PriceIndices – a Package for Bilateral and Multilateral Price Index Calculations

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Goals of PriceIndices are as follows: a) data processing before price index calculations; b) bilateral and multilateral price index calculations; c) extending multilateral price indices. You can download the package documentation from here. Too read more about the package please see (and cite :)) papers:

Białek, J. (2021). PriceIndices – a New R Package for Bilateral and Multilateral Price Index Calculations, Statistika – Statistics and Economy Journal, Vol. 2/2021, 122-141, Czech Statistical Office, Praga.

Białek, J. (2022). Scanner data processing in a newest version of the PriceIndices package, Statistical Journal of the IAOS, 38 (4), 1369-1397, DOI: 10.3233/SJI-220963.

Installation

You can install the released version of **PriceIndices** from CRAN with:

```
install.packages("PriceIndices")
```

You can install the development version of **PriceIndices** from GitHub with:

```
library("remotes")
remotes::install_github("JacekBialek/PriceIndices")
```

The functionality of this package can be categorized as follows:

1. Data sets included in the package and generating artificial scanner data sets
2. Functions for data processing
3. Functions providing dataset characteristics
4. Functions for bilateral unweighted price index calculations
5. Functions for bilateral weighted price index calculations
6. Functions for chain price index calculations
7. Functions for multilateral price index calculations
8. Functions for extending multilateral price indices by using splicing methods
9. Functions for extending multilateral price indices by using the FBEW method
10. Functions for extending multilateral price indices by using the FBMW method
11. General functions for price index calculations
12. Functions for comparisons of price indices
13. Functions for price and quantity indicator calculations

Data sets included in the package and generating artificial scanner data sets

This package includes seven data sets: artificial and real.

1) dataAGGR

The first one, **dataAGGR**, can be used to demonstrate the **data_aggregating** function. This is a collection of artificial scanner data on milk products sold in three different months and it contains the following columns: **time** - dates of transactions (Year-Month-Day: 4 different dates); **prices** - prices of sold products (PLN); **quantities** - quantities of sold products (liters); *prodID* - unique product codes (3 different prodIDs); **retID** - unique codes identifying outlets/retailer sale points (4 different retIDs); **description** - descriptions of sold products (two subgroups: goat milk, powdered milk).

2) dataMATCH

The second one, **dataMATCH**, can be used to demonstrate the **data_matching** function and it will be described in the next part of the guidelines. Generally, this artificial data set contains the following columns: **time** - dates of transactions (Year-Month-Day); **prices** - prices of sold products; **quantities** - quantities of sold products; **codeIN** - internal product codes from the retailer; **codeOUT** - external product codes, e.g. GTIN or SKU in the real case; **description** - descriptions of sold products, eg. 'product A', 'product B', etc.

3) dataCOICOP

The third one, **dataCOICOP**, is a ollection of real scanner data on the sale of milk products sold in a period: Dec, 2020 - Feb, 2022. It is a data frame with 10 columns and 139600 rows. The used variables are as follows: **time** - dates of transactions (Year-Month-Day); **prices** - prices of sold products (PLN); **quantities** - quantities of sold products; **description** - descriptions of sold products (original: in Polish); **codeID** - retailer product codes; **retID** - IDs of retailer outlets; **grammage** - product grammages; **unit** - sales units, e.g. 'kg', 'ml', etc.; **category** - product categories (in English) corresponding to COICOP 6 levels; **coicop6** - identifiers of local COICOP 6 groups (6 levels). Please note that this data set can serve as a training or testing set in product classification using machine learning methods (see the functions: **model_classification** and **data_classifying**).

4) milk

This data set, **milk**, is a collection of scaner data on the sale of milk in one of Polish supermarkets in the period from December 2018 to August 2020. It is a data frame with 6 columns and 4386 rows. The used variables are as follows: **time** - dates of transactions (Year-Month-Day); **prices** - prices of sold products (PLN); **quantities** - quantities of sold products (liters); **prodID** - unique product codes obtained after product matching (data set contains 68 different prodIDs); **retID** - unique codes identifying outlets/retailer sale points (data set contains 5 different retIDs); **description** - descriptions of sold milk products (data set contains 6 different product descriptions corresponding to *subgroups* of the milk group).

5) coffee

This data set, **coffee**, is a collection of scanner data on the sale of coffee in one of Polish supermarkets in the period from December 2017 to October 2020. It is a data frame with 6 columns and 42561 rows. The used variables are as follows: **time** - dates of transactions (Year-Month-Day); **prices** - prices of sold products (PLN); **quantities** - quantities of sold products (kg); **prodID** - unique product codes obtained after product matching (data set contains 79 different prodIDs); **retID** - unique codes identifying outlets/retailer sale points (data set contains 20 different retIDs); **description** - descriptions of sold coffee products (data set contains 3 different product descriptions corresponding to *subgroups* of the coffee group).

6) sugar

This data set, **sugar**, is a collection of scanner data on the sale of coffee in one of Polish supermarkets in the period from December 2017 to October 2020. It is a data frame with 6 columns and 7666 rows. The used variables are as follows: **time** - dates of transactions (Year-Month-Day); **prices** - prices of sold products (PLN); **quantities** - quantities of sold products (kg); **prodID** - unique product codes obtained after product matching (data set contains 11 different prodIDs); **retID** - unique codes identifying outlets/retailer sale points (data set contains 20 different retIDs); **description** - descriptions of sold sugar products (data set contains 3 different product descriptions corresponding to *subgroups* of the sugar group).

7) dataU

This data set, **dataU**, is a collection of artificial scanner data on 6 products sold in Dec, 2018. Product descriptions contain the information about their grammage and unit. It is a data frame with 5 columns and 6 rows. The used variables are as follows: **time** - dates of transactions (Year-Month-Day); **prices** - prices of sold products (PLN); **quantities** - quantities of sold products (item); **prodID** - unique product codes; **description** - descriptions of sold products (data set contains 6 different product descriptions).

The set **milk** represents a typical data frame used in the package for most calculations and is organized as follows:

```
library(PriceIndices)


head(milk)
#>         time prices quantities prodID retID   description
#> 1 2018-12-01   8.78        9.0  14215  2210 powdered milk
#> 2 2019-01-01   8.78       13.5  14215  2210 powdered milk
#> 3 2019-02-01   8.78        0.5  14215  1311 powdered milk
#> 4 2019-02-01   8.78        8.0  14215  2210 powdered milk
#> 5 2019-03-01   8.78        0.5  14215  1311 powdered milk
#> 6 2019-03-01   8.78        1.5  14215  2210 powdered milk
```

Available subgroups of sold milk are

```
unique(milk$description)
#> [1] "powdered milk"              "low-fat milk pasteurized"
#> [3] "low-fat milk UHT"           "full-fat milk pasteurized"
#> [5] "full-fat milk UHT"          "goat milk"
```

Generating artificial scanner data sets in the package

The package includes the **generate** function which provides an artificial scanner data sets where prices and quantities are lognormally distributed. The characteristics for these lognormal distributions are set by **pmi**, **sigma**, **qmi** and **qsigma** parameters. This function works for the fixed number of products and outlets (see **n** and **r** parameters). The generated data set is ready for further price index calculations. For instance:

```
dataset<-generate(pmi=c(1.02,1.03,1.04),psigma=c(0.05,0.09,0.02),
                  qmi=c(3,4,4),qsigma=c(0.1,0.1,0.15),
                  start="2020-01")
head(dataset)


#>         time prices quantities prodID retID
#> 1 2020-01-01   2.59         20      1     1
#> 2 2020-01-01   2.83         21      2     1
#> 3 2020-01-01   2.85         24      3     1
#> 4 2020-01-01   2.81         18      4     1
#> 5 2020-01-01   2.83         22      5     1
#> 6 2020-01-01   2.68         20      6     1
```

From the other hand you can use **tindex** function to obtain the theoretical value of the unweighted price index for lognormally distributed prices (the month defined by **start** parameter plays a role of the fixed base period). The characteristics for these lognormal distributions are set by **pmi** and **sigma** parameters. The **ratio** parameter is a logical parameter indicating how we define the theoretical unweighted price index. If it is set to TRUE then the resulting value is a ratio of expected price values from compared months; otherwise the resulting value is the expected value of the ratio of prices from compared months.The function provides a data frame consisting of dates and corresponding expected values of the theoretical unweighted price index. For example:

```
tindex(pmi=c(1.02,1.03,1.04),psigma=c(0.05,0.09,0.02),
start="2020-01",ratio=FALSE)

#>      date   tindex
#> 1 2020-01 1.000000
#> 2 2020-02 1.012882
#> 3 2020-03 1.019131
```

The User may also generate an artificial scanner dataset where prices are log-normally distributed and quantities are calculated under the assumption that consumers have CES

(Constant Elasticity of Substitution) preferences and their spending on all products is fixed (see the **generate_CES** function). Please watch the following example:

```
#Generating an artificial dataset (the elasticity of substitution is 1.25)
df<-generate_CES(pmi=c(1.02,1.03),psigma=c(0.04,0.03),
elasticity=1.25,start="2020-01",n=100,days=TRUE)
head(df)


#>         time prices quantities prodID retID
#> 1 2020-01-27   2.76 2.98441537      1     1
#> 2 2020-01-07   2.88 0.02414233      2     1
#> 3 2020-01-19   2.87 8.80781350      3     1
#> 4 2020-01-16   2.64 6.96559885      4     1
#> 5 2020-01-08   2.57 6.18105228      5     1
#> 6 2020-01-18   2.71 0.49255161      6     1
```

Now, we can verify the value of elasticity of substitution using this generated dataset:

```
#Verifying the elasticity of substitution
elasticity(df, start="2020-01",end="2020-02")
#> [1] 1.25
```

