Seasonal adjustment of high frequency data
  - **{rjd3highfreq}** (extended airline model + extended AMB decomposition)
  - **{rjd3x11plus}** (extended X11)
  - **{rjd3sts}** (basic structural models, SA)
  - **{rjd3stl}** (SA with local regression)

JDemetra+ algorithms in R (2/3)

By domain of use:

- Filtering and trend estimation
  - **{rjd3filters}**
  - **{rjd3x11plus}** (local polynomials)
- General purpose tools
  - **{rjd3toolkit}** (specifications, tests, regressors)
  - **{rjd3sts}** (state space framework)
  - **{rjd3filters}** (generating moving averages)

JDemetra+ algorithms in R (3/3)

By domain of use:

- Non Seasonal Adjustment related tools
  - **{rjd3bench}** (benchmarking and temporal disaggregation)
  - **{rjd3revisions}** (revision analysis)
  - **{rjd3nowcasting}** (...nowcasting !)
- Tools related to GUI (workspaces)
  - **{rjd3providers}** (input data)
  - **{rjd3workspace}** (workspace wrangling)

Installing rjd3 packages: Java configuration

You can find here : https://jdemetra-new-documentation.netlify.app/#Rconfig a tutorial to configure Java on your computer.

Installing rjd3 packages: latest release

```
# install.packages("remotes")
remotes::install_github("rjdverse/rjd3toolkit@*release")
remotes::install_github("rjdverse/rjd3x13@*release")
remotes::install_github("rjdverse/rjd3tramoseats@*release")
remotes::install_github("rjdverse/rjd3providers@*release")
remotes::install_github("rjdverse/rjd3filters@*release")
remotes::install_github("rjdverse/rjd3sts@*release")
remotes::install_github("rjdverse/rjd3highfreq@*release")
remotes::install_github("rjdverse/rjd3x11plus@*release")
remotes::install_github("rjdverse/rjd3stl@*release")
remotes::install_github("rjdverse/rjd3workspace@*release")
remotes::install_github("rjdverse/rjd3revisions@*release")
remotes::install_github("rjdverse/rjd3bench@*release")
remotes::install_github("rjdverse/rjd3nowcasting@*release")
remotes::install_github("AQLT/ggdemetra3@*release") # additional graphics
```

Installing rjd3 packages: runiverse

```
# install.packages("remotes")
options(repos = c(runiverse = "https://rjdverse.r-universe.dev",
                  CRAN = "https://cloud.r-project.org"))

install.packages("rjd3toolkit")
install.packages("rjd3x13")
install.packages("rjd3tramoseats")
install.packages("rjd3providers")
install.packages("rjd3filters")
install.packages("rjd3sts")
install.packages("rjd3highfreq")
install.packages("rjd3x11plus")
install.packages("rjd3stl")
install.packages("rjd3workspace")
install.packages("rjd3revisions")
install.packages("rjd3bench")
install.packages("rjd3nowcasting")
install.packages("ggdemetra3", repos = c("https://aqlt.r-universe.dev",
                                         "https://cloud.r-project.org"))
```

Installing rjd3 packages (develop version)

Installing (the develop version) from the GitHub home repo

```
# install.packages("remotes")
remotes::install_github("rjdverse/rjd3toolkit")
remotes::install_github("rjdverse/rjd3x13")
remotes::install_github("rjdverse/rjd3tramoseats")
remotes::install_github("rjdverse/rjd3providers")
remotes::install_github("rjdverse/rjd3filters")
remotes::install_github("rjdverse/rjd3sts")
remotes::install_github("rjdverse/rjd3highfreq")
remotes::install_github("rjdverse/rjd3x11plus")
remotes::install_github("rjdverse/rjd3stl")
remotes::install_github("rjdverse/rjd3workspace")
remotes::install_github("rjdverse/rjd3revisions")
remotes::install_github("rjdverse/rjd3bench")
remotes::install_github("rjdverse/rjd3nowcasting")
remotes::install_github("AQLT/ggdemetra3") # additional graphics
```

Loading packages

```
library("rjd3toolkit")
library("rjd3x13")
library("rjd3tramoseats")
library("rjd3filters")
library("rjd3highfreq")
library("rjd3x11plus")
library("rjd3revisions")
library("rjd3bench")
library("rjd3nowcasting")
library("rjd3sts")
library("rjd3stl")
library("ggdemetra3")
```

Section 2

Time series tools

Time series tools

JDemetra+ 3.x offers stand alone tools (mainly in **{rjd3toolkit}**)

- Tests (seasonality, auto-correlation, normality, randomness...)
- (Fast) Arima Modelling
- Flexible Calendar regressors generation
- Auxiliary variables for pre-adjustment in seasonal adjustment
- Spectral analysis
- Detection of multiple seasonal patterns (Canova-Hansen test)
- State space frame work as a toolbox (**{rjd3sts}**)

Testing for seasonality

In **{rjd3toolkit}**:

- Canova-Hansen (`rjd3toolkit::seasonality_canovahansen_trigs()`)
- X-12 combined test (`rjd3toolkit::seasonality_combined()`)
- F-test on seasonal dummies (`rjd3toolkit::seasonality_f()`)
- Friedman Seasonality Test (`rjd3toolkit::seasonality_friedman()`)
- Kruskall-Wallis Seasonality Test (`rjd3toolkit::seasonality_kruskalwallis()`)
- Periodogram Seasonality Test (`rjd3toolkit::seasonality_periodogram()`)
- QS Seasonality Test (`rjd3toolkit::seasonality_qs()`)

Subsection 1

Sarima modelling in rjdverse

Sarima modelling in rjd3verse

- (Reg)-Sarima model estimation: `rjd3toolkit::sarima_estimate()`
- (Reg)-Sarima model identification and estimation pre-adjustment part of Seasonal Adjustment Processes, available in **{rjd3x13}** and **{rjd3tramoseats}** packages

example: `rjd3x13::regarima()`

Sarima estimation

```
library("microbenchmark")

y_example ← log(rjd3toolkit::ABS$X0.2.09.10.M)
microbenchmark(
    JD_arima = rjd3toolkit::sarima_estimate(
        x = y_example,
        order = c(2, 1, 1), seasonal = list(order = c(0, 1, 1), period = 12)
    ),
    built_in_arima = stats::arima(
        x = y_example,
        order = c(2, 1, 1), seasonal = list(order = c(0, 1, 1), period = 12)
    ), times = 10
)
```

```
Unit: milliseconds
           expr      min       lq      mean   median       uq      max neval
       JD_arima  19.3741  20.5738  97.23758  49.6997  69.8089 558.7571    10
 built_in_arima 343.4431 381.7584 534.71129 568.8089 609.3523 767.4766    10
```

Generating User-defined auxilary variables

What is useful for sa and examples below

- Calendar correction : specific regressors, see below in SA part

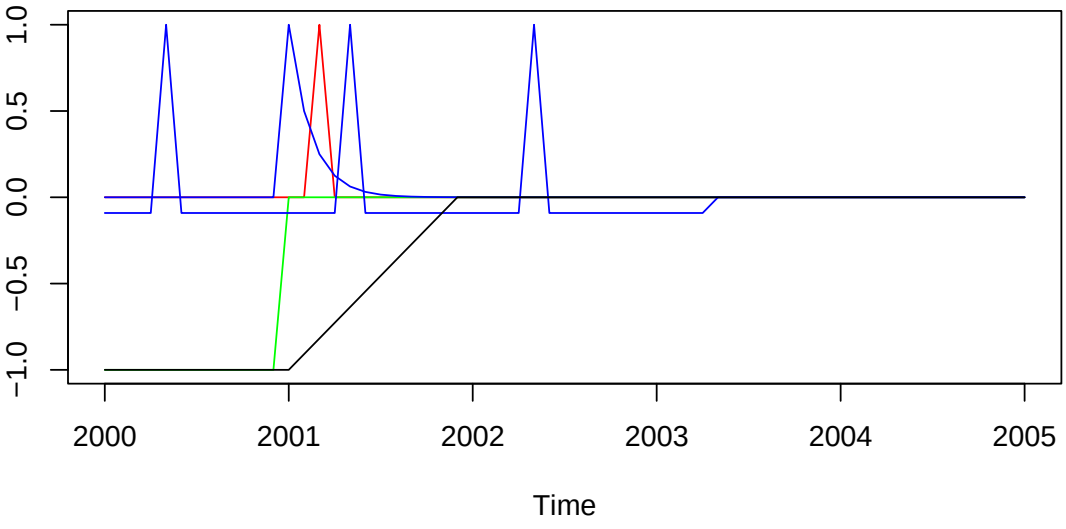
Outliers and intervention variables

- Outliers regressors (AO, LS, TC, SO, Ramp (quadratic to be added)
- Trigonometric variables
- Seasonal dummies

