PEC 3: Desing & Implementation - Data load, clean-up, transformation & model selection

UOC - Alumno: Álvaro Rodríguez Sans

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Índex

This is an R Markdown Notebook. When you execute code within the notebook, the results appear beneath the code. Try executing this chunk by clicking the *Run* button within the chunk or by placing your cursor inside it and pressing *Ctrl+Shift+Enter*.

Add a new chunk by clicking the *Insert Chunk* button on the toolbar or by pressing *Ctrl+Alt+I*. When you save the notebook, an HTML file containing the code and output will be saved alongside it (click the *Preview* button or press *Ctrl+Shift+K* to preview the HTML file). The preview shows you a rendered HTML copy of the contents of the editor. Consequently, unlike *Knit*, *Preview* does not run any R code chunks. Instead, the output of the chunk when it was last run in the editor is displayed.

The bibliographic references used for this practice have been: (Baayen 2008; Hothorn and Everitt 2014; Hyndman and Athanasopoulos 2021; Liviano Solas and Pujol Jover, n.d.; Teetor 2011; Vegas Lozano, n.d.).

```
if(!require(knitr)){
    install.packages('knitr', repos='http://cran.us.r-project.org')
    library(knitr)}
```

```
## Loading required package: knitr
```

```
if(!require(latexpdf)){
    install.packages('latexpdf', repos='http://cran.us.r-project.org')
    library(latexpdf)}
```

```
## Loading required package: latexpdf
```

```
if(!require(latex2exp)){
    install.packages('latex2exp', repos='http://cran.us.r-project.org')
    library(latex2exp)}
```

```
## Loading required package: latex2exp
```

```
if(!require(lubridate)){
    install.packages('lubridate', repos='http://cran.us.r-project.org')
    library(lubridate)}
```

```
## Loading required package: lubridate

##
## Attaching package: 'lubridate'

## The following objects are masked from 'package:base':
##
##     date, intersect, setdiff, union
```

```
if(!require(psych)){
    install.packages("psych", repos='http://cran.us.r-project.org')
    library(psych)}
```

```
## Loading required package: psych
```

```
if(!require(DescTools)){
    install.packages("DescTools", repos='http://cran.us.r-project.org')
    library(DescTools)}
```

```
## Loading required package: DescTools

##
## Attaching package: 'DescTools'

## The following objects are masked from 'package:psych':
##
##     AUC, ICC, SD
```

```
if(!require(tidyverse)){
    install.packages("tidyverse", repos='http://cran.us.r-project.org')
    library(tidyverse)}
```

```
## Loading required package: tidyverse

## -- Attaching packages ---------------------------------------------------------------------------------

## v ggplot2 3.3.3     v purrr   0.3.3
```

```
## v tibble  3.0.0     v dplyr   1.0.5
## v tidyr   1.1.3     v stringr 1.4.0
## v readr   1.3.1     v forcats 0.5.0
```

```
## -- Conflicts ------------------------------------------------------------------------
## x ggplot2::%+%()           masks psych::%+%()
## x ggplot2::alpha()         masks psych::alpha()
## x lubridate::as.difftime() masks base::as.difftime()
## x lubridate::date()        masks base::date()
## x dplyr::filter()          masks stats::filter()
## x lubridate::intersect()   masks base::intersect()
## x dplyr::lag()             masks stats::lag()
## x lubridate::setdiff()     masks base::setdiff()
## x lubridate::union()       masks base::union()
```

```
if(!require(imputeTS)){
    install.packages("imputeTS", repos='http://cran.us.r-project.org')
    library(imputeTS)}
```

```
## Loading required package: imputeTS
```

```
## Registered S3 method overwritten by 'quantmod':
##   method            from
##   as.zoo.data.frame zoo
```

```
if(!require(stats)){
    install.packages("stats", repos='http://cran.us.r-project.org')
    library(stats)}
if(!require(tsbox)){
    install.packages("tsbox", repos='http://cran.us.r-project.org')
    library(tsbox)}
```

```
## Loading required package: tsbox
```

```
if(!require(fable)){
    install.packages("fable", repos='http://cran.us.r-project.org')
    library(fable)}
```

```
## Loading required package: fable
```

```
## Loading required package: fabletools
```

```
##
## Attaching package: 'fabletools'
```

```
## The following objects are masked from 'package:DescTools':
##
##     MAE, MAPE, MSE, RMSE
```

```
if(!require(fpp3)){
    install.packages("fpp3", repos='http://cran.us.r-project.org')
    library(fpp3)}
```

```
## Loading required package: fpp3
```

```
## -- Attaching packages -------------------------------------------------------------
```

```
## v tsibble     1.0.0     v feasts      0.2.1
## v tsibbledata 0.3.0
```

```
## -- Conflicts ------------------------------------------------------------------------
```

```
## x ggplot2::%+%()       masks psych::%+%()
## x ggplot2::alpha()     masks psych::alpha()
## x lubridate::date()    masks base::date()
## x dplyr::filter()      masks stats::filter()
## x tsibble::intersect() masks base::intersect()
## x tsibble::interval()  masks lubridate::interval()
## x dplyr::lag()         masks stats::lag()
## x fabletools::MAE()    masks DescTools::MAE()
## x fabletools::MAPE()   masks DescTools::MAPE()
## x fabletools::MSE()    masks DescTools::MSE()
## x fabletools::RMSE()   masks DescTools::RMSE()
## x tsibble::setdiff()   masks base::setdiff()
## x tsibble::union()     masks base::union()
```

```
if(!require(corrplot)){
    install.packages('corrplot', repos='http://cran.us.r-project.org')
    library(corrplot)}
```

```
## Loading required package: corrplot

## corrplot 0.84 loaded
```

```
knitr::opts_chunk$set(echo = TRUE)
```

1 Data load

Data is loaded from the sources stated at PEC1 and PEC2 (CNE, INE and Google).

- CNE-Covid-19
- INE-Covid-19
- Google-Covid-19

```
library(dplyr)
# Source INE
EM3 <- read.csv('EM3-Movimiento de personas por provincias.csv',
                header=TRUE,
                sep = ";",
                stringsAsFactors = FALSE)

# Source Google
Google <- read.csv('Google-2020_ES_Region_Mobility_Report.csv',
                   header=TRUE,
                   sep = ";",
                   stringsAsFactors = FALSE)

# Source CNE
CNE_tecnica <- read.csv('CNE-casos_tecnica_provincia.csv',
                        header=TRUE,
                        sep = ",",
                        stringsAsFactors = FALSE)
CNE_casos <- read.csv('CNE-casos_hosp_uci_def_sexo_edad_provres.csv',
                      header=TRUE,
                      sep = ",",
                      stringsAsFactors = FALSE)
```

2 Initial descriptive statistics and visualization

2.1 Data types and modifications

We are gonig to check the **type of variable** that corresponds to each of the variables (numerical, factor, etc.) and **missing data / values or other anomalies** in each dataset.

2.1.1 EM3 review

We have the movement of people by provinces (we can see 146 rows by province, that correspond to days). In order to facilitate the comparison and have a valid reference on to what extent the mobility of the population should be considered to have varied, the data of a day of a week that can be considered "normal" are taken as a reference. For this study, the "normal" day that has been considered is the one that results from the average of the days 18 (Monday) to 21 (Thursday) of November 2019. It is indicated in the tables as the reference date 18/11/2019.

```
# Source INE
head(str(EM3,vec.len=2))
```

```
## 'data.frame':    9198 obs. of  3 variables:
##  $ Zonas.de.movilidad: chr  "Almería" "Almería" ...
##  $ Periodo           : chr  "30/12/2020" "27/12/2020" ...
##  $ Total             : chr  "17,17" "11,53" ...
```

```
## NULL
```

```
summary(EM3)
```

```
##  Zonas.de.movilidad   Periodo              Total
##  Length:9198        Length:9198        Length:9198
##  Class :character   Class :character   Class :character
##  Mode  :character   Mode  :character   Mode  :character
```

```
table(EM3$Zonas.de.movilidad)
```

```
##
##              Albacete       Alicante/Alacant               Almería
##                   146                    146                   146
##           Araba/Álava               Asturias                 Ávila
##                   146                    146                   146
##               Badajoz        Balears, Illes             Barcelona
##                   146                    146                   146
##               Bizkaia                 Burgos               Cáceres
##                   146                    146                   146
##                 Cádiz              Cantabria     Castellón/Castelló
##                   146                    146                   146
##                 Ceuta            Ciudad Real               Córdoba
##                   146                    146                   146
##             Coruña, A                 Cuenca            Formentera
##                   146                    146                   146
##         Fuerteventura               Gipuzkoa                Girona
##                   146                    146                   146
##             Gomera, La          Gran Canaria               Granada
##                   146                    146                   146
##           Guadalajara             Hierro, El                Huelva
##                   146                    146                   146
##                Huesca                  Ibiza                  Jaén
##                   146                    146                   146
```

```
##               Lanzarote                    León                 Lleida
##                     146                     146                    146
##                    Lugo                  Madrid                 Málaga
##                     146                     146                    146
##                Mallorca                 Melilla                Menorca
##                     146                     146                    146
##                  Murcia                 Navarra                Ourense
##                     146                     146                    146
##                Palencia               Palma, La            Palmas, Las
##                     146                     146                    146
##              Pontevedra               Rioja, La              Salamanca
##                     146                     146                    146
## Santa Cruz de Tenerife                  Segovia                Sevilla
##                     146                     146                    146
##                   Soria               Tarragona               Tenerife
##                     146                     146                    146
##                  Teruel                  Toledo      Valencia/València
##                     146                     146                    146
##              Valladolid                  Zamora               Zaragoza
##                     146                     146                    146
```