Functions for data processing

data_preparing

This function returns a prepared data frame based on the user's data set (you can check if your data set it is suitable for further price index calculation by using **data_check** function). The resulting data frame is ready for further data processing (such as data selecting, matching or filtering) and it is also ready for price index calculations (if only it contains the required columns). The resulting data frame is free from missing values, zero or negative prices and quantities. As a result, the column **time** is set to be **Date** type (in format: 'Year-Month-01'), while the columns **prices** and **quantities** are set to be **numeric**. If the **description** parameter is set to *TRUE* then the column **description** is set to be **character** type (otherwise it is deleted). Please note that the **milk** set is an already prepared dataset but let us assume for a moment that we want to make sure that it does not contain missing values and we do not need the column **description** for further calculations. For this purpose, we use the **data_preparing** function as follows:

```
head(data_preparing(milk,time="time",prices="prices",quantities="quantities"))


#>         time prices quantities
#> 1 2018-12-01   8.78        9.0
#> 2 2019-01-01   8.78       13.5
#> 3 2019-02-01   8.78        0.5
#> 4 2019-02-01   8.78        8.0
#> 5 2019-03-01   8.78        0.5
#> 6 2019-03-01   8.78        1.5
```

data_imputing

This function imputes missing prices (unit values) and (optionally) zero prices by using carry forward/backward prices. The imputation can be done for each outlet separately or for aggragated data (see the outlets parameter). If a missing product has a previous price then that previous price is carried forward until the next real observation. If there is no previous price then the next real observation is found and carried backward. The quantities for imputed prices are set to zeros. The function returns a data frame which is ready for price index calculations, for instance:

```
#Creating a data frame with zero prices (df)
data<-dplyr::filter(milk,time >= as.Date("2018-12-01")
& time <= as.Date("2019-03-01"))
sample<-dplyr::sample_n(data, 100)
rest<-setdiff(data, sample)
sample$prices<-0
df<-rbind(sample, rest)
#The Fisher price index calculated for the original data set
fisher(df, "2018-12","2019-03")
#> [1] 1.029504
#Zero price imputations:
df2<-data_imputing(df, start="2018-12", end="2019-03",
              zero_prices=TRUE,
              outlets=TRUE)
#The Fisher price index calculated for the data set with imputed prices:
fisher(df2, "2018-12","2019-03")
#> [1] 1.027674
```

data_aggregating

The function aggregates the user's data frame over time and/or over outlets. Consequently, we obtain monthly data, where the unit value is calculated instead of a price for each **prodID** observed in each month (the time column gets the Date format: "Year-Month-01"). If paramter **join_outlets** is *TRUE*, then the function also performs aggregation over outlets (*retIDs*) and the **retID** column is removed from the data frame. The main advantage of using this function is the ability to reduce the size of the data frame and the time needed to calculate the price index. For instance, let us consider the following data set:

```
dataAGGR
#>         time prices quantities prodID retID   description
#> 1 2018-12-01     10        100 400032  4313     goat milk
#> 2 2018-12-01     15        100 400032  1311     goat milk
#> 3 2018-12-01     20        100 400032  1311     goat milk
#> 4 2020-07-01     20        100 400050  1311     goat milk
#> 5 2020-08-01     30         50 400050  1311     goat milk
#> 6 2020-08-01     40         50 400050  2210     goat milk
#> 7 2018-12-01     15        200 403249  2210 powdered milk
#> 8 2018-12-01     15        200 403249  2210 powdered milk
#> 9 2018-12-01     15        300 403249  2210 powdered milk
```

After aggregating this data set over time and outlets we obtain:

```
data_aggregating(dataAGGR)
#> # A tibble: 4 x 4
#>   time       prodID prices quantities
#>   <date>      <int>  <dbl>      <int>
#> 1 2018-12-01 400032     15        300
#> 2 2018-12-01 403249     15        700
#> 3 2020-07-01 400050     20        100
#> 4 2020-08-01 400050     35        100
```

data_unit

The function returns the user's data frame with two additional columns: **grammage** and **unit** (both are character type). The values of these columns are extracted from product descriptions on the basis of provided **units**. Please note, that the function takes into consideration a sign of the multiplication, e.g. if the product description contains: '2x50 g', we will obtain: **grammage: 100** and **unit: g** for that product (for **multiplication** set to 'x'). For example:

```
data_unit(dataU,units=c("g","ml","kg","l"),multiplication="x")
#>         time prices quantities prodID         description grammage unit
#> 1 2018-12-01   8.00        200  40033 drink 0,75l 3% corma     0.75    l
#> 2 2018-12-01   5.20        300  12333          sugar 0.5kg      0.5   kg
#> 3 2018-12-01  10.34        100  20345         milk 4x500ml     2000   ml
#> 4 2018-12-01   2.60        500  15700 xyz 3 4.34 xyz 200 g      200    g
#> 5 2018-12-01  12.00       1000  13022                  abc        1 item
#> 6 2019-01-01   3.87        250  10011      ABC 2A/350 g mnk      350    g
```

data_norm

The function returns the user's data frame with two transformed columns: **grammage** and **unit**, and two rescaled columns: **prices** and **quantities**. The above-mentioned transformation and rescaling take into consideration the user **rules**. Recalculated prices and quantities concern grammage units defined as the second parameter in the given rule. For instance:

```
# Preparing a data set
data<-data_unit(dataU,units=c("g","ml","kg","l"),multiplication="x")


# Normalization of grammage units
data_norm(data, rules=list(c("ml","l",1000),c("g","kg",1000)))
#>         time   prices quantities prodID          description grammage unit
#> 1 2018-12-01  5.17000      200.0  20345          milk 4x500ml        2    l
#> 2 2018-12-01 10.66667      150.0  40033 drink 0,75l 3% corma     0.75    l
#> 3 2018-12-01 13.00000      100.0  15700 xyz 3 4.34 xyz 200 g      0.2   kg
#> 4 2019-01-01 11.05714       87.5  10011      ABC 2A/350 g mnk     0.35   kg
#> 5 2018-12-01 10.40000      150.0  12333          sugar 0.5kg      0.5   kg
#> 6 2018-12-01 12.00000     1000.0  13022                  abc        1 item
```

data_selecting

The function returns a subset of the user's data set obtained by selection based on keywords and phrases defined by parameters: **include**, **must** and **exclude** (an additional column **coicop** is optional). Providing values of these parameters, please remember that the procedure distinguishes between uppercase and lowercase letters only when **sensitivity** is set to *TRUE*.

For instance, please use

```
subgroup1<-data_selecting(milk, include=c("milk"), must=c("UHT"))
head(subgroup1)
#>         time prices quantities prodID retID      description
#> 1 2018-12-01   2.97         78  17034  1311 low-fat milk uht
#> 2 2018-12-01   2.97        167  17034  2210 low-fat milk uht
#> 3 2018-12-01   2.97        119  17034  6610 low-fat milk uht
#> 4 2018-12-01   2.97         32  17034  7611 low-fat milk uht
#> 5 2018-12-01   2.97         54  17034  8910 low-fat milk uht
#> 6 2019-01-01   2.95         71  17034  1311 low-fat milk uht
```

to obtain the subset of **milk** limited to *UHT* category:

```
unique(subgroup1$description)
#> [1] "low-fat milk uht"  "full-fat milk uht"
```

You can use

```
subgroup2<-data_selecting(milk, must=c("milk"), exclude=c("past","goat"))
head(subgroup2)


#>         time prices quantities prodID retID   description
#> 1 2018-12-01   8.78        9.0  14215  2210 powdered milk
#> 2 2019-01-01   8.78       13.5  14215  2210 powdered milk
#> 3 2019-02-01   8.78        0.5  14215  1311 powdered milk
#> 4 2019-02-01   8.78        8.0  14215  2210 powdered milk
#> 5 2019-03-01   8.78        0.5  14215  1311 powdered milk
#> 6 2019-03-01   8.78        1.5  14215  2210 powdered milk
```

to obtain the subset of **milk** with products which are not *pasteurized* and which are not **goat**:

```
unique(subgroup2$description)
#> [1] "powdered milk"     "low-fat milk uht"  "full-fat milk uht"
```

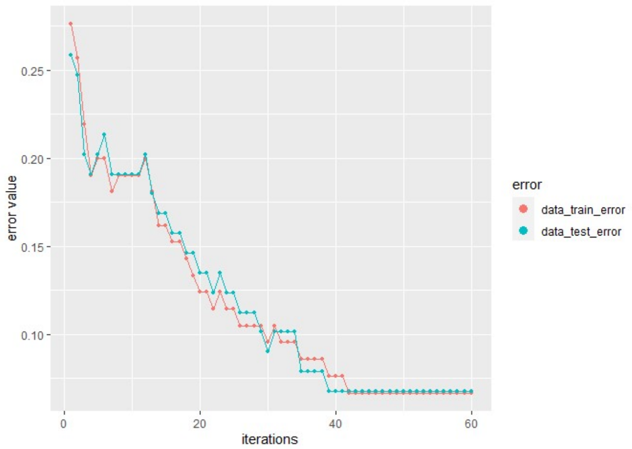
data_classifying

This function predicts product COICOP levels (or any other defined product levels) using the selected machine learning model (see the **model** parameter). It provides the indicated data set with an additional column, i.e. *coicop_predicted*. The selected model must be built previously (see the **model_classification** function) and after the training process it can be saved on your disk (see the **save_model** function) and then loaded at any time (see the **load_model** function). Please note that the machine learning process is based on the XGBoost algorithm (from the XGBoost package) which is an implementation of gradient boosted decision trees designed for speed and performance. For example, let us build a machine learning model

```
my.grid=list(eta=c(0.01,0.02,0.05),subsample=c(0.5,0.8))
data_train<-dplyr::filter(dataCOICOP,dataCOICOP$time<=as.Date("2021-10-01"))
data_test<-dplyr::filter(dataCOICOP,dataCOICOP$time==as.Date("2021-11-01"))
ML<-model_classification(data_train,
                         data_test,
                         coicop="coicop6",
                         grid=my.grid,
                         indicators=c("description","codeIN",”grammage”),
                         key_words=c("uht"),
                         rounds=60)
```