Example of outliers I

```
library("rjd3toolkit")

# ts for initialization
s ← ts(0, start = 2000, end = 2005, frequency = 12)
# You can use an initialization ts or provide frequency, start and length
# Creating outliers
ao ← ao_variable(s = s, date = "2001-03-01")
ls ← ls_variable(s = s, date = "2001-01-01")
tc ← tc_variable(s = s, date = "2001-01-01", rate = 0.5)
# Customizable rate
so ← so_variable(s = s, date = "2003-05-01")
ramp ← ramp_variable(s = s, range = c("2001-01-01", "2001-12-01"))
ts.plot(ts.union(ao, ls, tc, so, ramp),
        col = c("red", "green", "Blue", "blue", "black"))
```

Example of outliers II



Section 3

Seasonal adjustment using JDemetra+ in R

Subsection 1

Low frequency data

Seasonal Adjustment Algorithms in JDemetra+

Algorithm	Version 2.x		Version 3.x	
	Access in GUI	Access in R	Access in GUI	Access in R
X-13 Arima	yes	RJDemetra	yes	`rjd3x13`
Tramo-Seats	yes	RJDemetra	yes	`rjd3tramoseats`
X12plus			yes	`rjd3x11plus`
STL			yes	`rjd3stl`
BSM			yes	`rjd3sts`
SEATS+			upcoming	upcoming

Two categories of algorithms for low frequency data:

- Historical core (main): X-13-Arima and Tramo-Seats
- Version 3 (recent) additional algorithms

Additional algorithms

Tramo-Seats and X-13-Arima share a very similar and sophisticated pre-adjustment process for the Arima model selection phase.

For additional algorithms, the new philosophy is to offer

- A simplified pre-adjustment on the arima modelling side, reduced to airline model
- Several enhanced decomposition options
  - **stl+** ("+" stands for airline based pre-adjustment)
  - **x12+**: airline based pre-adjustment + new trend estimation filters (Local Polynomials)
  - **seats+** (to come in the target v3 version): airline based pre-adjustment + AMB decomposition

Subsection 2

Quick Launch with default specifications

Seasonal Adjustment: common steps

- Testing for seasonality (identify seasonal patterns for HF data)
- Pre-treatment
- Create customised variables for pre-treatment (e.g calendar regressors)
- Decomposition
- Retrieve output series
- Retrieve diagnostics
- Customize parameters
- Refresh data (bonus)
- ...
- Repeat...

Acceptable frequencies: data with p in $2, 3, 4, 6, 12$ is admissible in all algorithms.

Importing data

Here we import the data from the french industrial production index:

We create a ts object with one of the series:

```
library("readr")
library("dplyr")

ipi ← read_delim("Data/IPI_nace4.csv", delim = ";") ▷
    mutate(date = as.Date(date, format = "%d/%m/%Y"),
           across(!date, as.numeric))
y_raw ← ts(data = ipi[, "RF3030"], frequency = 12, start = c(1990, 1))
```

Subsection 3

Quick launch with default specifications

Quick launch with default specifications

In this section, we will use the packages **{rjd3x13}** and **{rjd3tramoseats}**:

```
library("rjd3x13")
library("rjd3tramoseats")
```

Different processing I

Running a full Seasonal Adjustment processing

```
# X13
sa_x13_v3 ← rjd3x13::x13(y_raw, spec = "RSA5")

# Tramo seats
sa_ts_v3 ← rjd3tramoseats::tramoseats(y_raw, spec = "RSAfull")
```

Running only pre-adjustment

Different processing II

```
# X13
sa_regarima_v3 ← rjd3x13::regarima(y_raw, spec = "RG5c")

# Tramo seats
sa_tramo_v3 ← rjd3tramoseats::tramo(y_raw, spec = "TRfull")

# "fast_XXX" versions ... (just results, cf output structure)
```

Running only decomposition

```
# X11 is a specific function
x11_v3 ← rjd3x13::x11(y_raw)
```

Subsection 4

Retrieving output and data visualization

"Model_sa" object structure I

Results vs specification...and then by domain

```
# Model_sa = sa_x13_v3
sa_x13_v3 ← rjd3x13::x13(y_raw, spec = "RSA5")
```

```
sa_x13_v3$result
sa_x13_v3$estimation_spec
sa_x13_v3$result_spec
sa_x13_v3$user_defined
```

Retrieve output series

Input and output series are TS objects in R

- final series

```
# final seasonally adjusted series
sa_x13_v3$result$final$d11final
```

```
           Jan       Feb       Mar       Apr       May       Jun       Jul
2015 101.00943 107.77175 103.00131  94.23577  96.69935  98.80666  98.23143
2016 107.16594 102.22538 104.12974 110.10259 106.94256 108.05816  99.38677
2017 108.45470 104.31209 111.38200 107.67890 111.45404 103.49818 104.07304
2018 107.40292 104.69368 103.66255 112.65495 110.93944 116.46396 120.32502
2019 112.03770 117.71382 113.65766 112.74112 115.12816 106.17979 112.27642
2020 105.12123 107.97116  79.92035  65.67288  59.22572  70.01258  67.38306
2021  72.91616  63.38023  70.46020  70.87969  71.13369  72.27524  76.98557
           Aug       Sep       Oct       Nov       Dec
2015 100.19901 106.04675  99.31709  95.83252  97.33066
2016  98.46974 103.05138 106.20451 100.80206 102.89267
2017 121.14561 106.80214 106.75247 115.60535 104.16300
2018 116.86920 111.76512 109.73788 116.70961 121.76784
```

Series from decomposition

Check output names:

```
# tables from D1 to D13
sa_x13_v3$result$decomposition$d5
```

	Jan	Feb	Mar	Apr	May	Jun	Jul
2015	0.9671969	1.0259171	1.1433522	0.9977630	0.9344235	1.1512369	0.8502556
2016	0.9912076	0.9998156	1.1413886	1.0114885	0.9559634	1.1345715	0.8512917
2017	0.9948506	0.9799265	1.1293967	1.0007843	0.9685890	1.1052400	0.8712689
2018	0.9792026	0.9614345	1.1029869	0.9836683	0.9660983	1.0922782	0.9003009
2019	0.9633474	0.9593604	1.0900038	0.9493774	0.9514231	1.0739355	0.9251931
2020	0.9547157	0.9482438	1.0868284	0.9268561	0.9374488	1.0770919	0.9406608
2021	0.9571768	0.9371914	1.0926323	0.9134289	0.9290156	1.0763504	0.9494751
2022	0.9602994	0.9263622	1.0973870	0.9134289	0.9290156	1.0763504	0.9494751

	Aug	Sep	Oct	Nov	Dec
2015	0.7250049	1.1026940	1.1232296	1.0430244	0.9232794
2016	0.7254213	1.0950852	1.1088890	1.0696157	0.9356648
2017	0.7433354	1.0981051	1.0941449	1.1166228	0.9472417
2018	0.7569311	1.0944032	1.0821739	1.1554418	0.9759946
2019	0.7689645	1.1015712	1.0853035	1.1802980	0.9852067

Retrieving Diagnostics

Just fetch the needed objects in the relevant part of the output structure or print the whole "model"

```
sa_x13_v3$result$diagnostics$td.ftest.i
```

```
Value: 0.03063328
P-Value: 0.9999
```

What is missing (series or diagnostics) can be retrieved adding user-defined output in the options

Retrieving user defined-output I

First define the vector of objects you wish to add

Lists of available diagnostics or series

```
rjd3x13::userdefined_variables_x13("regarima") # restriction
rjd3x13::userdefined_variables_x13()

rjd3tramoseats::userdefined_variables_tramoseats("tramo") # restriction
rjd3tramoseats::userdefined_variables_tramoseats("tramoseats")
```

Select the objects and customize estimation function

```
ud ← rjd3x13::userdefined_variables_x13()[15:17] # b series
ud
```

```
[1] "cal"      "cal_b"    "cal_b(?)"
```

Retrieving user defined-output II

```
sa_x13_v3_ud ← rjd3x13::x13(y_raw, "RSA5c", userdefined = ud)

# Retrieve the object
sa_x13_v3_ud$user_defined$cal
```

```
           Jan       Feb       Mar       Apr       May       Jun       Jul
1990 1.0363890 0.9911504 1.0153134 0.9652130 1.0190605 0.9971963 1.0012305
1991 1.0190605 0.9911504 0.9364198 1.0662135 1.0208211 0.9479590 1.0363890
1992 1.0208211 1.0043748 1.0207756 0.9824016 0.9661709 1.0333817 1.0208211
1993 0.9661709 0.9911504 1.0566204 0.9983698 0.9627990 1.0204147 0.9958729
1994 0.9627990 0.9911504 1.0002567 1.0159425 1.0012305 1.0015791 0.9661709
1995 1.0012305 0.9911504 1.0407486 0.9298082 1.0363890 1.0178591 0.9627990
1996 1.0363890 1.0251863 0.9726470 1.0265012 1.0208211 0.9479590 1.0363890
1997 1.0208211 0.9911504 0.9331517 1.0528344 0.9958729 0.9840550 1.0190605
```