2.1.2 EM3 data transformation

We are going to **transform**:

- "Total" from "character" to "numerical"
- "Periodo" from "character" to "date"

```
EM3$Total <- sub(",", ".", EM3$Total)
EM3$Total <- as.numeric(EM3$Total)
EM3$Periodo <- as.Date(EM3$Periodo,format="%d/%m/%Y")
head(EM3)
```

```
##   Zonas.de.movilidad    Periodo Total
## 1            Almería 2020-12-30 17.17
## 2            Almería 2020-12-27 11.53
## 3            Almería 2020-12-23 17.81
## 4            Almería 2020-12-20 12.13
## 5            Almería 2020-12-16 18.28
## 6            Almería 2020-12-13 11.97
```

2.1.3 EM3 transpose

Due to the nature of this dataset we have to transpose it in order to analyse the missing values and impute them.

```
if(!require(data.table)){
    install.packages('data.table', repos='http://cran.us.r-project.org')
    library(data.table)}

# Transpose dataframe
EM3_t<-dcast(EM3, Periodo~Zonas.de.movilidad, fill=NA)

# Create dates missing (for time series).
# Note: Acccording INE some dates are not provided.
EM3_t<-EM3_t %>%
```

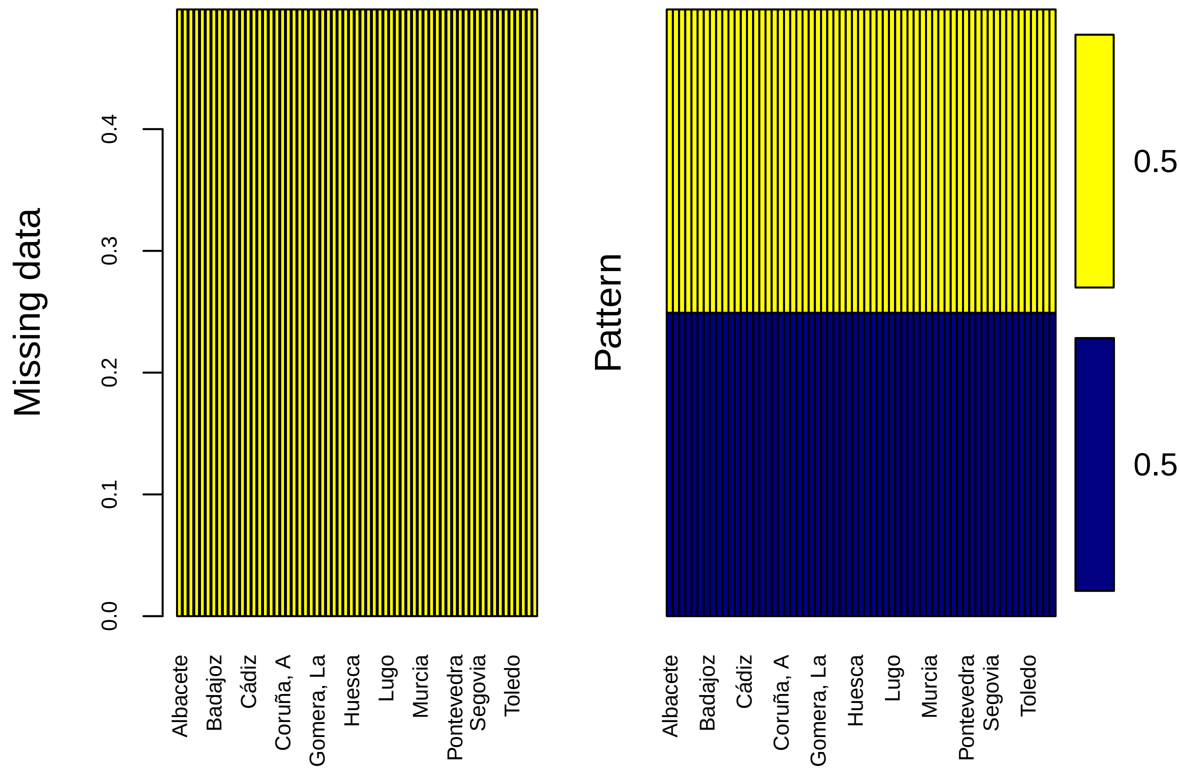
```r
  complete(Periodo = seq.Date(min(Periodo), max(Periodo), by="day"))

# Filter the interest period according INE EM3 study
EM3_t<- EM3_t %>%
  filter(Periodo <= "2019-11-18" | Periodo >= "2020-03-16")

EM3_t
```

```
## # A tibble: 291 x 64
##    Periodo    Albacete `Alicante/Alaca~ Almería `Araba/Álava` Asturias Ávila
##    <date>        <dbl>            <dbl>   <dbl>         <dbl>    <dbl> <dbl>
##  1 2019-11-18    25.2             28.1    24.4          31.9     29.9  26.6
##  2 2020-03-16     9.9             14.4    11.0          15.9     13.1   9.44
##  3 2020-03-17    NA               NA      NA            NA       NA    NA
##  4 2020-03-18     9.51            13.4     7.28         14.5     12.0   9.17
##  5 2020-03-19    NA               NA      NA            NA       NA    NA
##  6 2020-03-20     8.75            12.0     6.87         11.9     11.3   8.69
##  7 2020-03-21    NA               NA      NA            NA       NA    NA
##  8 2020-03-22     4.5              6.14    4.19          6.46     5.64  4.53
##  9 2020-03-23    NA               NA      NA            NA       NA    NA
## 10 2020-03-24     9.02            10.9     8.98         13.3     11.2   8.26
## # ... with 281 more rows, and 57 more variables: Badajoz <dbl>, `Balears,
## #   Illes` <dbl>, Barcelona <dbl>, Bizkaia <dbl>, Burgos <dbl>, Cáceres <dbl>,
## #   Cádiz <dbl>, Cantabria <dbl>, `Castellón/Castelló` <dbl>, Ceuta <dbl>,
## #   `Ciudad Real` <dbl>, Córdoba <dbl>, `Coruña, A` <dbl>, Cuenca <dbl>,
## #   Formentera <dbl>, Fuerteventura <dbl>, Gipuzkoa <dbl>, Girona <dbl>,
## #   `Gomera, La` <dbl>, `Gran Canaria` <dbl>, Granada <dbl>, Guadalajara <dbl>,
## #   `Hierro, El` <dbl>, Huelva <dbl>, Huesca <dbl>, Ibiza <dbl>, Jaén <dbl>,
## #   Lanzarote <dbl>, León <dbl>, Lleida <dbl>, Lugo <dbl>, Madrid <dbl>,
## #   Málaga <dbl>, Mallorca <dbl>, Melilla <dbl>, Menorca <dbl>, Murcia <dbl>,
## #   Navarra <dbl>, Ourense <dbl>, Palencia <dbl>, `Palma, La` <dbl>, `Palmas,
## #   Las` <dbl>, Pontevedra <dbl>, `Rioja, La` <dbl>, Salamanca <dbl>, `Santa
## #   Cruz de Tenerife` <dbl>, Segovia <dbl>, Sevilla <dbl>, Soria <dbl>,
## #   Tarragona <dbl>, Tenerife <dbl>, Teruel <dbl>, Toledo <dbl>,
## #   `Valencia/València` <dbl>, Valladolid <dbl>, Zamora <dbl>, Zaragoza <dbl>
```

2.1.4 EM3 review missing values & impute

We check the missing values by province (we are close to 150 by province).