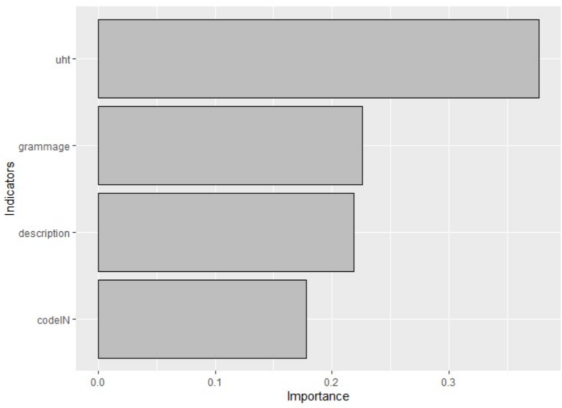
We can watch the results of the whole training process:

```
ML$figure_training
```



or we can observe the importance of the used indicators:

```
ML$figure_importance
```



Now, let us save the model on the disk. After saving the model we can load it and use at any time:

```
#Setting a temporary directory as a working directory
wd<-tempdir()
setwd(wd)


#Saving and loading the model
save_model(ML, dir="My_model")
ML_fromPC<-load_model("My_model")


#Prediction
data_predicted<-data_classifying(ML_fromPC, data_test)
head(data_predicted)
#>         time prices quantities                            description code
IN
#> 1 2021-11-01   3.03        379 g/wydojone mleko bez laktozyuht 3,2%1l  600
01
#> 2 2021-11-01   3.03        856 g/wydojone mleko bez laktozyuht 3,2%1l  600
01
#> 3 2021-11-01   3.03        369 g/wydojone mleko bez laktozyuht 3,2%1l  600
01
#> 4 2021-11-01   3.03        617 g/wydojone mleko bez laktozyuht 3,2%1l  600
01
#> 5 2021-11-01   3.03        613 g/wydojone mleko bez laktozyuht 3,2%1l  600
01
#> 6 2021-11-01   3.03        261 g/wydojone mleko bez laktozyuht 3,2%1l  600
01
#>   retID grammage unit       category coicop6 coicop_predicted
#> 1     2        1    l UHT whole milk 11411_1          11411_1
#> 2     3        1    l UHT whole milk 11411_1          11411_1
#> 3     4        1    l UHT whole milk 11411_1          11411_1
#> 4     5        1    l UHT whole milk 11411_1          11411_1
#> 5     6        1    l UHT whole milk 11411_1          11411_1
#> 6     7        1    l UHT whole milk 11411_1          11411_1
```

data_matching

If you have a dataset with information about products sold but they are not matched you can use the **data_matching** function. In an optimal situation, your data frame contains the **codeIN**, **codeOUT** and **description** columns (see documentation), which in practice will contain *retailer codes*, *GTIN* or *SKU* codes and *product labels*, respectively. The **data_matching** function returns a data set defined in the first parameter (*data*) with an additional column (*prodID*). Two products are treated as being matched if they have the same prodID value. The procedure of generating the above-mentioned additional column depends on the set of chosen columns for matching (see documentation for details). For instance, let us suppose you want to obtain matched products from the following, artificial data set:

```r
head(dataMATCH)
#> time    prices quantities codeIN codeOUT retID description
#> 1 2018-12-01  9.416371        309       1       1     1   product A
#> 2 2019-01-01  9.881875        325       1       5     1   product A
#> 3 2019-02-01 12.611826        327       1       1     1   product A
#> 4 2018-12-01  9.598252        309       3       2     1   product A
#> 5 2019-01-01  9.684900        325       3       2     1   product A
#> 6 2019-02-01  9.358420        327       3       2     1   product A
```

Let us assume that products with two identical codes (**codeIN** and **codeOUT**) or one of the codes identical and an identical description are automatically matched. Products are also matched if they have one of the codes identical and the *Jaro-Winkler similarity* of their descriptions is bigger than the fixed **precision** value (see documentation - *Case 1*). Let us also suppose that you want to match all products sold in the interval: December 2018 - February 2019. If you use the **data_matching** function (as below), an additional column (**prodID**) will be added to your data frame:

```r
data1<-data_matching(dataMATCH, start="2018-12",end="2019-02", codeIN=TRUE,
codeOUT=TRUE, precision=.98, interval=TRUE)
head(data1)
#>          time    prices quantities codeIN codeOUT retID description prodID
#> 1 2018-12-01  9.416371        309       1       1     1   product A      4
#> 2 2019-01-01  9.881875        325       1       5     1   product A      4
#> 3 2019-02-01 12.611826        327       1       1     1   product A      4
#> 4 2018-12-01  9.598252        309       3       2     1   product A      8
#> 5 2019-01-01  9.684900        325       3       2     1   product A      8
#> 6 2019-02-01  9.358420        327       3       2     1   product A      8
```

Let us now suppose you do not want to consider **codeIN** while matching and that products with an identical **description** are to be matched too:

```r
data2<-data_matching(dataMATCH, start="2018-12",end="2019-02",
                     codeIN=FALSE, onlydescription=TRUE, interval=TRUE)
head(data2)
#>          time    prices quantities codeIN codeOUT retID description prodID
#> 1 2018-12-01  9.416371        309       1       1     1   product A      7
#> 2 2019-01-01  9.881875        325       1       5     1   product A      7
#> 3 2019-02-01 12.611826        327       1       1     1   product A      7
#> 4 2018-12-01  9.598252        309       3       2     1   product A      7
#> 5 2019-01-01  9.684900        325       3       2     1   product A      7
#> 6 2019-02-01  9.358420        327       3       2     1   product A      7
```

Now, having a **prodID** column, your datasets are ready for further price index calculations, e.g.:

```r
fisher(data1, start="2018-12", end="2019-02")
#> [1] 1.018419
jevons(data2, start="2018-12", end="2019-02")
#> [1] 1.074934
```

data_filtering

This function returns a filtered data set, i.e. a reduced user's data frame with the same columns and rows limited by a criterion defined by the **filters** parameter (see documentation). If the set of filters is empty then the function returns the original data frame (defined by the **data** parameter). On the other hand, if all filters are chosen, i.e. *filters=c(extremeprices, dumpprices, lowsales)*, then these filters work independently and a summary result is returned. Please note that both variants of the *extremeprices* filter can be chosen at the same time, i.e. *plimits* and *pquantiles*, and they work also independently. For example, let us assume we consider three filters: **filter1** is to reject 1% of the lowest and 1% of the highest price changes comparing March 2019 to December 2018, **filter2** is to reject products with the price ratio being less than 0.5 or bigger than 2 in the same time, **filter3** rejects the same products as **filter2** rejects and also products with relatively *low sale* in compared months, **filter4** rejects products with the price ratio being less than 0.9 and with the expenditure ratio being less than 0.8 in the same time.

```
filter1<-data_filtering(milk,start="2018-12",end="2019-03",
                        filters=c("extremeprices"),pquantiles=c(0.01,0.99))
filter2<-data_filtering(milk,start="2018-12",end="2019-03",
                        filters=c("extremeprices"),plimits=c(0.5,2))
filter3<-data_filtering(milk,start="2018-12",end="2019-03",
                        filters=c("extremeprices","lowsales"),
                        plimits=c(0.5,2))
filter4<-data_filtering(milk,start="2018-12",end="2019-03",
                        filters=c("dumpprices"),dplimits=c(0.9,0.8))
```

These three filters differ from each other with regard to the data reduction level:

```
data_without_filters<-data_filtering(milk,start="2018-12",end="2019-03",filte
rs=c())
nrow(data_without_filters)
#> [1] 413
nrow(filter1)
#> [1] 378
nrow(filter2)
#> [1] 381
nrow(filter3)
#> [1] 170
nrow(filter4)
#> [1] 374
```

You can also use **data_filtering** for each pair of subsequent months from the considered time interval under the condition that this filtering is done for each outlet (**retID**) separately, e.g.

```
filter1B<-data_filtering(milk,start="2018-12",end="2019-03",
                         filters=c("extremeprices"),pquantiles=c(0.01,0.99),
                         interval=TRUE, retailers=TRUE)
nrow(filter1B)
#> [1] 773
```

Functions providing dataset characteristics

available

The function returns all values from the indicated column (defined by the **type** parameter) which occur at least once in one of compared periods or in a given time interval. Possible values of the **type** parameter are: **retID**, **prodID**, **codeIN**, **codeOUT** or **description** (see documentation). If the **interval** parameter is set to FALSE, then the function compares only periods defined by **period1** and **period2**. Otherwise the whole time period between period1 and period2 is considered. For example:

```
available(milk, period1="2018-12", period2="2019-12", type="retID",
interval=TRUE)
#> [1] 2210 1311 6610 7611 8910
```

matched

The function returns all values from the indicated column (defined by the **type** parameter) which occur simultaneously in the compared periods or in a given time interval.Possible values of the **type** parameter are: **retID**, **prodID**, **codeIN**, **codeOUT** or **description** (see documentation). If the **interval** parameter is set to FALSE, then the function compares only periods defined by **period1** and **period2**. Otherwise the whole time period between period1 and period2 is considered. For example:

```
matched(milk, period1="2018-12", period2="2019-12",
type="prodID",interval=TRUE)

#>  [1]  14216  15404  17034  34540  60010  70397  74431  82827  82830  82919
#> [11]  94256 400032 400033 400189 400194 400195 400196 401347 401350 402263
#> [21] 402264 402293 402569 402570 402601 402602 402609 403249 404004 404005
#> [31] 405419 405420 406223 406224 406245 406246 406247 407219 407220 407669
#> [41] 407670 407709 407859 407860 400099
```

matched_index

The function returns a ratio of values from the indicated column that occur simultaneously in the compared periods or in a given time interval to all available values from the above-mentioned column (defined by the **type** parameter) at the same time. Possible values of the **type** parameter are: **retID**, **prodID**, **codeIN**, **codeOUT** or **description** (see documentation). If the **interval** parameter is set to FALSE, then the function compares only periods defined by period1 and period2. Otherwise the whole time period between period1 and period2 is considered. The returned value is from 0 to 1. For example:

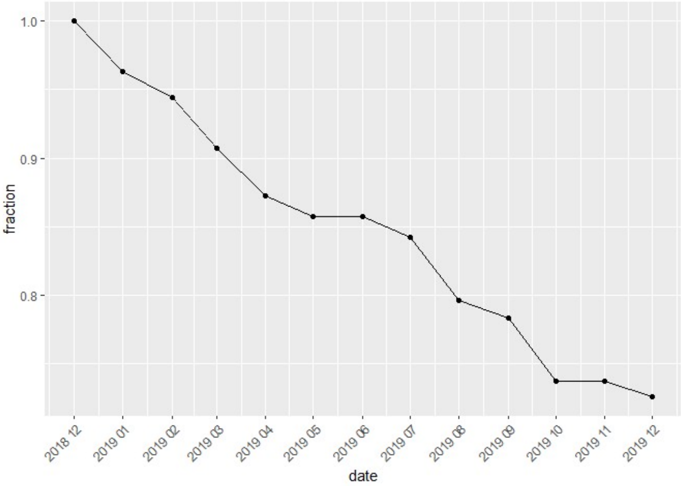
```
matched_index(milk, period1="2018-12", period2="2019-12",
type="prodID",interval=TRUE)

#> [1] 0.7258065
```

matched_fig

The function returns a **data frame** or a **figure** presenting the **matched_index** function calculated for the column defined by the **type** parameter and for each month from the considered time interval. The interval is set by the **start** and **end** parameters. The returned object (data frame or figure) depends on the value of the **figure** parameter. Examples:

```
matched_fig(milk, start="2018-12", end="2019-12", type="prodID")
```




```
matched_fig(milk, start="2018-12",end="2019-04", type="prodID", figure=FALSE)

#>      date  fraction
#> 1 2018-12 1.0000000
#> 2 2019-01 0.9629630
#> 3 2019-02 0.9444444
#> 4 2019-03 0.9074074
#> 5 2019-04 0.8727273
```

products

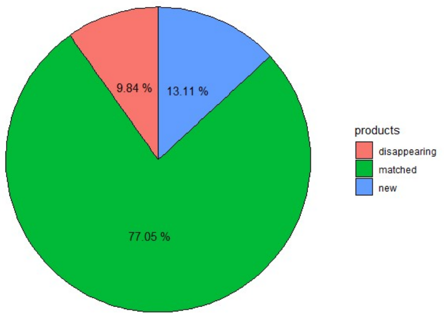
This function detects and summarises available, matched, new and disappearing products on the basis of their prodIDs. It compares products from the base period (**start**) with products from the current period (**end**). It returns a list containing the following objects: details with prodIDs of available, matched, new and disappearing products, statistics with basic statistics for them and figure with a pie chart describing a contribution of matched, new and disappearing products in a set of available products. Please see the following example:

```
list<-products(milk, "2018-12","2019-12")
```

```r
list$statistics
```

```
#>       products volume shares
#> 1    available     61 100.00
#> 2      matched     47  77.05
#> 3          new      8  13.11
#> 4 disappearing      6   9.84
```

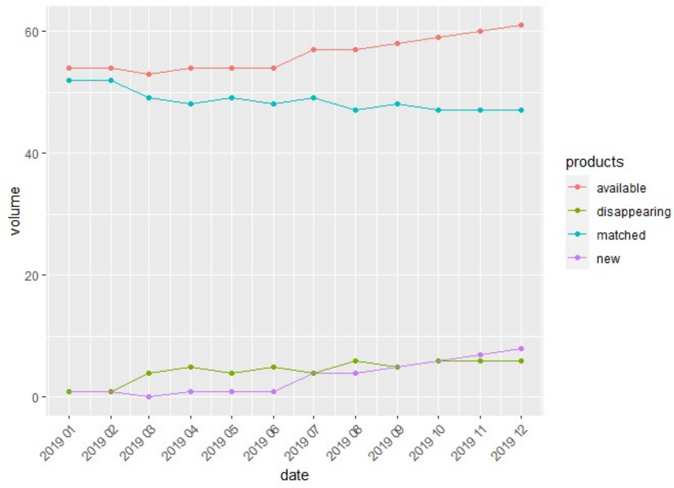
```r
list$figure
```



products_fig

This function returns a figure with plots of volume (or contributions) of available, matched, new as well as disappearing products. The User may control which groups of products are to be taken into consideration. Available options are **available**, **matched**, **new** and **disappearing**. Please follow the example:

```r
products_fig(milk, "2018-12","2019-12",
fixed_base=TRUE, contributions=FALSE,
show=c("new","disappearing","matched","available"))
```



prices

The function returns prices (unit value) of products with a given ID (**prodID** column) and being sold in the time period indicated by the **period** parameter. The **set** parameter means a set of unique product IDs to be used for determining prices of sold products. If the set is empty the function returns prices of all products being available in the **period**. Please note that the function returns the price values for sorted prodIDs and in the absence of a given prodID in the data set, the function returns nothing (it does not return zero).To get prices (unit values) of all available milk products sold in July, 2019, please use:

```
prices(milk, period="2019-06")
#>  [1]  8.700000  8.669455  1.890000  2.950000  1.990000  2.990000  2.834464
#>  [8]  4.702051  2.163273  2.236250  2.810000  2.860000  2.400000  2.588644
#> [15]  3.790911  7.980000 64.057143  7.966336 18.972121 12.622225  9.914052
#> [22]  7.102823  3.180000  2.527874  1.810000  1.650548  2.790000  2.490000
#> [29]  2.590000  7.970131  9.901111 15.266667 19.502286  2.231947  2.674401
#> [36]  2.371819  2.490000  6.029412  6.441176  2.090000  1.990000  1.890000
#> [43]  1.450000  2.680000  2.584184  2.683688  2.390000  3.266000  2.813238
```

quantities

The function returns quantities of products with a given ID (**prodID** column) and being sold in the time period indicated by the **period** parameter. The **set** parameter means a set of unique product IDs to be used for determining prices of sold products. If the set is empty the function returns quantities of all products being available in the **period**. Please note that the function returns the quantity values for sorted prodIDs and in the absence of a given prodID in the data set, the function returns nothing (it does not return zero). To get a data frame containing quantities of milk products with prodIDs: 400032, 71772 and 82919, and sold in July, 2019, please use:

```
quantities(milk, period="2019-06", set=c(400032, 71772, 82919), ID=TRUE)
#> # A tibble: 3 x 2
#>       by     q
#>    <int> <dbl>
#> 1  71772  117
#> 2  82919  102
#> 3 400032  114.
```

sales

The function returns values of sales of products with a given ID (**prodID** column) and being sold in the time period indicated by **period** parameter. The **set** parameter means a set of unique product IDs to be used for determining prices of sold products. If the set is empty the function returns values of sales of all products being available in the **period** (see also **expenditures** function which returns the expenditure values for sorted prodIDs). To get values of sales of milk products with prodIDs: 400032, 71772 and 82919, and sold in July, 2019, please use:

```
sales(milk, period="2019-06", set=c(400032, 71772, 82919))
#> [1] 913.71 550.14 244.80
```

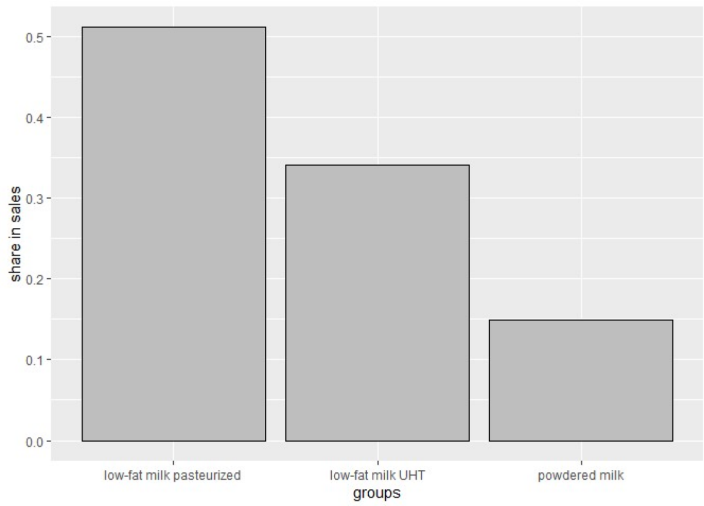
sales_groups

The function returns **values of sales** of products from one or more **datasets** or the corresponding **barplot** for these sales (if **barplot** is set to TRUE). Alternatively, it calculates the **sale shares** (if the **shares** parameter is set to TRUE). Please see also the **sales_groups2** function. As an example, let us create 3 subgroups of **milk** products and let us find out their sale shares for the time interval: April, 2019 - July, 2019. We can obtain precise values for the given **period**:

```
ctg<-unique(milk$description)
categories<-c(ctg[1],ctg[2],ctg[3])
milk1<-dplyr::filter(milk, milk$description==categories[1])
milk2<-dplyr::filter(milk, milk$description==categories[2])
milk3<-dplyr::filter(milk, milk$description==categories[3])
sales_groups(datasets=list(milk1,milk2,milk3),start="2019-04", end="2019-07")
#> [1]  44400.76 152474.55 101470.76
sales_groups(datasets=list(milk1,milk2,milk3),start="2019-04", end="2019-07",
shares=TRUE)
#> [1] 0.1488230 0.5110661 0.3401109
```

or a barplot presenting these results:

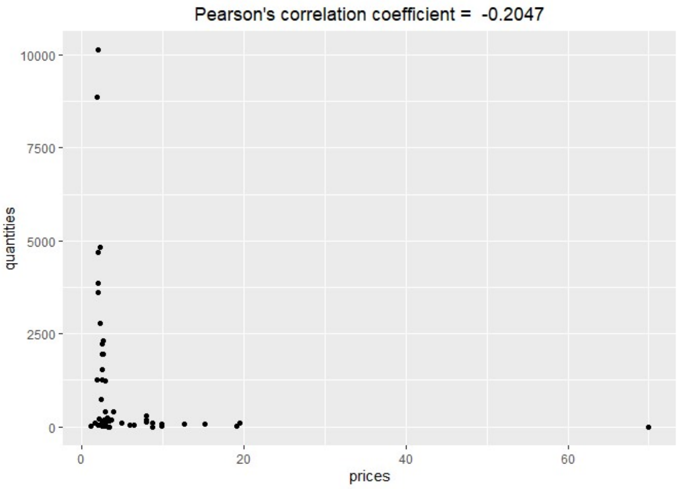
```
sales_groups(datasets=list(milk1,milk2,milk3),start="2019-04", end="2019-07",
             barplot=TRUE, shares=TRUE, names=categories)
```



pqcor

The function returns **Pearson's correlation coefficient** for price and quantity of products with given IDs (defined by the **set** parameter) and sold in the **period.** If the **set** is empty, the function works for all products being available in the **period.** The **figure** parameter indicates whether the function returns a figure with a correlation coefficient (TRUE) or just a correlation coefficient (FALSE). For instance:

```
pqcor(milk, period="2019-05")
#> [1] -0.2047
pqcor(milk, period="2019-05",figure=TRUE)
```