Retrieving user defined-output III

1998	0.9958729	0.9911504	1.0207756	0.9824016	0.9661709	1.0333817	1.0208211
1999	0.9661709	0.9911504	1.0237213	1.0304542	0.9627990	1.0204147	0.9958729
2000	0.9627990	1.0444659	1.0407486	0.9298082	1.0363890	1.0178591	0.9627990
2001	1.0363890	0.9911504	1.0153134	0.9652130	1.0190605	0.9971963	1.0012305
2002	1.0190605	0.9911504	0.9364198	1.0662135	1.0208211	0.9479590	1.0363890
2003	1.0208211	0.9911504	0.9815939	1.0008765	0.9958729	0.9840550	1.0190605
2004	0.9958729	0.9946100	1.0566204	0.9983698	0.9627990	1.0204147	0.9958729
2005	0.9627990	0.9911504	0.9876808	1.0288784	1.0012305	1.0015791	0.9661709
2006	1.0012305	0.9911504	1.0407486	0.9298082	1.0363890	1.0178591	0.9627990
2007	1.0363890	0.9911504	1.0089106	0.9713385	1.0190605	0.9971963	1.0012305
2008	1.0190605	1.0462704	0.9331517	1.0528344	0.9958729	0.9840550	1.0190605
2009	0.9958729	0.9911504	1.0207756	0.9824016	0.9661709	1.0333817	1.0208211
2010	0.9661709	0.9911504	1.0237213	1.0304542	0.9627990	1.0204147	0.9958729
2011	0.9627990	0.9911504	1.0389536	0.9781027	1.0012305	1.0015791	0.9661709
2012	1.0012305	1.0295360	1.0089106	0.9713385	1.0190605	0.9971963	1.0012305

Retrieving user defined-output IV

```
2013 1.0190605 0.9911504 0.9364198 1.0662135 1.0208211 0.9479590 1.0363890
2014 1.0208211 0.9911504 0.9815939 1.0008765 0.9958729 0.9840550 1.0190605
2015 0.9958729 0.9911504 0.9952690 1.0075784 0.9661709 1.0333817 1.0208211
2016 0.9661709 1.0426190 0.9876808 1.0288784 1.0012305 1.0015791 0.9661709
2017 1.0012305 0.9911504 1.0407486 0.9298082 1.0363890 1.0178591 0.9627990
2018 1.0363890 0.9911504 0.9652072 1.0153195 1.0190605 0.9971963 1.0012305
2019 1.0190605 0.9911504 0.9850316 1.0135953 1.0208211 0.9479590 1.0363890
2020 1.0208211 1.0043748 1.0207756 0.9824016 0.9661709 1.0333817 1.0208211
2021 0.9661709 0.9911504 1.0237213 1.0304542 0.9627990 1.0204147 0.9958729
```

	Aug	Sep	Oct	Nov	Dec
1990	1.0208211	0.9479590	1.0363890	1.0178591	0.9627990
1991	0.9958729	0.9840550	1.0190605	0.9971963	1.0012305
1992	0.9627990	1.0204147	0.9958729	0.9840550	1.0190605
1993	1.0012305	1.0015791	0.9661709	1.0333817	1.0208211
1994	1.0363890	1.0178591	0.9627990	1.0204147	0.9958729

Retrieving user defined-output V

```
1995 1.0190605 0.9971963 1.0012305 1.0015791 0.9661709
1996 0.9958729 0.9840550 1.0190605 0.9971963 1.0012305
1997 0.9661709 1.0333817 1.0208211 0.9479590 1.0363890
1998 0.9627990 1.0204147 0.9958729 0.9840550 1.0190605
1999 1.0012305 1.0015791 0.9661709 1.0333817 1.0208211
2000 1.0190605 0.9971963 1.0012305 1.0015791 0.9661709
2001 1.0208211 0.9479590 1.0363890 1.0178591 0.9627990
2002 0.9958729 0.9840550 1.0190605 0.9971963 1.0012305
2003 0.9661709 1.0333817 1.0208211 0.9479590 1.0363890
2004 1.0012305 1.0015791 0.9661709 1.0333817 1.0208211
2005 1.0363890 1.0178591 0.9627990 1.0204147 0.9958729
2006 1.0190605 0.9971963 1.0012305 1.0015791 0.9661709
2007 1.0208211 0.9479590 1.0363890 1.0178591 0.9627990
2008 0.9661709 1.0333817 1.0208211 0.9479590 1.0363890
2009 0.9627990 1.0204147 0.9958729 0.9840550 1.0190605
```

Retrieving user defined-output VI

```
2010 1.0012305 1.0015791 0.9661709 1.0333817 1.0208211
2011 1.0363890 1.0178591 0.9627990 1.0204147 0.9958729
2012 1.0208211 0.9479590 1.0363890 1.0178591 0.9627990
2013 0.9958729 0.9840550 1.0190605 0.9971963 1.0012305
2014 0.9661709 1.0333817 1.0208211 0.9479590 1.0363890
2015 0.9627990 1.0204147 0.9958729 0.9840550 1.0190605
2016 1.0363890 1.0178591 0.9627990 1.0204147 0.9958729
2017 1.0190605 0.9971963 1.0012305 1.0015791 0.9661709
2018 1.0208211 0.9479590 1.0363890 1.0178591 0.9627990
2019 0.9958729 0.9840550 1.0190605 0.9971963 1.0012305
2020 0.9627990 1.0204147 0.9958729 0.9840550 1.0190605
2021 1.0012305 1.0015791
```

```
# Get all output
sa_x13_v3_ud$user_defined # remainder of the names
```

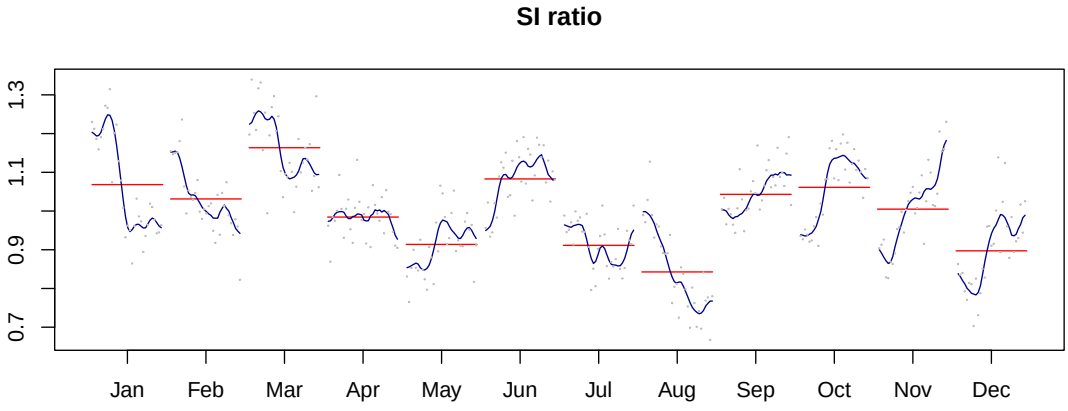
Plots and data visualisation I

Examples

- Final + "autoplot" layout
- Regarima not available (yet ?) !!!
- SI ratios (ggplot layout)

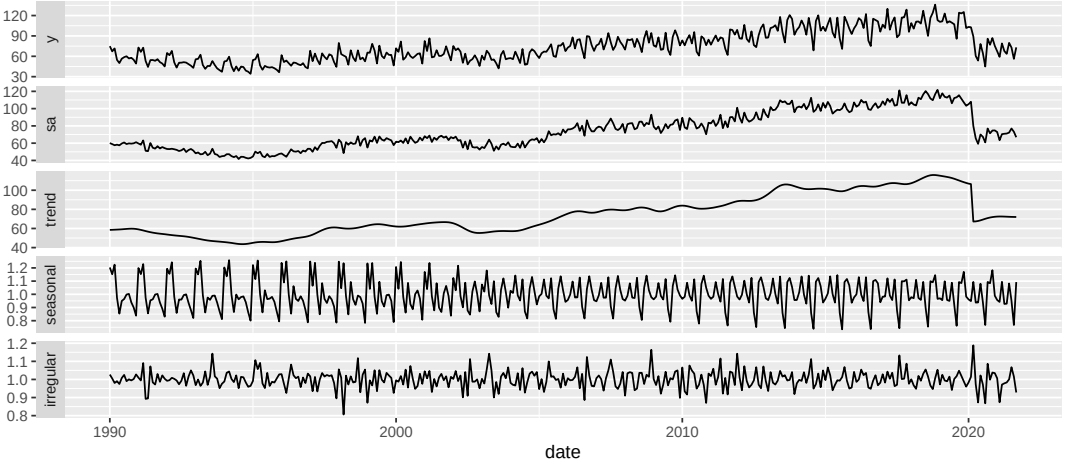
```
library("ggdemetra3")
siratioplot(sa_x13_v3)
```

Plots and data visualisation II




```
library("ggplot2")
autoplot(sa_x13_v3)
```