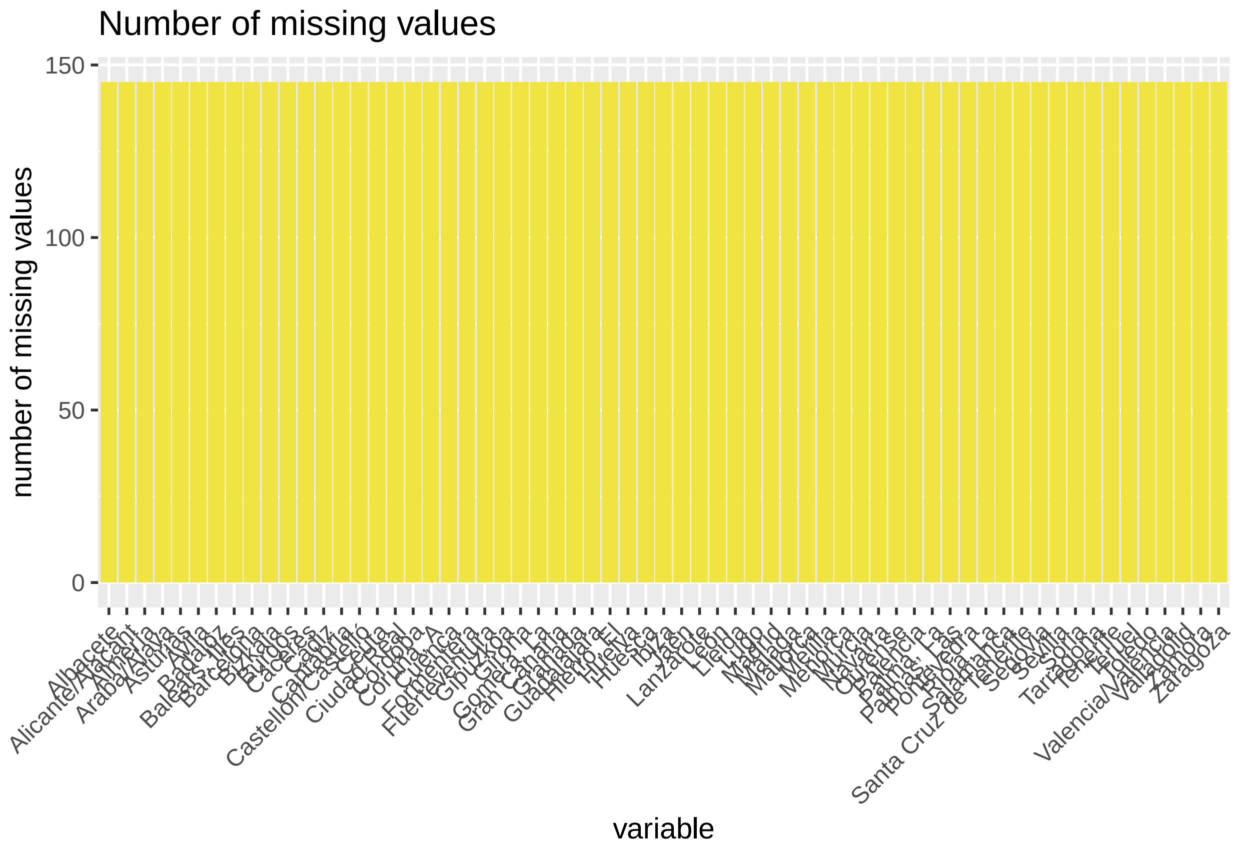
```r
if(!require(VIM)){
    install.packages('VIM', repos='http://cran.us.r-project.org')
    library(VIM)}

aggr(EM3_t[,-1], col=c('navyblue','yellow'),
     numbers=TRUE, sortVars=TRUE,
     labels=names(EM3_t[,-1]), cex.axis=.7,
     gap=3, ylab=c("Missing data","Pattern"))
```




```
##
## Variables sorted by number of missings:
##               Variable     Count
##               Albacete 0.4982818
##       Alicante/Alacant 0.4982818
##                Almería 0.4982818
##            Araba/Álava 0.4982818
##               Asturias 0.4982818
##                  Ávila 0.4982818
##                Badajoz 0.4982818
##         Balears, Illes 0.4982818
##              Barcelona 0.4982818
##                Bizkaia 0.4982818
##                 Burgos 0.4982818
##                Cáceres 0.4982818
##                  Cádiz 0.4982818
##              Cantabria 0.4982818
##    Castellón/Castelló 0.4982818
##                  Ceuta 0.4982818
##            Ciudad Real 0.4982818
##                Córdoba 0.4982818
##              Coruña, A 0.4982818
##                 Cuenca 0.4982818
##             Formentera 0.4982818
##          Fuerteventura 0.4982818
##              Gipuzkoa 0.4982818
```

```
##                  Girona 0.4982818
##              Gomera, La 0.4982818
##            Gran Canaria 0.4982818
##                 Granada 0.4982818
##             Guadalajara 0.4982818
##              Hierro, El 0.4982818
##                  Huelva 0.4982818
##                  Huesca 0.4982818
##                   Ibiza 0.4982818
##                    Jaén 0.4982818
##               Lanzarote 0.4982818
##                    León 0.4982818
##                  Lleida 0.4982818
##                    Lugo 0.4982818
##                  Madrid 0.4982818
##                  Málaga 0.4982818
##                Mallorca 0.4982818
##                 Melilla 0.4982818
##                 Menorca 0.4982818
##                  Murcia 0.4982818
##                 Navarra 0.4982818
##                 Ourense 0.4982818
##                Palencia 0.4982818
##               Palma, La 0.4982818
##             Palmas, Las 0.4982818
##              Pontevedra 0.4982818
##               Rioja, La 0.4982818
##               Salamanca 0.4982818
##  Santa Cruz de Tenerife 0.4982818
##                 Segovia 0.4982818
##                 Sevilla 0.4982818
##                   Soria 0.4982818
##               Tarragona 0.4982818
##                Tenerife 0.4982818
##                  Teruel 0.4982818
##                  Toledo 0.4982818
##       Valencia/València 0.4982818
##              Valladolid 0.4982818
##                  Zamora 0.4982818
##                Zaragoza 0.4982818
```

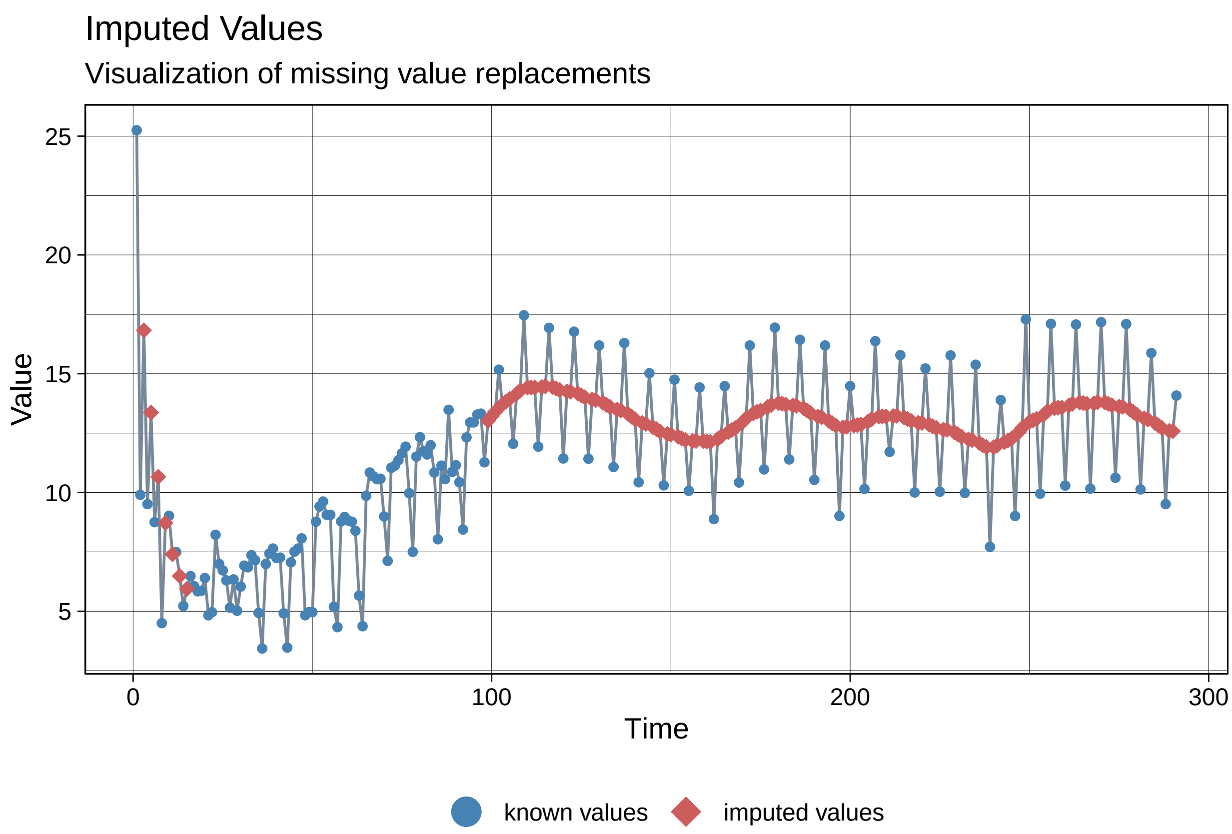
```
EM3_t %>%
    gather(key = "key", value = "val") %>%
    mutate(is.missing = is.na(val)) %>%
    group_by(key, is.missing) %>%
    summarise(num.missing = n()) %>%
    filter(is.missing==T) %>%
    select(-is.missing) %>%
    arrange(desc(num.missing)) %>%
    ggplot() +
    geom_bar(aes(x=key, y=num.missing), stat = 'identity',fill="#F0E442") +
    labs(x='variable', y="number of missing values",
         title='Number of missing values') +
    theme(axis.text.x = element_text(angle = 45, hjust = 1))
```