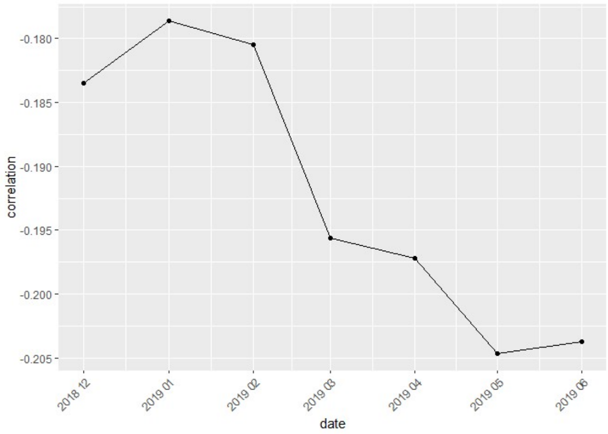


pqcor_fig

The function returns **Pearson's correlation coefficients** between price and quantity of products with given IDs (defined by the **set** parameter) and sold in the time interval defined by the **start** and **end** parameters. If the **set** is empty the function works for all available products. Correlation coefficients are calculated for each month separately. Results are presented in tabular or graphical form depending on the **figure** parameter. Both cases are presented below:

```
pqcor_fig(milk, start="2018-12", end="2019-06", figure=FALSE)
#>      date correlation
#> 1 2018-12     -0.1835
#> 2 2019-01     -0.1786
#> 3 2019-02     -0.1805
#> 4 2019-03     -0.1956
#> 5 2019-04     -0.1972
#> 6 2019-05     -0.2047
#> 7 2019-06     -0.2037
```

```r
pqcor_fig(milk, start="2018-12", end="2019-06")
```



dissimilarity

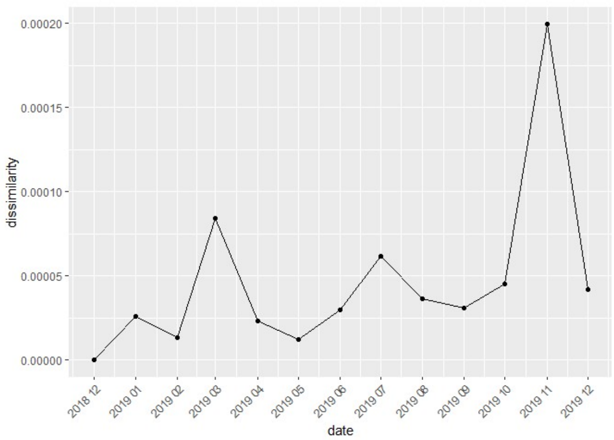
This function returns a value of the relative price (dSP) and/or quantity (dSQ) dissimilarity measure. In a special case, when the **type** parameter is set to **pq**, the function provides the value of dSPQ measure (relative price and quantity dissimilarity measure calculated as **min(dSP,dSQ)**. For instance:

```r
dissimilarity(milk, period1="2018-12",period2="2019-12",type="pq")
#> [1] 0.00004175192
```

dissimilarity_fig

This function presents values of the relative price and/or quantity dissimilarity measure over time. The user can choose a benchmark period (defined by **benchmark**) and the type of dissimilarity measure is to be calculated (defined by **type**). The obtained results of dissimilarities over time can be presented in a dataframe form or via a figure (the default value of **figure** is TRUE which results a figure). For instance:

```r
dissimilarity_fig(milk, start="2018-12",end="2019-12",type="pq",
benchmark="start")
```



elasticity

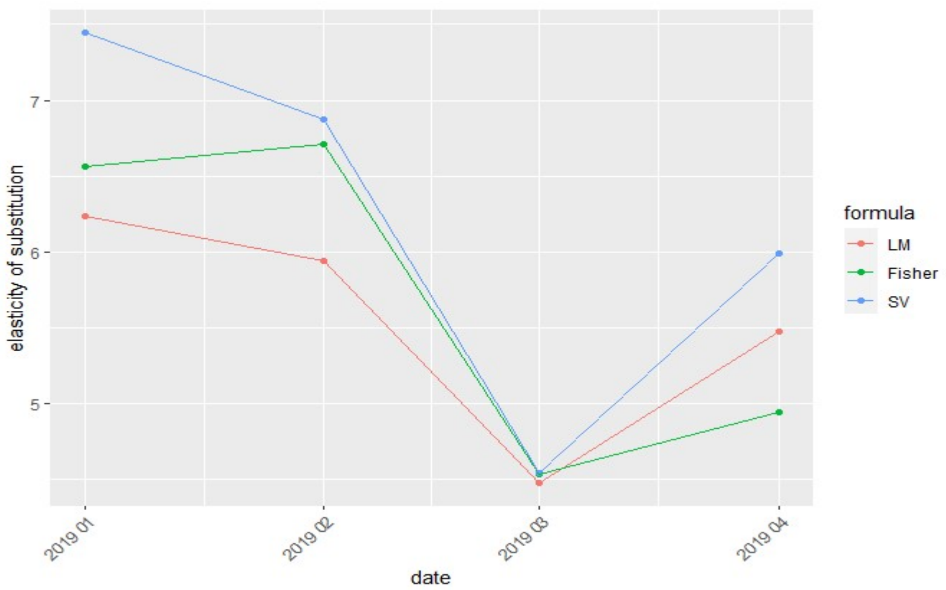
This function returns a value of the elasticity of substitution. If the **method** parameter is set to **lm** (it is a default value), the procedure of estimation solves the equation: LM(sigma)-CW(sigma)=0 numerically, where LM denotes the Lloyd-Moulton price index, the CW denotes a current weight counterpart of the Lloyd-Moulton price index, and sigma is the elasticity of substitution parameter, which is estimated. If the **method** parameter is set to **f**, the Fisher price index formula is used instead of the CW price index. If the **method** parameter is set to **t**, the Törnqvist price index formula is used instead of the CW price index. If the **method** parameter is set to **w**, the Walsh price index formula is used instead of the CW price index. If the **method** parameter is set to **sv**, the Sato-Vartia price index formula is used instead of the CW price index. The procedure continues until the absolute value of this difference is greater than the value of the 'precision' parameter. For example:

```
elasticity(coffee, start = "2018-12", end = "2019-01")
#> [1] 4.241791
```

elasticity_fig

The function provides a data frame or a figure presenting elasticities of substitution calculated for time interval (see the **figure** parameter). The elasticities of substitution can be calculated for subsequent months or for a fixed base month (see the **start** parameter) and rest of months from the given time interval (it depends on the **fixedbase** parameter). The presented function is based on the **elasticity** function. For instance, to get elasticities of substitution calculated for milk products for subsequent months we run:

```
elasticity_fig (milk,start="2018-12",end="2019-04",figure=TRUE,
method=c("lm","f","sv"),names=c("LM","Fisher", "SV"))
```



Functions for bilateral unweighted price index calculation

This package includes 6 functions for calculating the following bilateral unweighted price indices:

Price Index	Function
BMW (2007)	bmw
Carli (1804)	carli
CSWD (1980,1992)	cswd
Dutot (1738)	dutot
Jevons (1865)	jevons
Harmonic	harmonic

Each of these functions returns a value (or vector of values) of the choosen unweighted bilateral price index depending on the **interval** parameter. If the interval parameter is set to TRUE, the function returns a vector of price index values without dates. To get information about both price index values and corresponding dates please see general functions: **price_indices** or **final_index.** None of these functions takes into account aggregating over outlets or product subgroups (to consider these types of aggregating please use the **final_index** function.) Below are examples of calculations for the Jevons index (in the second case a *fixed base month* is set to December 2018):

```
jevons(milk, start="2018-12", end="2020-01")
#> [1] 1.028223


jevons(milk, start="2018-12", end="2020-01", interval=TRUE)
#>  [1] 1.0000000 1.0222661 1.0300191 1.0353857 1.0075504 1.0395393 0.9853148
#>  [8] 1.0053100 1.0033727 1.0177604 1.0243906 1.0086291 1.0249373 1.0282234
```

Functions for bilateral weighted price index calculation

This package includes 30 functions for calculating the following bilateral weighted price indices:

Price Index	Function
AG Mean (2009)	agmean
Banajree (1977)	banajree
Bialek (2012,2013)	bialek
Davies (1924)	davies
Drobisch (1871)	drobisch
Fisher (1922)	fisher
Geary-Khamis (1958,1970)	geary_khamis

Geo-Laspeyres	geolaspeyres
Geo-Lowe	geolowe
Geo-Paasche	geopaasche
Geo-Young	geoyoung
Geo-hybrid (2020)	geohybrid
Hybrid (2020)	hybrid
Laspeyres (1871)	laspeyres
Lehr (1885)	lehr
Lloyd-Moulton (1975,1996)	lloyd_moulton
Lowe	lowe
Marshall-Edgeworth (1887)	marshall_edgeworth
Paasche (1874)	paasche
Palgrave (1886)	palgrave
Sato-Vartia (1976)	sato_vartia
Stuvel (1957)	stuvel
Törnqvist (1936)	tornqvist
Vartia (1976)	vartia
Walsh (1901)	walsh
Young	young
Quadratic mean of order r price index	QMp
Implicit quadratic mean of order r price index	IQMp
Value Index	value_index
Unit Value Index	unit_value_index

and the general quadratic mean of order r quantity index: QMq.