Plots and data visualisation III



Subsection 5

Customizing specifications

Customising specifications: general steps

To customise a specification:

- Start with a valid specification, usually one of the default specs (equivalent to cloning a spec in GUI)
- Create a new specification
- Apply the new specification to raw series

Customising specifications: local functions

Use of specific `set_` functions

- For the **pre-processing** step (functions defined in **{rjd3toolkit}**):

`set_arima()`, `set_automodel()`, `set_basic()`, `set_easter()`, `set_estimate()`, `set_outlier()`, `set_tradingdays()`, `set_transform()`, `add_outlier()` and `remove_outlier()`, `add_ramp()` and `remove_ramp()`, `add_usrdefvar()`

- For the decomposition step with **X11** (function defined in **{rjd3x13}**): `set_x11()`
- For the decomposition step with **Tramo-Seats** (function defined in **{rjd3tramoseats}**): `set_seats()`
- For the **benchmarking** step (function defined in **{rjd3toolkit}**): `set_benchmarking()`

Simple examples I

```
# start with default spec
spec_1 ← spec_x13("RSA3")
# or start with existing spec (no extraction function needed)
# spec_1 ← sa_x13_v3_UD$estimation_spec
```

```
# set a new spec
## add outliers
spec_2 ← rjd3toolkit::add_outlier(spec_1,
    type = "AO", c("2015-01-01", "2010-01-01")
)
```

```
## set trading days
spec_3 ← rjd3toolkit::set_tradingdays(spec_2,
    option = "workingdays"
) # JD+ regressors
```

Simple examples II

```r
# set x11 options
spec_4 <- set_x11(spec_3, henderson.filter = 13)
# apply with `fast.x13` (results only)
fast_x13(y_raw, spec_4)
```

```
Model: X-13
Log-transformation: yes
SARIMA model: (0,1,1) (0,1,1)

SARIMA coefficients:
 theta(1) btheta(1)
  -0.7440   -0.5815

Regression model:
```

Simple examples III

```
            td AO (2010-01-01) AO (2015-01-01) LS (2020-03-01)
      0.009482        0.128942       -0.004723       -0.468454

Seasonal filter: S3X3; Trend filter: H-13 terms
M-Statistics: q Good (0.792); q-m2 Good (0.794)
QS test on SA: Good (1.000); F-test on SA: Good (0.995)

For a more detailed output, use the 'summary()' function.
```

Adding user-defined calendar or other regressors

When adding regressors which are not predefined (like outliers or ramps):

- `rjd3toolkit::set_tradingdays()` to be used when allocating a regressor to the **calendar** component
- `rjd3toolkit::add_usrdefvar()` is used for any other component

Step 1: Creating regressors (1/2)

```
# create national (or other) calendar if needed
frenchCalendar ← national_calendar(days = list(
    fixed_day(7, 14), # Bastille Day
    fixed_day(5, 8, validity = list(start = "1982-05-08")), # End of 2nd WW
    special_day("NEWYEAR"),
    special_day("CHRISTMAS"),
    special_day("MAYDAY"),
    special_day("EASTERMONDAY"),
    special_day("ASCENSION"),
    special_day("WHITMONDAY"),
    special_day("ASSUMPTION"),
    special_day("ALLSAINTSDAY"),
    special_day("ARMISTICE")
))
```

Step 1: Creating regressors (2/2)

```r
# create set of 6 regressors every day is different, contrast with Sunday, based on french nat
regs_td ← rjd3toolkit::calendar_td(
    calendar = frenchCalendar,
    # formats the regressor like your raw series (length, frequency..)
    s = y_raw,
    groups = c(1, 2, 3, 4, 5, 6, 0),
    contrasts = TRUE
)

# create an intervention variable (to be allocated to "trend")
iv1 ← intervention_variable(
    s = y_raw,
    starts = "2015-01-01",
    ends = "2015-12-01"
)
```

Regressors can be any TS object

Step 2: Creating a modelling context I

Modelling context is necessary for any external regressor (new v3 set up)

```
# Gather regressors into a list
my_regressors ← list(
    Monday = regs_td[, 1],
    Tuesday = regs_td[, 2],
    Wednesday = regs_td[, 3],
    Thursday = regs_td[, 4],
    Friday = regs_td[, 5],
    Saturday = regs_td[, 6],
    reg1 = iv1
)
```

```
# create modelling context
my_context ← modelling_context(variables = my_regressors)
# check variables present in modelling context
rjd3toolkit::.r2jd_modellingcontext(my_context)$getTsVariableDictionary()
```

Step 2: Creating a modelling context II

```
[1] "Java-Object{[r.Monday, r.Tuesday, r.Wednesday, r.Thursday, r.Friday, r.Saturday, r
```

Step 3: Adding regressors to specification (calendar)

```r
# Add calendar regressors to spec
x13_spec ← rjd3x13::x13_spec("rsa3")
x13_spec_user_defined ← rjd3toolkit::set_tradingdays(
    x = x13_spec,
    option = "UserDefined",
    uservariable = c(
        "r.Monday", "r.Tuesday", "r.Wednesday",
        "r.Thursday", "r.Friday", "r.Saturday"
    ),
    test = "None"
)
```

Step 3: Adding regressors to specification (trend)

```
# Add intervention variable to spec, choosing the component to allocate the e
x13_spec_user_defined ← add_usrdefvar(
    x = x13_spec_user_defined,
    group = "r",
    name = "reg1",
    label = "iv1",
    regeffect = "Trend"
)
```

```
x13_spec_user_defined$regarima$regression$users
```

Step 4: Estimating with context

Applying full user-defined specification

```
sa_x13_ud ← rjd3x13::x13(y_raw, x13_spec_user_defined,
                         context = my_context)
sa_x13_ud$result$preprocessing
```

```
Log-transformation: yes
SARIMA model: (0,1,1) (0,1,1)

SARIMA coefficients:
 theta(1) btheta(1)
  -0.7393   -0.5659

Regression model:
         iv1       r.Monday      r.Tuesday    r.Wednesday      r.Thursday
   -0.045028       0.007131       0.016860       0.005819       0.003516
```

Seasonal adjustment of unusual frequencies with rjd3x11 plus I

Example of periodicity p: decomposition with **rjd3x11plus**

Production prices in agriculture : some products are not available several months.

But the data are not missing, they are just not available and never will be : it's structural !

```
fl ← read.csv("Data/fruits_legumes_base_2015_F4.csv", sep = ";")
fl[fl[] == 0] ← NA
strawberry ← fl$FL6
```

Seasonal adjustment of unusual frequencies with rjd3x11 plus II

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2018	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
2019	NA	NA	1.210	0.875	0.775	0.788	0.836	NA	NA	NA	NA	NA
2020	NA	NA	0.925	1.029	1.012	1.018	0.915	NA	NA	NA	NA	NA
2021	NA	NA	1.441	1.130	1.041	0.745	1.036	NA	NA	NA	NA	NA
2022	NA	NA	1.557	1.036	0.731	0.908	1.017	NA	NA	NA	NA	NA
2023	NA	NA	1.292	1.074	0.983	0.980	1.055	NA	NA	NA	NA	NA

Data treatment :

1. Remove the useless months

```
strawberry ← matrix(fl$FL6, nrow = 12)[, 10:14]
strawberry_cut ← as.numeric(strawberry[-c(1:2, 8:12), ])
```

2. Use the function `x11plus` from the package **{rjd3x11plus}**

Seasonal adjustment of unusual frequencies with rjd3x11 plus III

```
library("rjd3x11plus")
mod_strawberry ← x11plus(
    y = strawberry_cut,
    period = 5,
    mul = TRUE,
    trend.horizon = 5 + 2,  # 1/2 Filter length : not too long vs p
    trend.degree = 3,                          # Polynomial degree
    trend.kernel = "Henderson",                # Kernel function
    trend.asymmetric = "CutAndNormalize",      # Truncation method
    seas.s0 = "S3X1", seas.s1 = "S3X1",        # Seasonal filters
    extreme.lsig = 1.5, extreme.usig = 2.5   # Sigma-limits
)
```