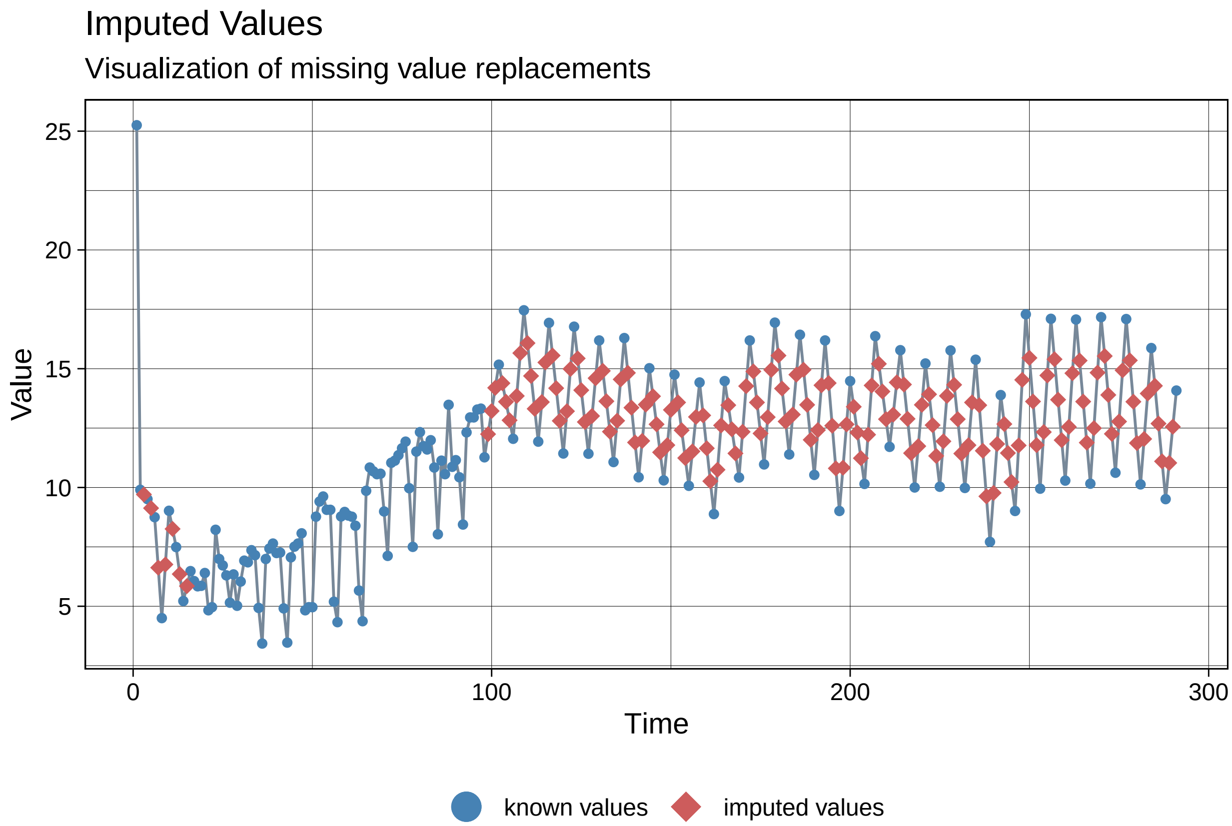
We impute the missing values following the principales stated for imputeTS. Thanks to this approach we almost double the amount of data for analysis by province (It was selected “na_seadec” due to it covers seasonality aspects -weekdays/weekends in our case-).

It is needed to transform the dataframe to a time series object.

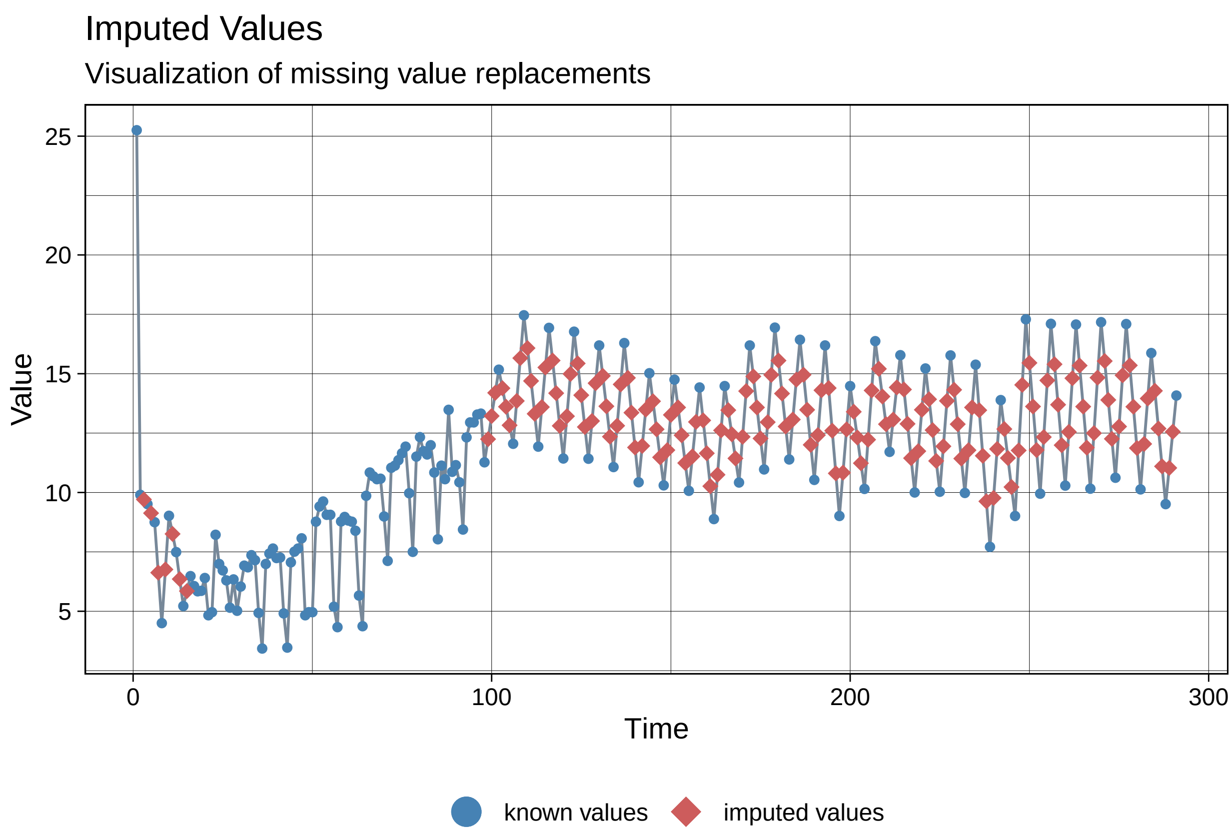
```
# Used to convert dataframe to ts object
library(xts)
EM3_t_ts<-xts(EM3_t[-1],EM3_t$Periodo)

# Impute the missing values with na_kalman, na_seadec, na_interpolation & na_seasplit
imp <- na_kalman(EM3_t_ts[,1])
ggplot_na_imputations(EM3_t_ts[,1], imp)
```