Each of these functions returns a value (or vector of values) of the choosen weighted bilateral price index depending on the **interval** parameter. If interval parameter is set to TRUE, the function returns a vector of price index values without dates. To get information about both price index values and corresponding dates please see general functions: **price_indices** or **final_index**. None of these functions takes into account aggregating over outlets or product subgroups (to consider these types of aggregating please use the **final_index** function.) Below are examples of calculations for the Fisher, the Lloyd-Moulton and the Lowe indices (in the last case, the *fixed base month* is set to December 2019 and the *prior* period is December 2018):

```
fisher(milk, start="2018-12", end="2020-01")
#> [1] 0.9615501
```

```
lloyd_moulton(milk, start="2018-12", end="2020-01", sigma=0.9)
#> [1] 0.9835069

lowe(milk, start="2019-12", end="2020-02", base="2018-12", interval=TRUE)
#> [1] 1.0000000 0.9880546 1.0024443
```

Functions for chain price index calculation

This package includes 35 functions for calculating the following chain indices (weighted and unweighted):

Price Index	Function
Chain BMW	chbmw
Chain Carli	chcarli
Chain CSWD	chcswd
Chain Dutot	chdutot
Chain Jevons	chjevons
Chain Harmonic	chharmonic
Chain AG Mean	chagmean
Chain Banajree	chbanajree
Chain Bialek	chbialek
Chain Davies	chdavies
Chain Drobisch	chdrobisch
Chain Fisher	chfisher
Chain Geary-Khamis	chgeary_khamis
Chain Geo-Laspeyres	chgeolaspeyres
Chain Geo-Lowe	chgeolowe
Chain Geo-Paasche	chgeopaasche
Chain Geo-Young	chgeoyoung
Chain Geo-hybrid	chgeohybrid
Chain Hybrid	chhybrid
Chain Laspeyres	chlaspeyres
Chain Lehr	chlehr
Chain Lloyd-Moulton	chlloyd_moulton
Chain Lowe	chlowe
Chain Marshall-Edgeworth	chmarshall_edgeworth
Chain Paasche	chpaasche
Chain Palgrave	chpalgrave

Chain Sato-Vartia	chsato_vartia
Chain Stuvel	chstuvel
Chain Tornqvist	chtornqvist
Chain Vartia	chvartia
Chain Walsh	chwalsh
Chain Young	chyoung
Chain quadratic mean of order r price index	chQMp
Chain implicit quadratic mean of order r price index	chIQMp
Chain quadratic mean of order r quantity index	chQMq

Each time, the **interval** parameter has a logical value indicating whether the function is to compare the research period defined by **end** to the base period defined by **start** (then **interval** is set to FALSE and it is a default value) or all fixed base indices are to be calculated. In this second case, all months from the time interval are considered and **start** defines the base period (**interval** is set to TRUE). Here are examples for the Fisher chain index:

```
chfisher(milk, start="2018-12", end="2020-01")
#> [1] 0.9618094


chfisher(milk, start="2018-12", end="2020-01", interval=TRUE)
#>  [1] 1.0000000 1.0021692 1.0004617 0.9862756 0.9944042 0.9915704 0.9898026
#>  [8] 0.9876325 0.9981591 0.9968851 0.9786428 0.9771951 0.9874251 0.9618094
```

Functions for multilateral price index calculation

This package includes 22 functions for calculating multilateral price indices and one additional and general function (**QU**) which calculates the quality adjusted unit value index, i.e.:

Price Index	Function
CCDI	ccdi
GEKS	geks
WGEKS	wgeks
GEKS-J	geksj
GEKS-W	geksw
GEKS-L	geksl
WGEKS-L	wgeksl
GEKS-GL	geksgl
WGEKS-GL	wgeksgl
GEKS-AQU	geksaqu

WGEKS-AQU	wgeksaqu
GEKS-AQI	geksaqi
WGEKS-AQI	wgeksaqi
GEKS-GAQI	geksgaqi
GEKS-IQM	geksiqm
GEKS-QM	geksqm
GEKS-LM	gekslm
WGEKS-GAQI	wgeksgaqi
Geary-Khamis	gk
Quality Adjusted Unit Value	QU
Time Product Dummy	tpd
Unweighted Time Product Dummy	utpd
SPQ	SPQ

The above-mentioned 21 multilateral formulas (the **SPQ** index is an exception) consider the time window defined by the **wstart** and **window** parameters, where **window** is a length of the time window (typically multilateral methods are based on a 13-month time window). It measures the price dynamics by comparing the **end** period to the **start** period (both **start** and **end** must be inside the considered time window). To get information about both price index values and corresponding dates, please see functions: **price_indices** or **final_index**. These functions do not take into account aggregating over outlets or product subgroups (to consider these types of aggregating please use function: **final_index**). Here are examples for the GEKS formula (see documentation):

```
geks(milk, start="2019-01", end="2019-04",window=10)
#> [1] 0.9912305


geksl(milk, wstart="2018-12", start="2019-03", end="2019-05")
#> [1] 1.002251
```

The **QU** function returns a value of the *quality adjusted unit value index* (QU index) for the given set of adjustment factors. An additional **v** parameter is a data frame with adjustment factors for at least all matched **prodIDs**. It must contain two columns: **prodID** with unique product IDs and **value** with corresponding adjustment factors (see documentation). The following example starts from creating a data frame which includes sample adjusted factors:

```
prodID<-base::unique(milk$prodID)
values<-stats::runif(length(prodID),1,2)
v<-data.frame(prodID,values)
head(v)
#>   prodID   values
#> 1  14215 1.580344
#> 2  14216 1.769872
#> 3  15404 1.004895
```

```
#> 4  17034 1.606677
#> 5  34540 1.865757
#> 6  51583 1.995211
```

and the next step is calculating the QU index which compares December 2019 to December 2018:

```
QU(milk, start="2018-12", end="2019-12", v)
#> [1] 1.028463
```

Functions for extending multilateral price indices by using splicing methods

This package includes 21 functions for calculating splice indices:

Price Index	Function
Splice CCDI	ccdi_splcie
Splice GEKS	geks_splice
Splice weighted GEKS	wgeks_splice
Splice GEKS-J	geksj_splice
Splice GEKS-W	geksw_splice
Splice GEKS-L	geksl_splice
Splice weighted GEKS-L	wgeksl_splice
Splice GEKS-GL	geksgl_splice
Splice weighted GEKS-GL	wgeksgl_splice
Splice GEKS-AQU	geksaqu_splice
Splice weighted GEKS-AQU	wgeksaqu_splice
Splice GEKS-AQI	geksaqi_splice
Splice weighted GEKS-AQI	wgeksaqi_splice
Splice GEKS-GAQI	geksgaqi_splice
Splice weighted GEKS-GAQI	wgeksgaqi_splice
Splice GEKS-IQM	geksiqm_splice
Splice GEKS-QM	geksqm_splice
Splice GEKS-LM	gekslm_splice
Splice Geary-Khamis	gk_splice
Splice Time Product Dummy	tpd_splice
Splice unweighted Time Product Dummy	utpd_splice

These functions return a value (or values) of the selected multilateral price index extended by using window splicing methods (defined by the **splice** parameter). Available splicing methods are: **movement splice**, **window splice**, **half splice**, **mean splice** and their additional variants: **window splice on published indices (WISP)**, **half splice on published**

indices (HASP) and **mean splice on published indices** (see documentation). The first considered time window is defined by the **start** and **window** parameters, where **window** is a length of the time window (typically multilateral methods are based on a 13-month time window). Functions measure the price dynamics by comparing the **end** period to the **start** period, i.e. if the time interval exceeds the defined time window then splicing methods are used. If the **interval** parameter is set to TRUE, then all fixed base multilateral indices are presented (the fixed base month is defined by **start**). To get information about both price index values and corresponding dates, please see functions: **price_indices** or **final_index**. These functions do not take into account aggregating over outlets or product subgroups (to consider these types of aggregating, please use the **final_index** function). For instance, let us calculate the **extended Time Product Dummy** index by using the **half splice method** with a 10-month time window:

```
tpd_splice(milk, start="2018-12", end="2020-02",window=10,splice="half",inter
val=TRUE)
#>  [1] 1.0000000 1.0038893 1.0000284 0.9837053 0.9954196 0.9924919 0.9913655
#>  [8] 0.9866847 0.9998615 0.9949000 0.9806788 0.9808493 0.9888003 0.9628623
#> [15] 1.0021956
```

Functions for extending multilateral price indices by using the FBEW method

This package includes 21 functions for calculating extensions of multilateral indices by using the Fixed Base Monthly Expanding Window (FBEW) method:

Price Index	Function
FBEW CCDI	ccdi_fbew
FBEW GEKS	geks_fbew
FBEW WGEKS	wgeks_fbew
FBEW GEKS-J	geksj_fbew
FBEW GEKS-W	geksw_fbew
FBEW GEKS-L	geksl_fbew
FBEW WGEKS-L	wgeksl_fbew
FBEW GEKS-GL	geksgl_fbew
FBEW WGEKS-GL	wgeksgl_fbew
FBEW GEKS-AQU	geksaqu_fbew
FBEW WGEKS-AQU	wgeksaqu_fbew
FBEW GEKS-AQI	geksaqi_fbew
FBEW WGEKS-AQI	wgeksaqi_fbew
FBEW GEKS-GAQI	geksgaqi_fbew
FBEW WGEKS-GAQI	wgeksgaqi_fbew
FBEW GEKS-QM	geksqm_fbew
FBEW GEKS-IQM	geksiqm_fbew

FBEW GEKS-LM	gekslm_fbew
FBEW Geary-Khamis	gk_fbew
FBEW Time Product Dummy	tpd_fbew
FBEW unweighted Time Product Dummy	utpd_fbew

These functions return a value (or values) of the selected multilateral price index extended by using the FBEW method. The FBEW method uses a time window with a fixed base month every year (December). The window is enlarged every month with one month in order to include information from a new month. The full window length (13 months) is reached in December of each year. These functions measure the price dynamics between the **end** and **start** periods. A month of the **start** parameter must be December (see documentation). If the distance between **end** and **start** exceeds 13 months, then internal Decembers play a role of chain-linking months. To get information about both price index values and corresponding dates please see functions: **price_indices** or **final_index**. These functions do not take into account aggregating over outlets or product subgroups (to consider these types of aggregating, please use the **final_index** function). For instance, let us calculate the **extended GEKS** index by using the FBEW method. Please note that December 2019 is the chain-linking month, i.e.:

```
geks_fbew(milk, start="2018-12", end="2020-03")
#> [1] 0.9891602


geks_fbew(milk, start="2018-12", end="2019-12")*
geks_fbew(milk, start="2019-12", end="2020-03")
#> [1] 0.9891602
```