3. Re-assemble the data

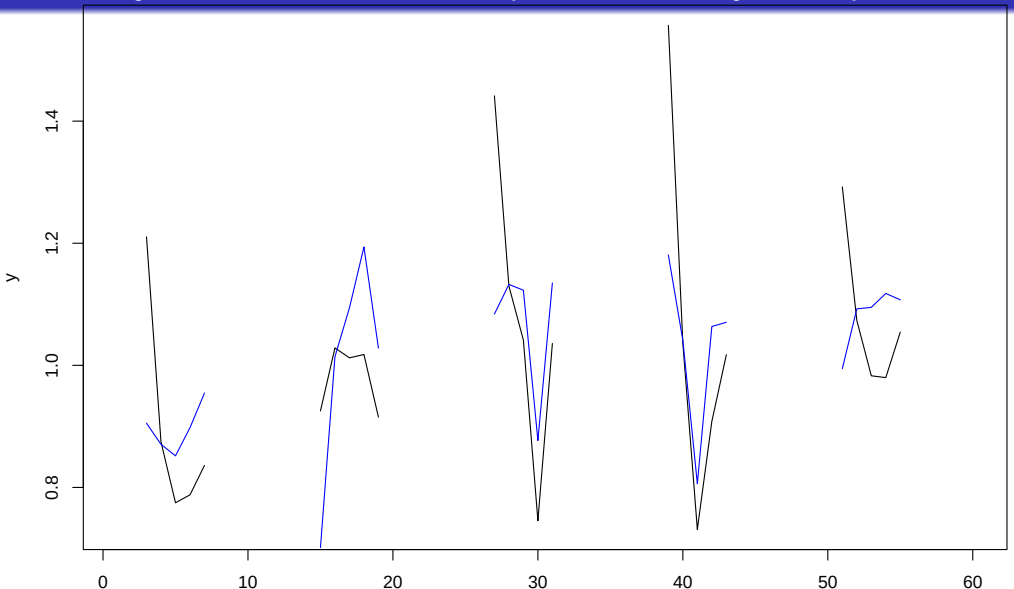
Seasonal adjustment of unusual frequencies with rjd3x11 plus IV

```
strawberry_sa ← mod_strawberry$decomposition$sa ▷
    matrix(nrow = 5)
strawberry_sa ← as.numeric(rbind(NA, NA, strawberry_sa, NA, NA, NA, NA, NA))

y ← as.numeric(strawberry)
sa ← strawberry_sa
```

4. Plot the output

```
plot(y, type = "l")
lines(sa, col = "blue")
```

Seasonal adjustment of unusual frequencies with rjd3x11 plus V



R packages around JDemetra+ - Part 2

A versatile toolbox for time series analysis

Anna Smyk and Tanguy Barthelemy (Insee, France)

UROS Conference, Athens (GR), Nov 27th 2024

Section 1

rjd3 packages part 2

Subsection 1

SA of High-Frequency data

High-Frequency data specificities

Specificity: High-frequency data can display multiple and non integer periodicities:

For example a daily series might display 3 periodicities:

- **weekly** ($p = 7$): Mondays are alike and different from Sundays (DOW)
- **intra-monthly** ($p = 30.44$): the last days of each month are different from the first ones (DOM)
- **yearly** ($p = 365.25$): from on year to another the 15th of June are alike, summer days are alike (DOY)

Classic algorithms not directly applicable

Two classes of solutions:

- round periodicities (might involve imputing data) (extended STL,..)
- use approximations for fractional backshift powers (extended X13-Arima and Tramo-Seats)

For methodologiocal details see JOS Paper, Webel and Smyk (2024)

High-Frequency data in rjd3 packages

In packages for HF data:

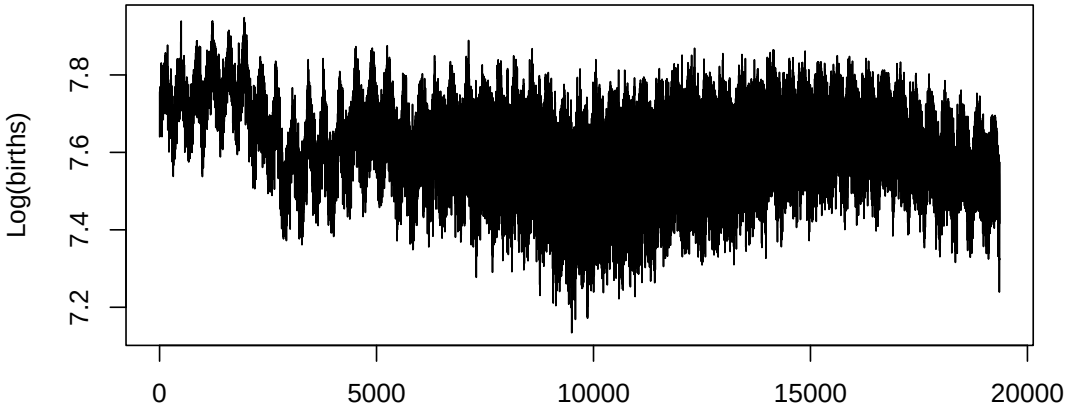
- No constraint on data input as no TS structure (numeric vector)
- Any seasonal patters, positive numbers
- Linearisation with **fractional airline model** (correction for calendar effects and outlier detection)
- Iterative decomposition (extended X-11 and Seats) starting with the highest frequency

Packages perimeters

- **{rjd3highfreq}**: Extended airline model, AMB decomposition (extended SEATS)
- **{rjd3x11plus}** contains all the Extended X11 functions for any (high) frequency data, and new trend estimation filters (weighted polynomials), depends on **{rjd3filters}**
- **{rjd3stl}** (Loess based) and **{rjd3sts}** (SSF based) are the two other tools to decompose high (any)- periodicity data.

Data initialization

```
df_daily ← read_csv2(file.path("Data", "TS_daily_births_franceM_1968_2020.cs
    mutate(log_births = log(births))
plot(df_daily$log_births, type = "l", ylab = "Log(births)")
```



Canova-Hansen test to identify (multiple) seasonal patterns

```
rjd3toolkit::seasonality_canovahansen_trigs(
    data = df_daily$births,
    periods = seq(from = 1 / 367, to = 1 / 2, by = 0.001)
)
```

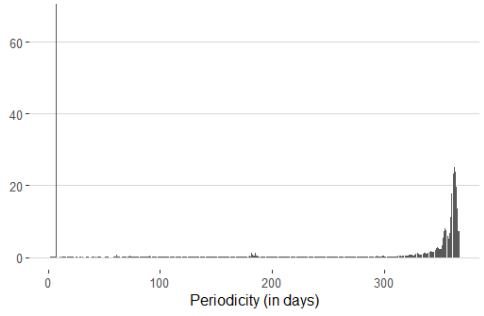


Figure 1: Canova Hansen seasonality test

Linearization

```
# calendar regressors can be defined with the rjd3toolkit package
# see below how to generate the calendar (here french_calendar) first
q ← rjd3toolkit::holidays(
    calendar = french_calendar,
    "1968-01-01", length = 200000, type = "All", nonworking = 7L
)
# pre-adjustment
rjd3highfreq::fractionalAirlineEstimation(
    y = df_daily$log_births, # here a daily series in log
    x = q, # q = calendar
    periods = 7, # approx  c(7,365.25)
    ndiff = 2, ar = FALSE, mean = FALSE,
    outliers = c("ao", "wo", "ls"),
    # WO compensation
    criticalValue = 0, # computed in the algorithm
    precision = 1e-9, approximateHessian = TRUE
)
```

See **{rjd3highfreq}** help pages

Decomposition with extended X-11

```
# step 1: p = 7
x11.dow ← rjd3x11plus::x11(
    ts = exp(pre.mult$model$linearized),
    period = 7, # DOW pattern
    mul = TRUE,
    trend.horizon = 9, # 1/2 Filter length : not too long vs p
    trend.degree = 3, # Polynomial degree
    trend.kernel = "Henderson", # Kernel function
    trend.asymmetric = "CutAndNormalize", # Truncation method
    seas.s0 = "S3X9", seas.s1 = "S3X9", # Seasonal filters
    extreme.lsig = 1.5, extreme.usig = 2.5
) # Sigma-limits
# step 2: p = 365.25
x11.doy ← rjd3highfreq::x11(x11.dow$decomposition$sa, # previous sa
    period = 365.2425, # DOY pattern
    mul = TRUE
) # other parameters skipped here
```

Decomposition with extended Seats

```
# step 1: p = 7
# step 2: p = 365.25
amb.doy ← rjd3highfreq::fractionalAirlineDecomposition(
    amb.dow$decomposition$sa, # DOW-adjusted linearised data
    period = 365.2425, # DOY pattern
    sn = FALSE, # Signal (SA)-noise decomposition
    stde = FALSE, # Compute standard deviations
    nbcasts = 0,
    nfcasts = 0
) # Numbers of back- and forecasts
```

Section 2

Revision Analysis

Revision Analysis

```
library("rjd3revisions")
```

The package **{rjd3revisions}** performs **revision analysis**.

It offers a battery of relevant tests on revisions and submit a visual report including both the main results and their interpretation. The tool can perform analysis on different types of revision intervals and on different vintage views.

The vignette is here.

What is revision analysis?

Revision analysis is composed on a selection of **parametric tests** which enable the users to detect potential bias (both mean and regression bias) and other sources of inefficiency in preliminary estimates.

Data structure

Your input data must be in a specific format: long, vertical or horizontal.

There are 2 types of period in the study of revisions:

- the `time_period`, which designates the reference period to which the value refers
- the `revision_date`, which designates the date on which the value was published

For example, for a series, the September 2023 point may be published for the first time in October 2023, then revised in November 2023 and even in September 2024.

Vertical format

Here we imagine a series in which each point is published from the 1st of the month.