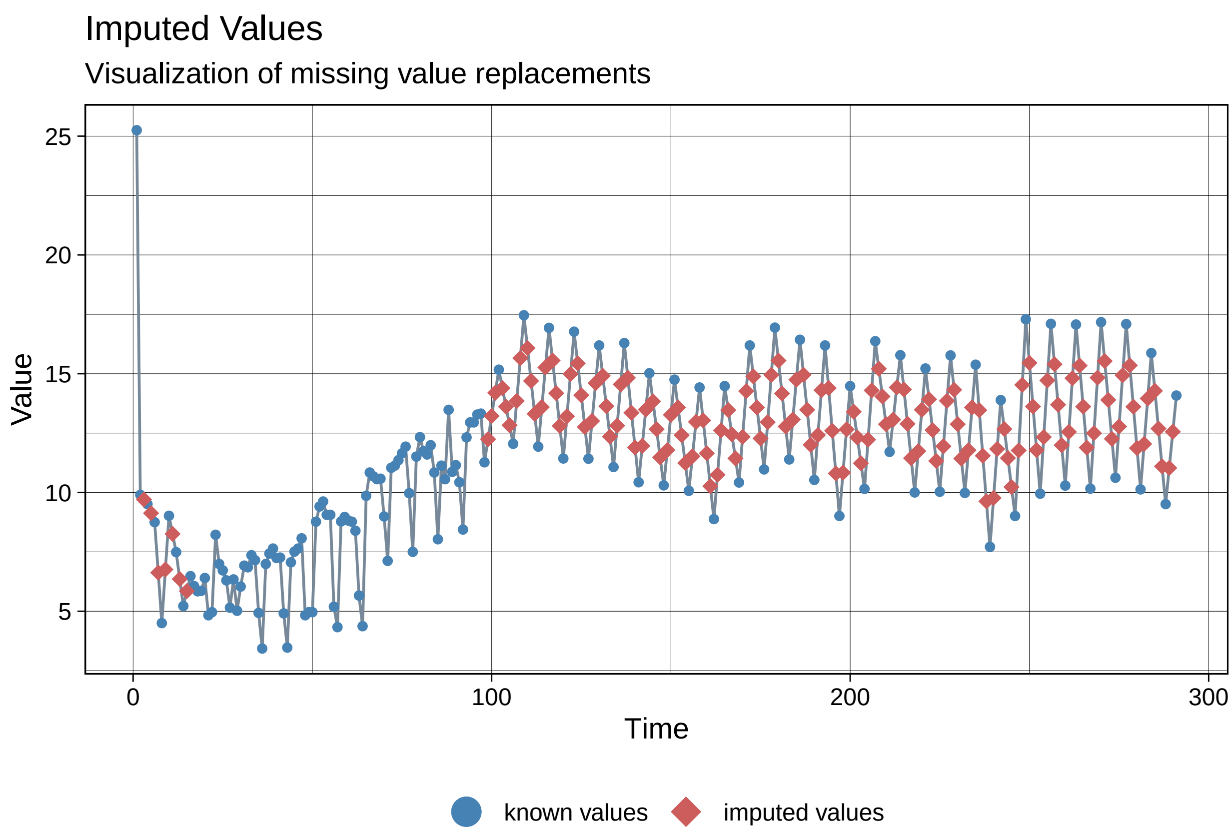

```
imp2 <- na_seadec(EM3_t_ts[,1])
ggplot_na_imputations(EM3_t_ts[,1], imp2)
```



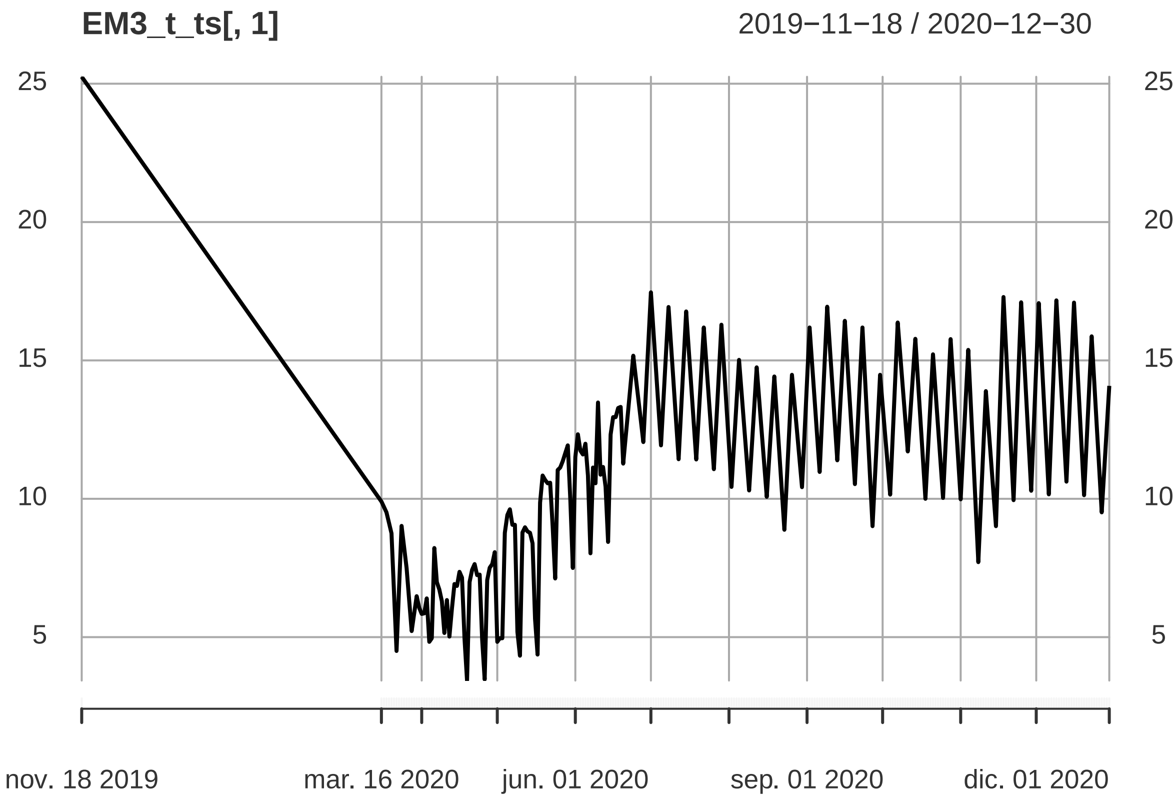

```
imp3 <- na_seasplit(EM3_t_ts[,1])
ggplot_na_imputations(EM3_t_ts[,1], imp3)
```