Functions for extending multilateral price indices by using the FBMW method

This package includes 21 functions for calculating extensions of multilateral indices by using the Fixed Base Moving Window (FBMW) method:

Price Index	Function
FBMW CCDI	ccdi_fbmw
FBMW GEKS	geks_fbmw
FBMW WGEKS	wgeks_fbmw
FBMW GEKS-J	geksj_fbmw
FBMW GEKS-W	geksw_fbmw
FBMW GEKS-L	geksl_fbmw
FBMW WGEKS-L	wgeksl_fbmw
FBMW GEKS-GL	geksgl_fbmw
FBMW WGEKS-GL	wgeksgl_fbmw

FBMW GEKS-AQU	geksaqu_fbmw
FBMW WGEKS-AQU	wgeksaqu_fbmw
FBMW GEKS-AQI	geksaqi_fbmw
FBMW WGEKS-AQI	wgeksaqi_fbmw
FBMW GEKS-GAQI	geksgaqi_fbmw
FBMW WGEKS-GAQI	wgeksgaqi_fbmw
FBMW GEKS-IQM	geksiqm_fbmw
FBMW GEKS-QM	geksqm_fbmw
FBMW GEKS-LM	gekslm_fbmw
FBMW Geary-Khamis	gk_fbmw
FBMW Time Product Dummy	tpd_fbmw
FBMW unweighted Time Product Dummy	utpd_fbmw

These functions return a value (or values) of the selected multilateral price index extended by using the FBMW method. They measure the price dynamics between the **end** and **start** periods and it uses a 13-month time window with a fixed base month taken as **year(end)-1**. If the distance between **end** and **start** exceeds 13 months, then internal Decembers play a role of chain-linking months. A month of the **start** parameter must be December (see documentation). To get information about both price index values and corresponding dates, please see functions: **price_indices** or **final_index**. These functions do not take into account aggregating over outlets or product subgroups (to consider these types of aggregating, please use the **final_index** function). For instance, let us calculate the **extended CCDI** index by using the FBMW method. Please note that December 2019 is the chain-linking month, i.e.:

```
ccdi_fbmw(milk, start="2018-12", end="2020-03")
#> [1] 0.9874252


ccdi_fbmw(milk, start="2018-12", end="2019-12")*
ccdi_fbmw(milk, start="2019-12", end="2020-03")
#> [1] 0.9874252
```

General functions for price index calculations

This package includes 3 general functions for price index calculation. The **start** and **end** parameters indicate the base and the research period respectively. These function provide value or values (depending on the **interval** parameter) of the selected price index formula or formulas. If the **interval** parameter is set to **TRUE** then it returns a data frame with two columns: **dates** and **index values**. Function **price_indices** does not take into account aggregating over outlets or product subgroups and to consider these types of aggregating, please use function: **final_index**.

price_indices

This function allows us to compare many price index formulas by using one command. The general character of this function mean that, for instance, your one command may calculate two CES indices for two different values of **sigma** parameter (the elasticity of substitution) or you can select several splice indices and calculate them by using different window lengths and different splicing method. You can control names of columns in the resulting data frame by defining additional parameters: **names.** Please note that this function is not the most general in the package, i.e. all selected price indices are calculated for the same data set defined by the **data** parameter and the aggregation over subgroups or outlets are not taken into consideration here (to consider it, please use function: **final_index**). For instance:

```
price_indices(milk,
         start = "2018-12", end = "2019-12",
         formula=c("geks","ccdi","hybrid","fisher",
         "QMp","young","geksl_fbew"),
         window = c(13, 13),
         base = c("2019-03", "2019-03"),
         r=c(3), interval=TRUE)


#>        time      geks      ccdi    hybrid    fisher       QMp     young
#> 1  2018-12 1.0000000 1.0000000 1.0000000 1.0000000 1.0000000 1.0000000
#> 2  2019-01 1.0020172 1.0018004 0.9967071 1.0021692 1.0025266 0.9982428
#> 3  2019-02 1.0001330 0.9997978 1.0009266 0.9983528 0.9983839 1.0005565
#> 4  2019-03 0.9839258 0.9840643 0.9737613 0.9868188 0.9866552 0.9766453
#> 5  2019-04 0.9936427 0.9932822 0.9861536 0.9954079 0.9956790 0.9875892
#> 6  2019-05 0.9899234 0.9898612 0.9866800 0.9904548 0.9905572 0.9874894
#> 7  2019-06 0.9889829 0.9888433 0.9808391 0.9906674 0.9908235 0.9827443
#> 8  2019-07 0.9862652 0.9864494 0.9889462 0.9848588 0.9845825 0.9893828
#> 9  2019-08 0.9981114 0.9978518 1.0012679 0.9987586 0.9989635 1.0005086
#> 10 2019-09 0.9952078 0.9951481 0.9985214 0.9959955 0.9962294 0.9976441
#> 11 2019-10 0.9776535 0.9773428 0.9747949 0.9767235 0.9770339 0.9746506
#> 12 2019-11 0.9805743 0.9815496 0.9948243 0.9771107 0.9762389 0.9943300
#> 13 2019-12 0.9876664 0.9876167 0.9952270 0.9868354 0.9868723 0.9939052
#>    geksl_fbew
#> 1   1.0000000
#> 2   1.0021692
#> 3   0.9964178
#> 4   0.9856119
#> 5   0.9914299
#> 6   0.9884677
#> 7   0.9873196
#> 8   0.9874639
#> 9   0.9957917
#> 10  0.9951035
#> 11  0.9739414
#> 12  0.9882475
#> 13  0.9844756
```

or

```
price_indices(coffee,
         start = "2018-12", end = "2019-12",
         formula=c("laspeyres","paasche","fisher"),
         interval=FALSE)
#>   price_index     value
#> 1   laspeyres    1.0167511
#> 2   paasche      0.9863043
#> 3   fisher       1.0014120
```

final_index

This general function returns a value or values of the selected final price index for the selected type of aggregation of partial results. If the interval parameter is set to TRUE, then it returns a data frame where its first column indicates dates and the remaining columns show corresponding values of all selected price index. A final price index formula can be any index formula which is available in the PriceIdices packages (bilateral or multilateral). The formula used for aggregating partial index results is selected by the **aggr** parameter and the User decides on directions of aggregation (see **outlets** and **groups** parameters).

Example. Let us calculate the final Fisher price index (with Laspeyres-type aggregation over outlets and product subgroups) for the data set on **milk**

```
final_index(milk, start = "2018-12", end = "2019-12",
         formula = "fisher", groups = TRUE, outlets = TRUE,
         aggr = "laspeyres", by = "description",
         interval = TRUE)


#>        time final_index
#> 1   2018-12   1.0000000
#> 2   2019-01   1.0043285
#> 3   2019-02   0.9994987
#> 4   2019-03   0.9909980
#> 5   2019-04   0.9955766
#> 6   2019-05   0.9922104
#> 7   2019-06   0.9910091
#> 8   2019-07   0.9862940
#> 9   2019-08   0.9981004
#> 10 2019-09   0.9978900
#> 11 2019-10   0.9764887
#> 12 2019-11   0.9837980
#> 13 2019-12   0.9871036
```

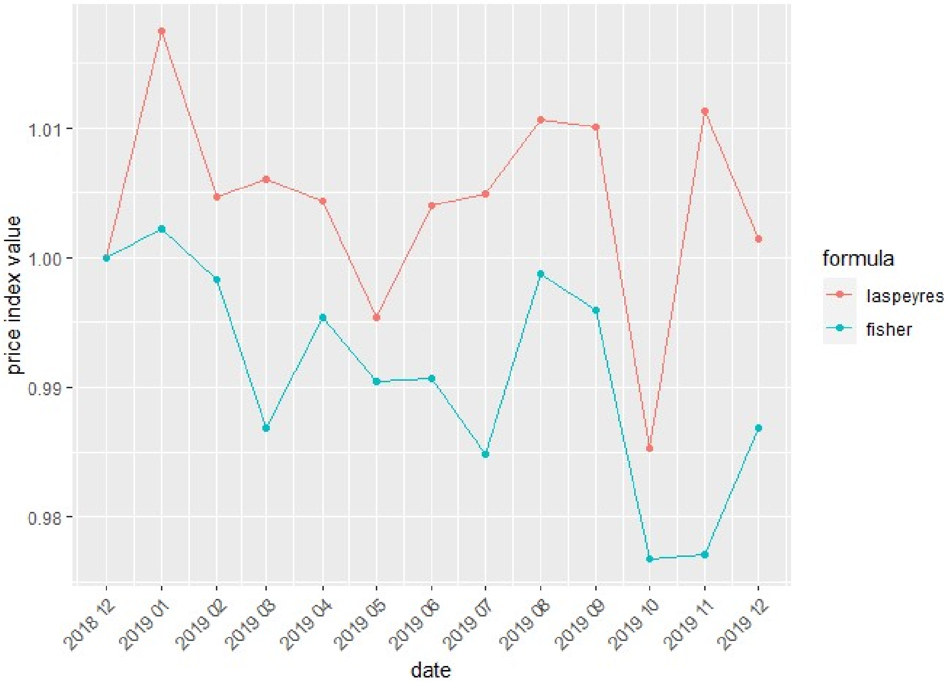
Functions for comparisons of price indices

This package includes two functions for a simple graphical comparison of price indices and two functions for calculating distances between indices. The first one, i.e. **compare_indices_df**, is based on the syntax of the **price_indices** function and thus it allows us to compare price indices calculated on the same data set. The second function, i.e. **compare_indices_list**, has a general character since its first argument is a list of data frames which contain results obtained by using the **price_indices** or **final_index** functions. The third one, i.e. **compare_distances**, calculates (average) distances between price indices, i.e. the mean absolute distance or root mean square distance is calculated. The last function, **compare_to_target** allows to compute distances between indices from the selected index group and the indicated target price index.