	2012-01-31	2012-02-09	2012-05-27
Jan 2012	12.3	13.2	12.8
Feb 2012	NA	16.4	16.8
Mar 2012	NA	NA	19.3
Apr 2012	NA	NA	15.0

Long format

	revdate	time	obs_values
1	2012-01-31	2012-01-01	12.3
2	2012-01-31	2012-02-01	NA
3	2012-01-31	2012-03-01	NA
4	2012-01-31	2012-04-01	NA
5	2012-02-09	2012-01-01	13.2
6	2012-02-09	2012-02-01	16.4
7	2012-02-09	2012-03-01	NA
8	2012-02-09	2012-04-01	NA
9	2012-05-27	2012-01-01	12.8
10	2012-05-27	2012-02-01	16.8
11	2012-05-27	2012-03-01	19.3
12	2012-05-27	2012-04-01	15.0

Horizontal format

	2012-01-01	2012-02-01	2012-03-01	2012-04-01
2012-01-31	12.3	NA	NA	NA
2012-02-09	13.2	16.4	NA	NA
2012-05-27	12.8	16.8	19.3	15

Diagonal format

	Release[1]	Release[2]	Release[3]
Jan 2012	12.3	13.2	12.8
Feb 2012	16.4	16.8	NA
Mar 2012	19.3	NA	NA
Apr 2012	15.0	NA	NA

Data simulation

The package **{rjd3revisions}** also lets you simulate data sets. You can choose :

- the periodicity,
- the number of revision periods,
- the number of study periods
- the start date of the period

```
long_format ← simulate_long(
    n_period = 12L * 5L,
    n_revision = 10L,
    periodicity = 12L
)
```

Creation of vintages

Then you can create your vintages with the function `create_vintages()`

```
vintages ← create_vintages(long_format, periodicity = 12L)
```

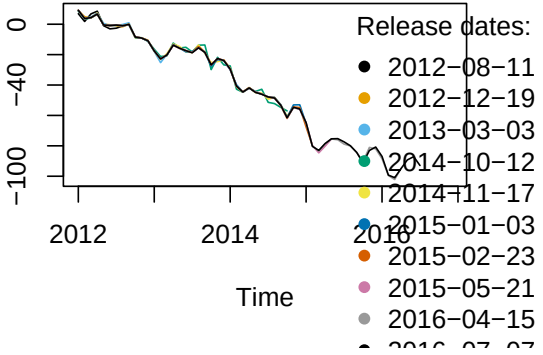
The function `get_revisions()` allows you to compute the revisions and observe the evolutions:

```
revisions ← get_revisions(vintages, gap = 2L)
```

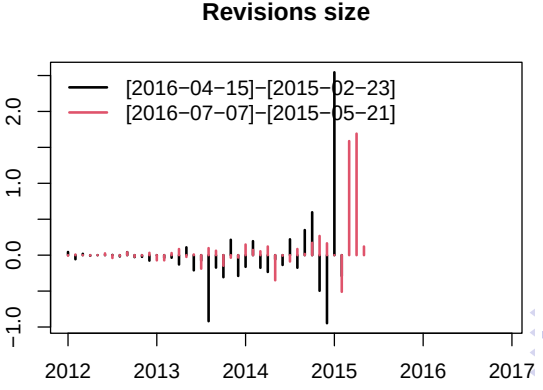
Plot

You can plot your vintages and the revisions :

```
plot(vintages)
```




```
plot(revisions)
```



Make the anaylsis of the revisions

Finally, you can make the analysis of the revisions with the function `revision_analysis()` :

```
rslt ← revision_analysis(vintages, gap = 1, view = "diagonal", n.releases =
```

Creating report

Additionnaly, to create a report and get a summary of the results, you can use

```
render_report(
    rslt,
    output_file = "my_report",
    output_dir = tempdir(),
    output_format = "pdf_document"
)
```

Section 3

Trend estimation

Local polynomial methods

Using **{rjd3filters}** for trend estimation

- Note detailed in this tutorial
- See examples in README file
- For more details see JOS Paper, Quartier-La-Tente (2024)

Section 4

Filtering data

Moving Averages

Moving Averages are used for smoothing and decomposition of time series:

$$M_\theta(X_t) = \sum_{k=-p}^{+f} \theta_k X_{t+k} = \left(\sum_{k=-p}^{+f} \theta_k B^{-k} \right) X_t \text{ with } B^k = X_{t-k}$$

{rjd3filters} offers features to

- Perform operations on MAs and build more complex ones
- Study their properties (plot, gain, phase...)

Using rjd3filters to wrangle Moving Averages I

(Notation: $B^i X_t = X_{t-i}$ et $F^i X_t = X_{t+i}$)

```
library("rjd3filters")
m1 ← moving_average(rep(1, 4), lags = -2) / 4
m1
```

```
[1] "0.2500 B^2 + 0.2500 B + 0.2500 + 0.2500 F"
```

```
m2 ← moving_average(rep(1, 3), lags = -1) / 3
m2
```

```
[1] "0.3333 B + 0.3333 + 0.3333 F"
```

```
m1 + m2
```

```
[1] "0.2500 B^2 + 0.5833 B + 0.5833 + 0.5833 F"
```

Using rjd3filters to wrangle Moving Averages II

```
m1 - m2
```

```
[1] "0.2500 B^2 - 0.0833 B - 0.0833 - 0.0833 F"
```

```
m1 * m2
```

```
[1] "0.0833 B^3 + 0.1667 B^2 + 0.2500 B + 0.2500 + 0.1667 F + 0.0833 F^2"
```

```
m1^2
```

```
[1] "0.0625 B^4 + 0.1250 B^3 + 0.1875 B^2 + 0.2500 B + 0.1875 + 0.1250 F + 0.0625 F
```

```
rev(m1)
```

```
[1] "0.2500 B + 0.2500 + 0.2500 F + 0.2500 F^2"
```

Seasonality suppression I

For quarterly data M2*4

```
library("rjd3filters")
e1 ← simple_ma(4, lags = -2)
e1
```

```
[1] "0.2500 B^2 + 0.2500 B + 0.2500 + 0.2500 F"
```

```
e2 ← simple_ma(4, lags = -1)
e2
```

```
[1] "0.2500 B + 0.2500 + 0.2500 F + 0.2500 F^2"
```

```
# averaging MA's
M2X4 ← (e1 + e2) / 2
M2X4
```

Seasonality suppression II

```
[1] "0.1250 B^2 + 0.2500 B + 0.2500 + 0.2500 F + 0.1250 F^2"
```

```
# or convolution 1
m ← simple_ma(2, lags = 0)
m
```

```
[1] "0.5000 + 0.5000 F"
```

```
M2X4_2 ← m * e1
M2X4_2
```

```
[1] "0.1250 B^2 + 0.2500 B + 0.2500 + 0.2500 F + 0.1250 F^2"
```

```
# or convolution 2
m ← simple_ma(2, lags = -1)
m
```

Seasonality suppression III

```
[1] "0.5000 B + 0.5000"
```

```
M2X4_3 ← m * e2
M2X4_3
```

```
[1] "0.1250 B^2 + 0.2500 B + 0.2500 + 0.2500 F + 0.1250 F^2"
```

```
M2X4 - M2X4_2
```

```
[1] ""
```

```
M2X4 - M2X4_3
```

```
[1] ""
```

Seasonality extraction I

M3*3 filter

```
m3_1 ← moving_average(rep(1, 3), lags = -1) / 3
m3_1
```

```
[1] "0.3333 B + 0.3333 + 0.3333 F"
```

```
m3_2 ← moving_average(rep(1, 3), lags = -2) / 3
m3_2
```

```
[1] "0.3333 B^2 + 0.3333 B + 0.3333"
```

```
m3_3 ← moving_average(rep(1, 3), lags = 0) / 3
m3_3
```

```
[1] "0.3333 + 0.3333 F + 0.3333 F^2"
```

Seasonality extraction II

```
# averaging MA's
M3X3 ← (m3_1 + m3_2 + m3_3) / 3
M3X3
```

```
[1] "0.1111 B^2 + 0.2222 B + 0.3333 + 0.2222 F + 0.1111 F^2"
```

```
# Or convolution
M3X3_2 ← m3_1 * m3_1
```

```
M3X3 - M3X3_2
```