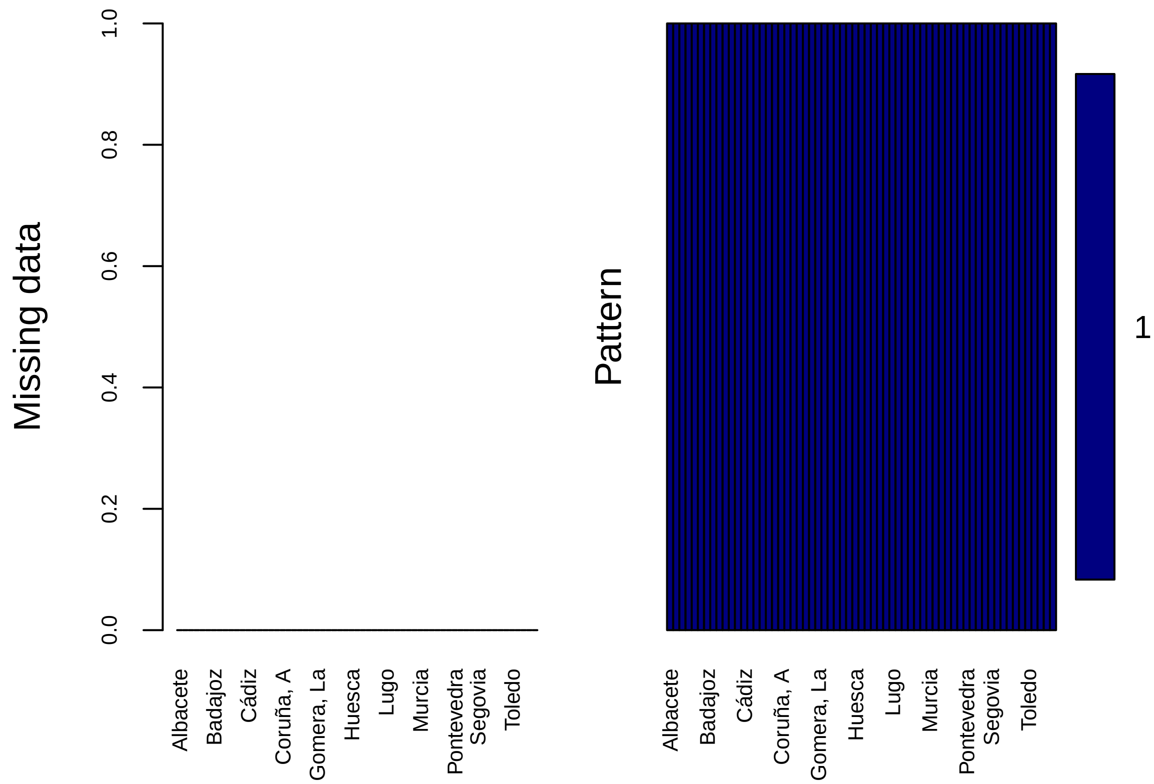

```
imp4 <- na_interpolation(EM3_t_ts[,1])
ggplot_na_imputations(EM3_t_ts[,1], imp4)
```




```r
# We select na_seadec for the dataset
EM3_t_ts <- na_seadec(EM3_t_ts)
plot(EM3_t_ts[,1])
```




```
# We convert the time series object to a dataframe
EM3 <- ts_df(EM3_t_ts)

names(EM3)[names(EM3) == "id"] <- "Zonas.de.movilidad"
names(EM3)[names(EM3) == "time"] <- "Periodo"
names(EM3)[names(EM3) == "value"] <- "Total"

# Transpose dataframe
EM3_t<-dcast(EM3, Periodo~Zonas.de.movilidad, fill=NA)

# We check again missing values (result should be zero)
aggr(EM3_t[,-1], col=c('navyblue','yellow'),
     numbers=TRUE, sortVars=TRUE,
     labels=names(EM3_t[,-1]), cex.axis=.7,
     gap=3, ylab=c("Missing data","Pattern"))
```




```
##
##  Variables sorted by number of missings:
##               Variable Count
##               Albacete     0
##       Alicante/Alacant     0
##                Almería     0
##            Araba/Álava     0
##               Asturias     0
##                  Ávila     0
##                Badajoz     0
##         Balears, Illes     0
##              Barcelona     0
##                Bizkaia     0
##                 Burgos     0
##                Cáceres     0
##                  Cádiz     0
##              Cantabria     0
##    Castellón/Castelló     0
##                  Ceuta     0
##            Ciudad Real     0
##                Córdoba     0
##              Coruña, A     0
##                 Cuenca     0
##             Formentera     0
##          Fuerteventura     0
##               Gipuzkoa     0
```

```
##                  Girona     0
##              Gomera, La     0
##            Gran Canaria     0
##                 Granada     0
##             Guadalajara     0
##              Hierro, El     0
##                  Huelva     0
##                  Huesca     0
##                   Ibiza     0
##                    Jaén     0
##               Lanzarote     0
##                    León     0
##                  Lleida     0
##                    Lugo     0
##                  Madrid     0
##                  Málaga     0
##                Mallorca     0
##                 Melilla     0
##                 Menorca     0
##                  Murcia     0
##                 Navarra     0
##                 Ourense     0
##                Palencia     0
##               Palma, La     0
##             Palmas, Las     0
##              Pontevedra     0
##               Rioja, La     0
##               Salamanca     0
##  Santa Cruz de Tenerife     0
##                 Segovia     0
##                 Sevilla     0
##                   Soria     0
##               Tarragona     0
##                Tenerife     0
##                  Teruel     0
##                  Toledo     0
##       Valencia/València     0
##              Valladolid     0
##                  Zamora     0
##                Zaragoza     0
```

```
EM3_t %>%
    gather(key = "key", value = "val") %>%
    mutate(is.missing = is.na(val)) %>%
    group_by(key, is.missing) %>%
    summarise(num.missing = n()) %>%
    filter(is.missing==T) %>%
    select(-is.missing) %>%
    arrange(desc(num.missing)) %>%
    ggplot() +
    geom_bar(aes(x=key, y=num.missing), stat = 'identity',fill="#F0E442") +
    labs(x='variable', y="number of missing values",
         title='Number of missing values') +
    theme(axis.text.x = element_text(angle = 45, hjust = 1))
```


```r
head(str(EM3,vec.len=2))
```

```
## 'data.frame':    18333 obs. of  3 variables:
##  $ Zonas.de.movilidad: chr  "Albacete" "Albacete" ...
##  $ Periodo           : Date, format: "2019-11-18" "2020-03-16" ...
##  $ Total             : num  25.2 9.9 ...

## NULL
```

```r
summary(EM3)
```

```
##  Zonas.de.movilidad    Periodo                Total
##  Length:18333       Min.   :2019-11-18   Min.   : 0.83
##  Class :character   1st Qu.:2020-05-26   1st Qu.:10.57
##  Mode  :character   Median :2020-08-07   Median :14.13
##                     Mean   :2020-08-06   Mean   :13.79
##                     3rd Qu.:2020-10-19   3rd Qu.:17.06
##                     Max.   :2020-12-30   Max.   :36.70
```

```r
table(EM3$Zonas.de.movilidad)
```

```
##
##              Albacete       Alicante/Alacant                Almería
##                   291                    291                    291
##           Araba/Álava               Asturias                  Ávila
##                   291                    291                    291
##               Badajoz         Balears, Illes              Barcelona
##                   291                    291                    291
```

```
##              Bizkaia                   Burgos                  Cáceres
##                  291                      291                      291
##                Cádiz                Cantabria     Castellón/Castelló
##                  291                      291                      291
##                Ceuta              Ciudad Real                  Córdoba
##                  291                      291                      291
##            Coruña, A                   Cuenca               Formentera
##                  291                      291                      291
##         Fuerteventura                 Gipuzkoa                   Girona
##                  291                      291                      291
##            Gomera, La             Gran Canaria                  Granada
##                  291                      291                      291
##           Guadalajara               Hierro, El                   Huelva
##                  291                      291                      291
##               Huesca                    Ibiza                     Jaén
##                  291                      291                      291
##            Lanzarote                     León                   Lleida
##                  291                      291                      291
##                 Lugo                   Madrid                   Málaga
##                  291                      291                      291
##             Mallorca                  Melilla                  Menorca
##                  291                      291                      291
##               Murcia                  Navarra                  Ourense
##                  291                      291                      291
##             Palencia                Palma, La              Palmas, Las
##                  291                      291                      291
##           Pontevedra                Rioja, La                Salamanca
##                  291                      291                      291
## Santa Cruz de Tenerife                  Segovia                  Sevilla
##                  291                      291                      291
##                Soria                Tarragona                 Tenerife
##                  291                      291                      291
##               Teruel                   Toledo        Valencia/València
##                  291                      291                      291
##           Valladolid                   Zamora                 Zaragoza
##                  291                      291                      291
```

2.1.5 Google review

Here we have data from autonomus communities and provinces.

```
#Source Google
head(str(Google,vec.len=1))
```

```
## 'data.frame':    24242 obs. of  15 variables:
##  $ country_region_code                               : chr  "ES" ...
##  $ country_region                                    : chr  "Spain" ...
##  $ sub_region_1                                      : chr  "" ...
##  $ sub_region_2                                      : chr  "" ...
##  $ metro_area                                        : logi  NA ...
##  $ iso_3166_2_code                                   : chr  "" ...
##  $ census_fips_code                                  : logi  NA ...
##  $ place_id                                          : chr  "ChIJi7xhMnjjQgwR7KNoB5Qs7KY" ...
##  $ date                                              : chr  "15/02/2020" ...
##  $ retail_and_recreation_percent_change_from_baseline: int  2 2 ...
```

```
##  $ grocery_and_pharmacy_percent_change_from_baseline : int  -1 3 ...
##  $ parks_percent_change_from_baseline                : int  26 13 ...
##  $ transit_stations_percent_change_from_baseline     : int  8 5 ...
##  $ workplaces_percent_change_from_baseline           : int  0 -1 ...
##  $ residential_percent_change_from_baseline          : int  -2 -2 ...
```

```
## NULL
```

```r
summary(Google)
```

```
##  country_region_code country_region     sub_region_1       sub_region_2
##  Length:24242        Length:24242       Length:24242       Length:24242
##  Class :character    Class :character   Class :character   Class :character
##  Mode  :character    Mode  :character   Mode  :character   Mode  :character
##
##
##
##
##  metro_area     iso_3166_2_code    census_fips_code   place_id
##  Mode:logical   Length:24242       Mode:logical     Length:24242
##  NA's:24242     Class :character   NA's:24242       Class :character
##                 Mode  :character                    Mode  :character
##
##
##
##
##      date           retail_and_recreation_percent_change_from_baseline
##  Length:24242       Min.   :-97.00
##  Class :character   1st Qu.:-53.00
##  Mode  :character   Median :-32.00
##                     Mean   :-36.42
##                     3rd Qu.:-17.00
##                     Max.   : 71.00
##                     NA's   :56
##  grocery_and_pharmacy_percent_change_from_baseline
##  Min.   :-96.000
##  1st Qu.:-18.000
##  Median : -4.000
##  Mean   : -9.973
##  3rd Qu.:  3.000
##  Max.   :194.000
##  NA's   :396
##  parks_percent_change_from_baseline
##  Min.   :-94.0000
##  1st Qu.:-30.0000
##  Median : -5.0000
##  Mean   : -0.0038
##  3rd Qu.: 22.0000
##  Max.   :543.0000
##  NA's   :305
##  transit_stations_percent_change_from_baseline
##  Min.   :-100.00
##  1st Qu.: -46.00
##  Median : -30.00
##  Mean   : -32.63
```

```
##  3rd Qu.: -16.00
##  Max.   : 177.00
##  NA's   :832
##  workplaces_percent_change_from_baseline
##  Min.   :-92.0
##  1st Qu.:-37.0
##  Median :-24.0
##  Mean   :-26.7
##  3rd Qu.:-13.0
##  Max.   : 55.0
##  NA's   :42
##  residential_percent_change_from_baseline
##  Min.   :-10.000
##  1st Qu.:  4.000
##  Median :  7.000
##  Mean   :  9.419
##  3rd Qu.: 13.000
##  Max.   : 48.000
##  NA's   :267
```

```
table(Google$sub_region_1)
```

```
##
##                               Andalusia             Aragon           Asturias
##                  385               3465               1540                385
##    Balearic Islands      Basque Country     Canary Islands          Cantabria
##                  385               1540               1155                385
##   Castile-La Mancha   Castile and LeÃ³n          Catalonia              Ceuta
##                 2310               3850               1925                378
## Community of Madrid         Extremadura            Galicia           La Rioja
##                  385               1155               1925                385
##              Melilla             Navarre   Region of Murcia Valencian Community
##                  379                385                385               1540
```

```
table(Google$sub_region_2)
```

```
##
##                                   A CoruÃ±a              Ã\201lava
##                 7687                    385                    385
##               Ã\201vila               Albacete               Alicante
##                  385                    385                    385
##               AlmerÃa                Badajoz              Barcelona
##                  385                    385                    385
##               Biscay                 Burgos               CÃ¡ceres
##                  385                    385                    385
##               CÃ¡diz              CÃ³rdoba             CastellÃ³n
##                  385                    385                    385
##          Ciudad Real                 Cuenca              Gipuzkoa
##                  385                    385                    385
##               Girona                Granada            Guadalajara
##                  385                    385                    385
##               Huelva                 Huesca                  JaÃ©n
##                  385                    385                    385
##           Las Palmas                  LeÃ³n                 Lleida
##                  385                    385                    385
```

```
##                   Lugo                 MÃ¡laga               Palencia 
##                    385                    385                    385 
##             Pontevedra    Province of Ourense              Salamanca 
##                    385                    385                    385 
## Santa Cruz de Tenerife                Segovia                Seville 
##                    385                    385                    385 
##                  Soria              Tarragona                 Teruel 
##                    385                    385                    385 
##                 Toledo               Valencia             Valladolid 
##                    385                    385                    385 
##                 Zamora               Zaragoza 
##                    385                    385
```

```r
table(Google$iso_3166_2_code)
```

```
## 
##        ES-A ES-AB ES-AL ES-AN ES-AR ES-AS ES-AV  ES-B ES-BA ES-BI ES-BU  ES-C 
##   385   385   385   385   385   385   385   385   385   385   385   385   385 
## ES-CA ES-CB ES-CC ES-CE ES-CL ES-CM ES-CN ES-CO ES-CR ES-CS ES-CT ES-CU ES-EX 
##   385   385   385   378   385   385   385   385   385   385   385   385   385 
## ES-GA ES-GC ES-GI ES-GR ES-GU  ES-H ES-HU ES-IB  ES-J  ES-L ES-LE ES-LU ES-MA 
##   385   385   385   385   385   385   385   385   385   385   385   385   385 
## ES-MC ES-MD ES-ML ES-NC ES-OR  ES-P ES-PO ES-PV ES-RI ES-SA ES-SE ES-SG ES-SO 
##   385   385   379   385   385   385   385   385   385   385   385   385   385 
## ES-SS  ES-T ES-TE ES-TF ES-TO  ES-V ES-VA ES-VC ES-VI  ES-Z ES-ZA 
##   385   385   385   385   385   385   385   385   385   385   385
```