compare_indices_df and **compare_indices_list**

These function return a figure with plots of selected price indices, which are provided as a data frame (**compare_indices_df**) or a list of data frames (**compare_indices_list**). For instance, let us compare the Laspeyres and Paasche indices calculated for the data set on milk:

```
df<-price_indices(milk, start = "2018-12", end = "2019-12",
formula=c("laspeyres", "fisher"), interval = TRUE)
compare_indices_df(df)
```



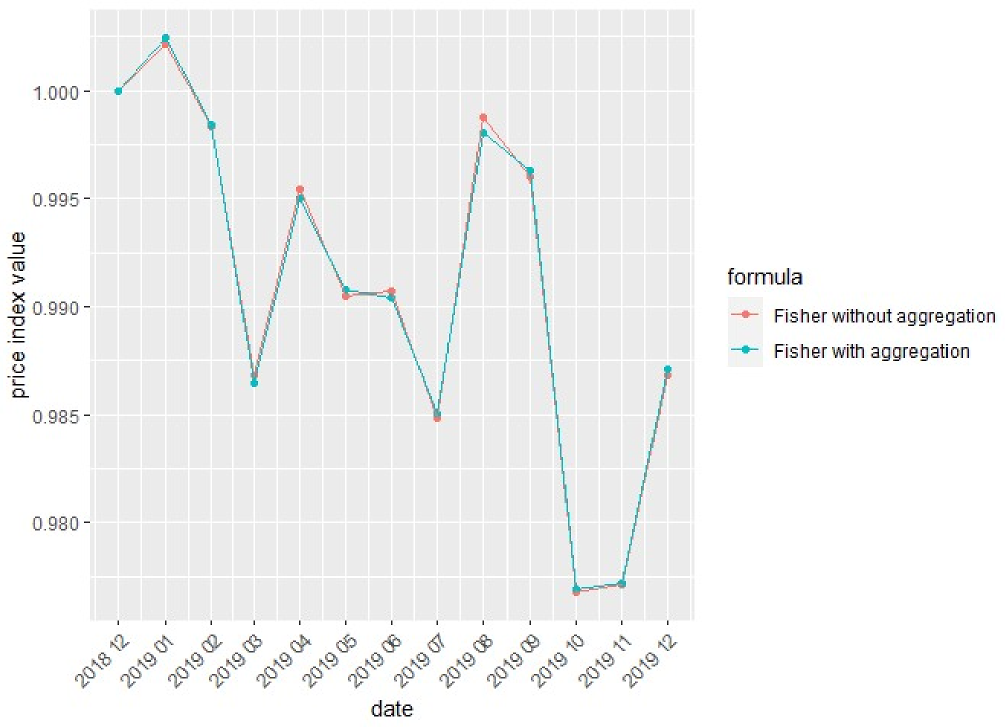
Now, let us compare the impact of the aggregating over outlets on the price index results (e.g. the Laspeyres formula is the assumed aggregating method). For this purpose, let us calculate the Fisher price index in two cases: **case1** without the above-mentioned aggregation and

case2 which considers that aggregation. We use the **milk** dataset and the yearly time interval:

```
case1<-price_indices(milk, start="2018-12",end="2019-12",
                   formula="fisher", interval=TRUE)
case2<-final_index(milk, start="2018-12", end="2019-12",
                   formula="fisher",
                   outlets=TRUE,
                   aggr = "laspeyres",
                   interval=TRUE)
```

The comparison of obtained results can be made as follows:

```
compare_indices_list(data=list(case1, case2),
                names=c("Fisher without aggregation",
                "Fisher with aggregation"))
```



compare_distances

The function calculates average distances between price indices and it returns a data frame with these values for each pair of price indices. The main **data** parameter is a data frame containing values of indices which are to be compared. The **measure** parameter specifies what measure should be used to compare the indexes. Possible parameter values are: "MAD" (Mean Absolute Distance) or "RMSD" (Root Mean Square Distance). The results may be presented in percentage points (see the **pp** parameter) and we can control how many decimal places are to be used in the presentation of results (see the **prec** parameter).

For instance, let us compare the Jevons, Dutot and Carli indices calculated for the **milk** data set and for the time interval: December 2018 - December 2019. Let us use the MAD measure for these comparisons:

```
#Creating a data frame with unweighted bilateral index values
df<-price_indices(milk,
                  formula=c("jevons","dutot","carli"),
                  start="2018-12",
                  end="2019-12",
                  interval=TRUE)


#Calculating average distances between indices (in p.p)


compare_distances(df)
#>         jevons dutot carli
#> jevons  0.000 2.482 2.093
#> dutot   2.482 0.000 4.420
#> carli   2.093 4.420 0.000
```

compare_to_target

The function calculates average distances between considered price indices and the target price index and it returns a data frame with: average distances on the basis of all values of compared indices (**distance** column), average semi-distances on the basis of values of compared indices which overestimate the target index values (**distance_upper** column) and average semi-distances on the basis of values of compared indices which underestimate the target index values (**distance_lower** column).

For instance, let us compare the Jevons, Laspeyres, Paasche and Walsh price indices (calculated for the **milk** data set and for the time interval: December 2018 - December 2019) with the target Fisher price index:

```
#Creating a data frame with example bilateral indices
df<-price_indices(milk,
                  formula=c("jevons","laspeyres","paasche","walsh"),
                  start="2018-12",end="2019-12",interval=TRUE)


#Calculating the target Fisher price index
target_index<-fisher(milk,start="2018-12",end="2019-12",interval=TRUE)


#Calculating average distances between considered indices and the Fisher inde
x (in p.p)
```

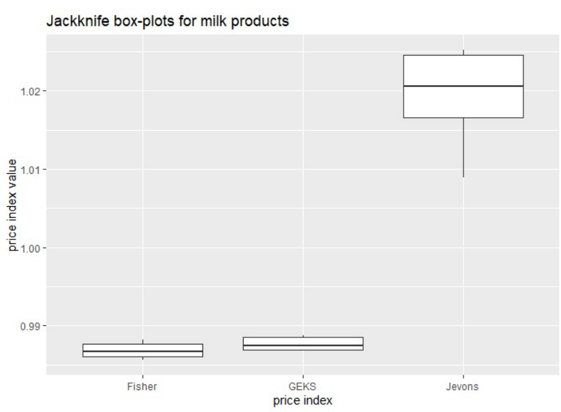
```
compare_to_target(df,target=target_index)
#>        index distance distance_lower distance_upper
#> 1     jevons    2.759          0.045          2.714
#> 2 laspeyres    1.429          0.000          1.429
#> 3    paasche    1.403          1.403          0.000
#> 4      walsh    0.174          0.113          0.061
```

compare_indices_jk

This function presents a comparison of selected indices obtained by using the jackknife method. In particular, it returns a list with two elements: **results**, which is a data frame with basic characteristics of the calculated indices (including the **jackknife estimates** for selected price indices), and **figure** which presents a box-plot for the considered indices. The User may control a way of creating product subgroups (subsamples) via the **by** parameter (in the classical jackknife method **by** should indicate **prodID**). Please follow the example, in which the Jevons, Fisher and GEKS indices are compared by using the jackknife method:

```
#creating a list with jackknife results
comparison<-compare_indices_jk(milk,
formula=c("jevons","fisher","geks"),
start="2018-12",
end="2019-12",
window=c(13),
names=c("Jevons","Fisher","GEKS"),
by="retID",
title="Jackknife box-plots for milk products")
#displaying a data frame with basic characteristics of the calculated indices
comparison$results
#>    index all_products mean_jack_knife sd_jack_knife
#> 1 Jevons    1.0249373       1.0479343   0.026703299
#> 2 Fisher    0.9868354       0.9867241   0.004328695
#> 3   GEKS    0.9876664       0.9876414   0.003637010

#displaying box-plotes created for the price index values obtained by using t
he jackknife method:
comparison$figure
```



13. Functions for price and quantity indicator calculations

There are two package functions for calculating price and quantity indicators. The **bennet** function returns the (bilateral) Bennet price and quantity indicators and optionally also the price and quantity contributions of individual products. The **mbennet** function returns the multilateral (transitive) Bennet price and quantity indicators and optionally also the price and quantity contributions of individual products. For instance, the following command calculates the Bennet price and quantity indicators for milk products:

```
bennet(milk, start = "2018-12", end = "2019-12", interval=TRUE)


#>       time Value_difference Price_indicator Quantity_indicator
#> 1  2019-01        -31942.53          628.05          -32570.58
#> 2  2019-02        -35995.09         -175.29          -35819.80
#> 3  2019-03        -42158.05        -3810.15          -38347.90
#> 4  2019-04        -56934.44        -2427.25          -54507.20
#> 5  2019-05        -50961.52        -2580.91          -48380.61
#> 6  2019-06        -48842.58        -2396.05          -46446.53
#> 7  2019-07        -33974.27        -3232.63          -30741.64
#> 8  2019-08        -37962.80         4500.45          -42463.26
#> 9  2019-09        -33833.42        -1092.32          -32741.09
#> 10 2019-10        -35001.60        -1665.10          -33336.50
#> 11 2019-11        -16928.94         2313.87          -19242.81
#> 12 2019-12          9859.34        -2151.48           12010.83
```

where price and quantity contributions of each subgroups of milk products can be obtained as follows:

```
milk$prodID<-milk$description
bennet(milk, start = "2018-12", end = "2019-12", contributions = TRUE)


#>                       prodID value_differences price_contributions
#> 1 full-fat milk pasteurized           -711.57             -633.65
#> 2          full-fat milk UHT           8767.34            -1927.29
#> 3                  goat milk           -602.29               -4.10
#> 4  low-fat milk pasteurized           1421.39              647.66
#> 5           low-fat milk UHT          -1525.62              369.49
#> 6              powdered milk           2510.09             1444.46
#>   quantity_contributions
#> 1                 -77.92
#> 2               10694.63
#> 3                -598.18
#> 4                 773.73
#> 5               -1895.11
#> 6                1065.63
```