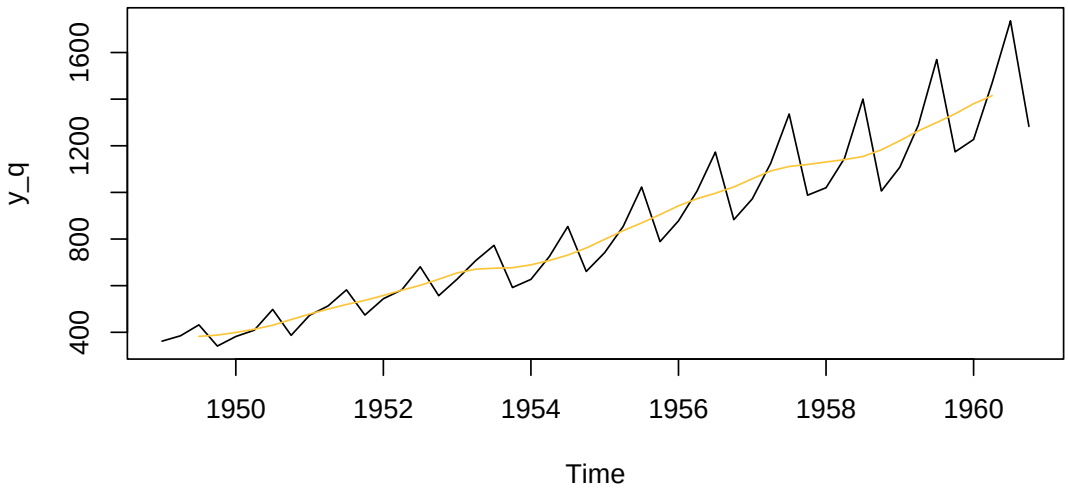
```
[1] ""
```

Seasonality extraction III

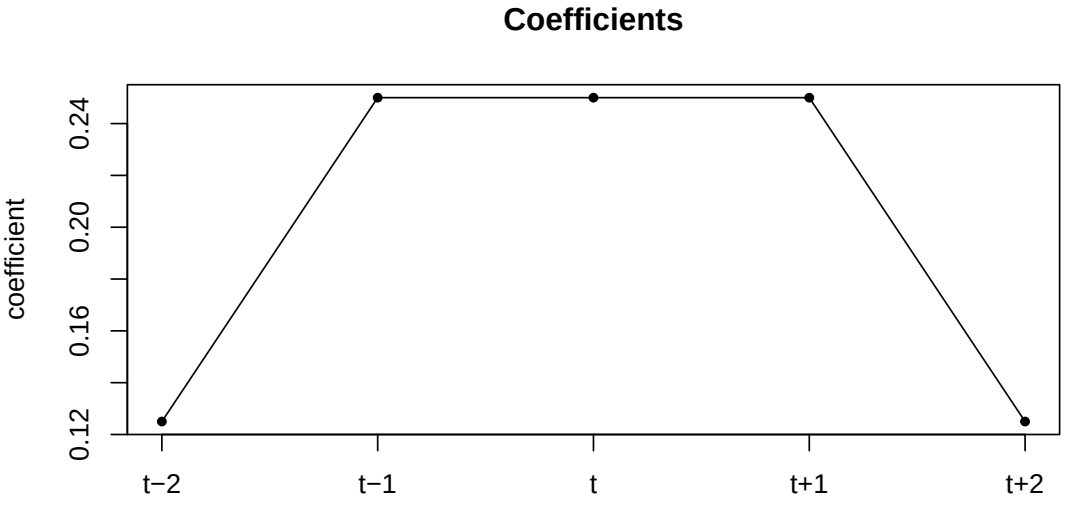
```
# Seasonal format
# q: horizon, q=0 : last data point

M3X3_s ← M3X3 * to_seasonal(M3X3, 4)
M3X3_s
```

```
[1] "0.0123 B^10 + 0.0247 B^9 + 0.0370 B^8 + 0.0247 B^7 + 0.0370 B^6 + 0.0494 B^5 +
```

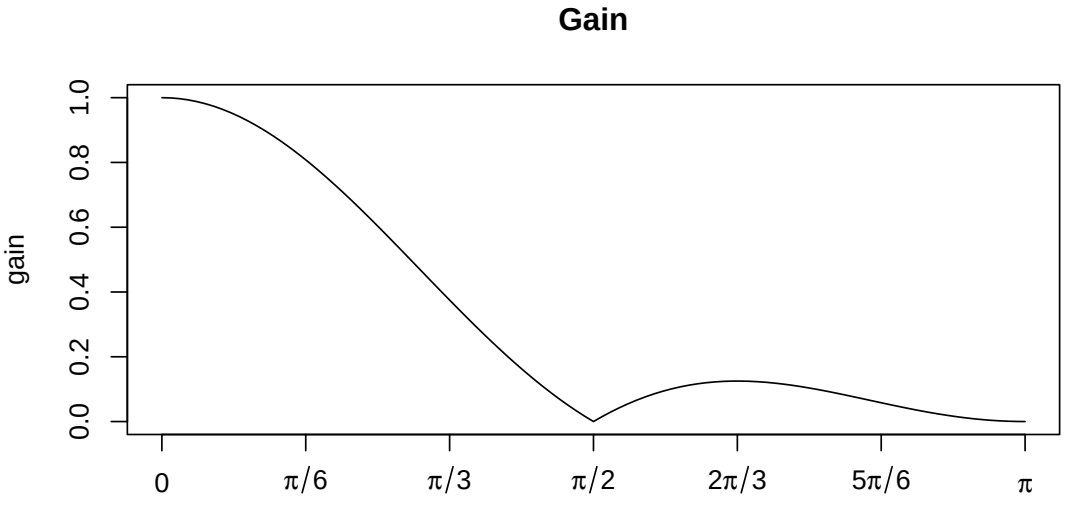
Using rjd3filters to wrangle Moving Averages I



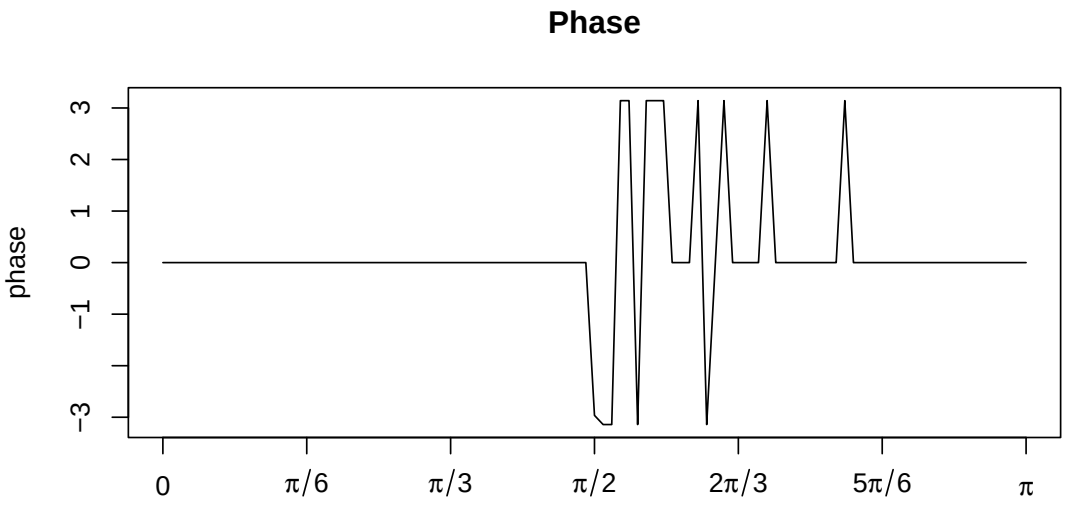
Using rjd3filters to wrangle Moving Averages II



Using rjd3filters to wrangle Moving Averages III



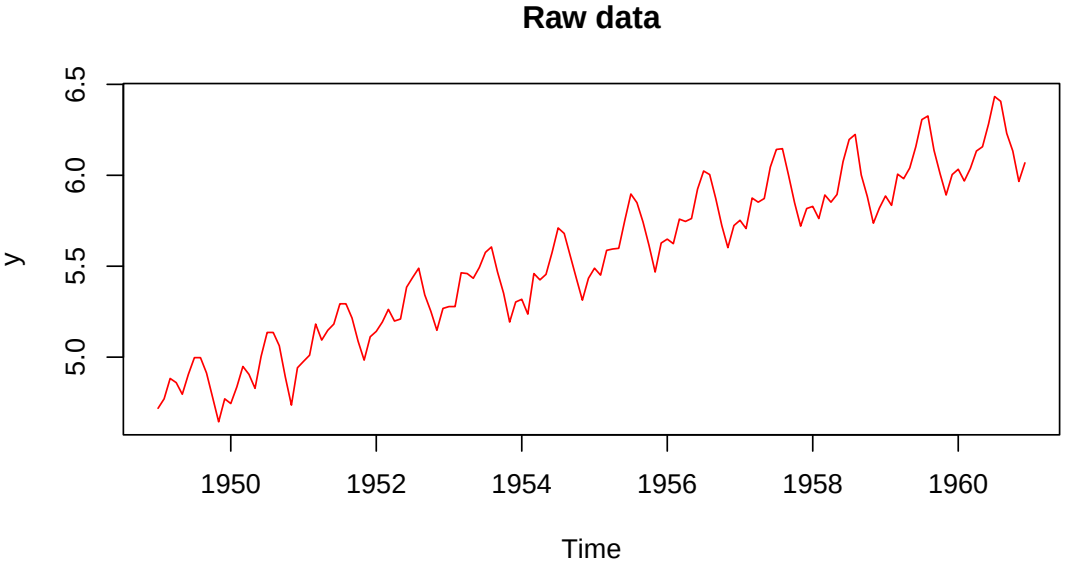
Using rjd3filters to wrangle Moving Averages IV



Simplified X-11 steps I

```
          q=2       q=1       q=0
t-2 0.1111111 0.1111111 0.1851852
t-1 0.2222222 0.2592593 0.4074074
t   0.3333333 0.3703704 0.4074074
t+1 0.2222222 0.2592593 0.0000000
t+2 0.1111111 0.0000000 0.0000000

len  ub
145  72
```

Simplified X-11 steps (2)



(Really) Reproducing X11 steps with `rjd3 filters`

Possibility de to reproduce X-11 algorithm fully, including correction for extreme values.