2.1.6 Google autonomous-communities & provinces

We check data grouped by autonomous communities and provinces.

```r
Google %>% group_by(sub_region_1) %>% tally()
```

```
## # A tibble: 20 x 2
##    sub_region_1               n
##    <chr>                  <int>
##  1 ""                       385
##  2 "Andalusia"             3465
##  3 "Aragon"                1540
##  4 "Asturias"               385
##  5 "Balearic Islands"       385
##  6 "Basque Country"        1540
##  7 "Canary Islands"        1155
##  8 "Cantabria"              385
##  9 "Castile-La Mancha"     2310
## 10 "Castile and LeÃ³n"     3850
## 11 "Catalonia"             1925
## 12 "Ceuta"                  378
## 13 "Community of Madrid"    385
## 14 "Extremadura"           1155
## 15 "Galicia"               1925
## 16 "La Rioja"               385
## 17 "Melilla"                379
## 18 "Navarre"                385
## 19 "Region of Murcia"       385
## 20 "Valencian Community"   1540
```

```r
Google %>% group_by(sub_region_1) %>% count(sub_region_2)
```

```
## # A tibble: 63 x 3
## # Groups:   sub_region_1 [20]
##    sub_region_1 sub_region_2     n
##    <chr>        <chr>        <int>
##  1 ""           ""             385
##  2 "Andalusia"  ""             385
##  3 "Andalusia"  "AlmerÃa"      385
##  4 "Andalusia"  "CÃ¡diz"       385
##  5 "Andalusia"  "CÃ³rdoba"     385
##  6 "Andalusia"  "Granada"      385
##  7 "Andalusia"  "Huelva"       385
##  8 "Andalusia"  "JaÃ©n"        385
##  9 "Andalusia"  "MÃ¡laga"      385
## 10 "Andalusia"  "Seville"      385
## # ... with 53 more rows
```

In Spain there are **autonomous communities (AC)** and **autonomous cities (C)** that are considered as **provinces (Pr)**. This is the case for:

- AC - Asturias, Principality - Pr - Asturias
- AC - Balears, Illes - Pr - Balears, Illes
- AC - Cantabria - Pr - Cantabria
- AC - Madrid, Community - Pr - Madrid
- AC - Murcia, Region - Pr- Murcia
- AC - Navarra, Foral Community - Pr - Navarra
- AC - Rioja, La - Pr - Rioja, La
- C - Ceuta - C/Pr - Ceuta
- C - Melilla - C/Pr - Melilla

In this data set, the empty values in the "sub_region_2" column, for the autonomous communities mentinoed, will be replaced by the value contained in the "sub_region_1" column (A). Also we are going to modify the names of the provinces that have special characters in order to adopt the INE standards (B). See note.