Example in related vignette
https://github.com/rjdverse/rjd3x11plus/blob/develop/vignettes/X11.Rmd

Section 5

Nowcasting

Different model types

```
library("rjd3nowcasting")
```

{rjd3nowcasting} proposes the implementation of Dynamic Factor model (DFM). These are factor models using a state-space modeling structure to provide consistent forecasts.

The vignette is here.

DFM - equation

This is the state-space representation.

The underlying idea here is that factors f_t generate and predict variables y_t.

$$y_t = Z f_t + \epsilon_t, \quad \epsilon_t \sim N(0, R_t)$$
$$f_t = A_1 f_{t-1} + ... + A_p f_{t-p} + \eta_t, \quad \eta_t \sim N(0, Q_t)$$

But what data? I

Here we will take the data provided by the package. It comes from the French national statistical institute: Insee.

```
data("data0", "data1")

tail(data0)
```

```
       date    FR_PVI FR_TURN FR_B1g_BCDE FR_BS FR_BS_prdexp EA_PVI EA_TURN
145 2024-01-01 -1.0000000    -1.8         NA  -8.4         6.0   -2.0    -3.7
146 2024-02-01  0.3988041     2.4         NA  -5.4         6.4    0.1     1.7
147 2024-03-01 -0.1000000    -1.2  0.9711108  -3.4         9.0    0.4    -0.6
148 2024-04-01  0.5000000      NA         NA  -7.7         6.5   -0.1      NA
149 2024-05-01         NA      NA         NA  -8.9         0.5     NA      NA
150       <NA>         NA      NA         NA    NA          NA     NA      NA
    EA_BS EA_BS_prdexp EA_PMI_manuf
```

But what data? II

```
145  -9.3          0.7          46.6
146  -9.5          0.8          46.5
147  -8.8          0.5          46.1
148 -10.3          0.6          45.7
149  -9.8          0.3          47.3
150    NA           NA            NA
```

```
tail(data1)
```

```
        date     FR_PVI   FR_TURN FR_B1g_BCDE FR_BS FR_BS_prdexp     EA_PVI
145 2024-01-01 -1.1916725 -1.689229         NA  -8.4         6.0 -2.2358655
146 2024-02-01  0.3988041  2.606285         NA  -5.4         6.4  0.0000000
147 2024-03-01 -0.1992033 -1.252626  0.9711108  -3.4         9.0  0.5125588
148 2024-04-01  0.5964232  1.501279         NA  -7.8         6.5  0.0000000
149 2024-05-01 -2.1032323        NA         NA  -8.9         0.5 -0.6153866
```

But what data? III

```
150 2024-06-01        NA        NA          NA  -7.9          2.3          NA
       EA_TURN EA_BS EA_BS_prdexp EA_PMI_manuf
145 -3.8781249  -9.3          0.7          46.6
146  1.5693435  -9.5          0.8          46.5
147 -0.4334641  -8.8          0.5          46.1
148  0.6063249 -10.4          0.6          45.7
149          NA  -9.9          0.3          47.3
150          NA -10.1          0.5          45.8
```

But what data?

These two datasets contain data on:

- Monthly industrial production index (PVI),
- Turnover (TURN),
- Quarterly GDP,
- Business survey data (BS)
- Other survey data (PMI) for both France and the Eurozone.

We will use these datasets to illustrate how one of these variable can be nowcasted using the others using a Dynamic Factor model.

Transforming our data

First we have to transform our data into ts object:

```
data0_ts ← data0 ▷
    select(-date) ▷
    ts(start = c(2012, 1), frequency = 12)
data1_ts ← data1 ▷
    select(-date) ▷
    ts(start = c(2012, 1), frequency = 12)
```

Here the `date` column will not be useful in the forecasting.

Creation of our first model

Our model here will initially be agnostic of our data, i.e. it does not depend on the values of our series but on the model we want to give to our forecasts. Nevertheless, it is important to know the structure of our data in order to structure our model properly.

```
dfm_model ← create_model(
    nfactors = 2,
    nlags = 2,
    factors_type = c("M", "M", "Q", "YoY", "YoY",
                     "M", "M", "YoY", "YoY", "YoY"),
    factors_loading = matrix(data = TRUE, nrow = ncol(data0_ts), ncol = 2),
    var_init = "Unconditional"
)
```

See `?create_model` to get the documentation of the argument.

Estimate the model

Then you can estimate your model with your initial data.

Parameters can be estimated using different algorithms:

- The function `estimate_pca()` estimates the model parameters using only **Principal Component Analysis (PCA)**. Although this is fast, this approach is not recommended, especially if some series are *quarterly series* or series associated to year-on-year growth rates
- The function `estimate_em()` estimates the model parameters using the **EM** algorithm;
- The function `estimate_ml()` estimates the model parameters by **Maximum Likelihood**.

```
dfm_estimated ← estimate_ml(dfm_model, data0_ts)
# dfm_estimated ← estimate_em(dfm_model, data0_ts)
# dfm_estimated ← estimate_pca(dfm_model, data0_ts)
```

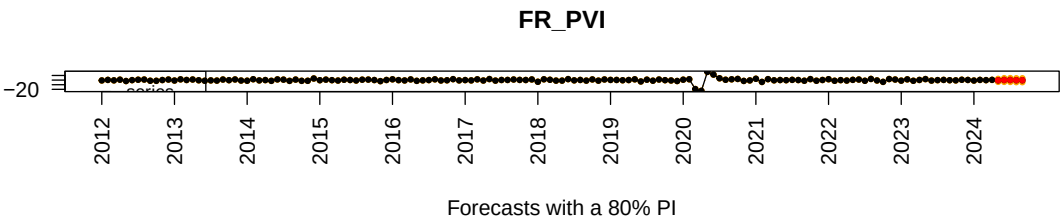
Get and analyse our results

Finally, you can get your results with the functions `get_results()` and `get_forecasts()`.

```
dfm_results ← get_results(dfm_estimated)
dfm_forcast ← get_forecasts(dfm_estimated, n_fcst = 3)
```

Plot the results results

```
plot(dfm_forcast, series_name = "FR_PVI")
```



Forecasts with a 80% PI

Study of news I

If you want to compare your forecasts with the actual results, the function get_news():

```
dfm_news ← get_news(dfm_estimates = dfm_estimated,
                    new_data = data1_ts,
                    target_series = "FR_PVI", n_fcst = 3)
dfm_news$impacts
```

```
       series period expected_value observed_value   news impacts(6-2024)
1      FR_PVI 5-2024         -0.552         -2.103 -1.552           0.063
2     FR_TURN 4-2024         -0.159          1.501  1.660          -0.103
3       FR_BS 6-2024         -9.164         -7.900  1.264          -0.032
4 FR_BS_prdexp 6-2024          3.892          2.300 -1.592          -0.013
5      EA_PVI 5-2024         -0.396         -0.615 -0.220           0.010
6     EA_TURN 4-2024         -0.021          0.606  0.628          -0.085
  impacts(7-2024) impacts(8-2024)
```

Study of news II

1	0.251	0.035
2	-0.021	0.032
3	-0.004	0.008
4	-0.003	0.005
5	0.040	0.006
6	-0.018	0.025

Section 6

Conclusion and useful links

rjdverse family of packages

Versatile toolbox as multiple algorithms and tools for

- Seasonal Adjustment, including High-Frequency data
- Building filters
- Revision Analysis
- Nowcasting

And also (not covered today..):

- Trend and cycle estimation
- Benchmarking and temporal disaggregation

Useful Links

To get the Software:

- R Packages giving access to JDemetra+: https://github.com/rjdverse
- Graphical User Interface: https://github.com/jdemetra

Documentation and news:

- Online documentation: https://jdemetra-new-documentation.netlify.app/
- Blog: https://jdemetra-universe-blog.netlify.app/
- YouTube channel (Tutorials, Webinars): https://www.youtube.com/@TSwithJDemetraandR

After the tutorial

Assistance with JDemetra+ use and SA production process set up can be provided

If you have any questions, just email us

- anna.smyk@insee.fr
- tanguy.barthelemy@insee.fr

THANK YOU FOR YOUR ATTENTION