Note The following links states the provinces in Spain INE CCAA and its ISO codes are going to be used as tables of referencence.

```r
# Modidication provinces - A
Google$sub_region_2[Google$sub_region_1=="Balearic Islands"] <- "Balears, Illes"
Google$iso_3166_2_code[Google$sub_region_2=="Balears, Illes"] <- "PM"

Google$sub_region_2[Google$sub_region_1=="Asturias"] <- "Asturias"
Google$iso_3166_2_code[Google$sub_region_2=="Asturias"] <- "O"

Google$sub_region_2[Google$sub_region_1=="Cantabria"] <- "Cantabria"
Google$iso_3166_2_code[Google$sub_region_2=="Cantabria"] <- "S"

Google$sub_region_2[Google$sub_region_1=="Community of Madrid"] <- "Madrid"
Google$iso_3166_2_code[Google$sub_region_2=="Madrid"] <- "M"

Google$sub_region_2[Google$sub_region_1=="Region of Murcia"] <- "Murcia"
Google$iso_3166_2_code[Google$sub_region_2=="Murcia"] <- "MU"

Google$sub_region_2[Google$sub_region_1=="Navarre"] <- "Navarra"
Google$iso_3166_2_code[Google$sub_region_2=="Navarra"] <- "NA"
```

```r
Google$sub_region_2[Google$sub_region_1=="La Rioja"] <- "Rioja, La"
Google$iso_3166_2_code[Google$sub_region_2=="Rioja, La"] <- "LO"

Google$sub_region_2[Google$sub_region_1=="Ceuta"] <- "Ceuta"
Google$iso_3166_2_code[Google$sub_region_2=="Ceuta"] <- "CE"

Google$sub_region_2[Google$sub_region_1=="Melilla"] <- "Melilla"
Google$iso_3166_2_code[Google$sub_region_2=="Melilla"] <- "ML"

# Modidication provinces - B
Google$sub_region_2[Google$sub_region_2=="A CoruÃ±a"]<-"Coruña, A"
Google$sub_region_2[Google$sub_region_2=="Ã\u0081lava"]<-"Araba/Álava"
Google$sub_region_2[Google$sub_region_2=="Ã\u0081vila"]<-"Ávila"
#Google$sub_region_2[Google$sub_region_2=="Albacete"]<-"Albacete"
Google$sub_region_2[Google$sub_region_2=="Alicante"]<-"Alicante/Alacant"
#Google$sub_region_2[Google$sub_region_2=="AlmerÃa"]<-"Almería"
#Google$sub_region_2[Google$sub_region_2=="Asturias"]<-"Asturias"
#Google$sub_region_2[Google$sub_region_2=="Badajoz"]<-"Badajoz"
#Google$sub_region_2[Google$sub_region_2=="Balears, Illes"]<-"Balears, Illes"
#Google$sub_region_2[Google$sub_region_2=="Barcelona"]<-"Barcelona"
Google$sub_region_2[Google$sub_region_2=="Biscay"]<-"Bizkaia"
#Google$sub_region_2[Google$sub_region_2=="Burgos"]<-"Burgos"
Google$sub_region_2[Google$sub_region_2=="CÃ¡ceres"]<-"Cáceres"
Google$sub_region_2[Google$sub_region_2=="CÃ¡diz"]<-"Cádiz"
Google$sub_region_2[Google$sub_region_2=="CÃ³rdoba"]<-"Córdoba"
#Google$sub_region_2[Google$sub_region_2=="Cantabria"]<-"Cantabria"
Google$sub_region_2[Google$sub_region_2=="CastellÃ³n"]<-"Castellón/Castelló"
#Google$sub_region_2[Google$sub_region_2=="Ceuta"]<-"Ceuta"
#Google$sub_region_2[Google$sub_region_2=="Ciudad Real"]<-"Ciudad Real"
#Google$sub_region_2[Google$sub_region_2=="Cuenca"]<-"Cuenca"
#Google$sub_region_2[Google$sub_region_2=="Gipuzkoa"]<-"Gipuzkoa"
#Google$sub_region_2[Google$sub_region_2=="Girona"]<-"Girona"
#Google$sub_region_2[Google$sub_region_2=="Granada"]<-"Granada"
#Google$sub_region_2[Google$sub_region_2=="Guadalajara"]<-"Guadalajara"
#Google$sub_region_2[Google$sub_region_2=="Huelva"]<-"Huelva"
#Google$sub_region_2[Google$sub_region_2=="Huesca"]<-"Huesca"
Google$sub_region_2[Google$sub_region_2=="JaÃ©n"]<-"Jaén"
Google$sub_region_2[Google$sub_region_2=="Las Palmas"]<-"Palmas, Las"
Google$sub_region_2[Google$sub_region_2=="LeÃ³n"]<-"León"
#Google$sub_region_2[Google$sub_region_2=="Lleida"]<-"Lleida"
#Google$sub_region_2[Google$sub_region_2=="Lugo"]<-"Lugo"
Google$sub_region_2[Google$sub_region_2=="MÃ¡laga"]<-"Málaga"
#Google$sub_region_2[Google$sub_region_2=="Madrid"]<-"Madrid"
#Google$sub_region_2[Google$sub_region_2=="Melilla"]<-"Melilla"
#Google$sub_region_2[Google$sub_region_2=="Murcia"]<-"Murcia"
#Google$sub_region_2[Google$sub_region_2=="Navarra"]<-"Navarra"
#Google$sub_region_2[Google$sub_region_2=="Palencia"]<-"Palencia"
#Google$sub_region_2[Google$sub_region_2=="Pontevedra"]<-"Pontevedra"
Google$sub_region_2[Google$sub_region_2=="Province of Ourense"]<-"Ourense"
#Google$sub_region_2[Google$sub_region_2=="Rioja, La"]<-"Rioja, La"
#Google$sub_region_2[Google$sub_region_2=="Salamanca"]<-"Salamanca"
#Google$sub_region_2[Google$sub_region_2=="Santa Cruz de Tenerife"]<-"Santa Cruz de Tenerife"
#Google$sub_region_2[Google$sub_region_2=="Segovia"]<-"Segovia"
```

```r
Google$sub_region_2[Google$sub_region_2=="Seville"]<-"Sevilla"
#Google$sub_region_2[Google$sub_region_2=="Soria"]<-"Soria"
#Google$sub_region_2[Google$sub_region_2=="Tarragona"]<-"Tarragona"
#Google$sub_region_2[Google$sub_region_2=="Teruel"]<-"Teruel"
#Google$sub_region_2[Google$sub_region_2=="Toledo"]<-"Toledo"
Google$sub_region_2[Google$sub_region_2=="Valencia"]<-"Valencia/València"
#Google$sub_region_2[Google$sub_region_2=="Valladolid"]<-"Valladolid"
#Google$sub_region_2[Google$sub_region_2=="Zamora"]<-"Zamora"
#Google$sub_region_2[Google$sub_region_2=="Zaragoza"]<-"Zaragoza"
Google$sub_region_2 <- with(Google, ifelse(grepl("^Almer", sub_region_2),
                                                     "Almería", sub_region_2))

table(Google$sub_region_2)
```

```
## 
##                                     Albacete       Alicante/Alacant 
##                   4235                    385                    385 
##                Almería           Araba/Álava               Asturias 
##                    385                    385                    385 
##                  Ávila                Badajoz         Balears, Illes 
##                    385                    385                    385 
##              Barcelona                Bizkaia                 Burgos 
##                    385                    385                    385 
##                Cáceres                  Cádiz              Cantabria 
##                    385                    385                    385 
##     Castellón/Castelló                  Ceuta            Ciudad Real 
##                    385                    378                    385 
##                Córdoba             Coruña, A                 Cuenca 
##                    385                    385                    385 
##               Gipuzkoa                 Girona                Granada 
##                    385                    385                    385 
##            Guadalajara                 Huelva                 Huesca 
##                    385                    385                    385 
##                   Jaén                   León                 Lleida 
##                    385                    385                    385 
##                   Lugo                 Madrid                 Málaga 
##                    385                    385                    385 
##                Melilla                 Murcia                Navarra 
##                    379                    385                    385 
##                Ourense               Palencia            Palmas, Las 
##                    385                    385                    385 
##             Pontevedra              Rioja, La              Salamanca 
##                    385                    385                    385 
## Santa Cruz de Tenerife                Segovia                Sevilla 
##                    385                    385                    385 
##                  Soria              Tarragona                 Teruel 
##                    385                    385                    385 
##                 Toledo      Valencia/València             Valladolid 
##                    385                    385                    385 
##                 Zamora               Zaragoza 
##                    385                    385
```

```r
table(Google$iso_3166_2_code)
```

```
##
##          CE  ES-A ES-AB ES-AL ES-AN ES-AR ES-AV  ES-B ES-BA ES-BI ES-BU  ES-C
##   385   378   385   385   385   385   385   385   385   385   385   385   385
## ES-CA ES-CC ES-CL ES-CM ES-CN ES-CO ES-CR ES-CS ES-CT ES-CU ES-EX ES-GA ES-GC
##   385   385   385   385   385   385   385   385   385   385   385   385   385
## ES-GI ES-GR ES-GU  ES-H ES-HU  ES-J  ES-L ES-LE ES-LU ES-MA ES-OR  ES-P ES-PO
##   385   385   385   385   385   385   385   385   385   385   385   385   385
## ES-PV ES-SA ES-SE ES-SG ES-SO ES-SS  ES-T ES-TE ES-TF ES-TO  ES-V ES-VA ES-VC
##   385   385   385   385   385   385   385   385   385   385   385   385   385
## ES-VI  ES-Z ES-ZA    LO     M    ML    MU    NA     O    PM     S
##   385   385   385   385   385   379   385   385   385   385   385
```

2.1.7 Google data transformation

We are going to **transform / eliminate**:

- A - Rows with “na” / ”” in “sub_region_1” and “sub_region_2” columns are eliminated.
- B - Date column is transformed from “character” to “date”.
- C - Some columns are eliminated due to they are not adding value or they contain blanks (country_region_code, country_region, metro_area, census_fips_code, pace_id).
- D - “ES-” is elimianted from “iso_3166_2_code” column.

```r
# Transform / eliminate A
Google <- filter(Google, sub_region_1 != "", sub_region_2 != "" )

# Transform / eliminate B
Google$date <- as.Date(Google$date ,format="%d/%m/%Y")

# Transform / eliminate C
Google<-within(Google, rm(country_region_code,
                  country_region,
                  metro_area,
                  census_fips_code,
                  place_id))

# Transform / eliminate D
Google$iso_3166_2_code <- gsub("ES-", "", Google$iso_3166_2_code)

#Google$retail_and_recreation_percent_change_from_baseline <- as.numeric(Google$retail_and_recreation_p
#Google$grocery_and_pharmacy_percent_change_from_baseline <- as.numeric(Google$grocery_and_pharmacy_per
#Google$parks_percent_change_from_baseline <- as.numeric(Google$parks_percent_change_from_baseline)
#Google$transit_stations_percent_change_from_baseline <- as.numeric(Google$transit_stations_percent_cha
#Google$workplaces_percent_change_from_baseline <- as.numeric(Google$workplaces_percent_change_from_bas
#Google$residential_percent_change_from_baseline <- as.numeric(Google$residential_percent_change_from_b

head(Google,5)
```

```
##   sub_region_1 sub_region_2 iso_3166_2_code       date
## 1    Andalusia      Almería              AL 2020-02-15
## 2    Andalusia      Almería              AL 2020-02-16
## 3    Andalusia      Almería              AL 2020-02-17
## 4    Andalusia      Almería              AL 2020-02-18
## 5    Andalusia      Almería              AL 2020-02-19
```

```
##   retail_and_recreation_percent_change_from_baseline
## 1                                                   5
## 2                                                  -2
## 3                                                   0
## 4                                                  -3
## 5                                                  -1
##   grocery_and_pharmacy_percent_change_from_baseline
## 1                                                -3
## 2                                                 0
## 3                                                -2
## 4                                                -3
## 5                                                -3
##   parks_percent_change_from_baseline
## 1                                 40
## 2                                 -2
## 3                                  3
## 4                                 -2
## 5                                  3
##   transit_stations_percent_change_from_baseline
## 1                                            10
## 2                                             1
## 3                                             5
## 4                                             5
## 5                                             4
##   workplaces_percent_change_from_baseline
## 1                                       1
## 2                                       1
## 3                                       3
## 4                                       3
## 5                                       3
##   residential_percent_change_from_baseline
## 1                                       -2
## 2                                       -1
## 3                                       -1
## 4                                        0
## 5                                        0
```

```
table(Google$sub_region_2)
```

```
##
##             Albacete       Alicante/Alacant              Almería
##                  385                    385                  385
##         Araba/Álava               Asturias                Ávila
##                  385                    385                  385
##              Badajoz         Balears, Illes            Barcelona
##                  385                    385                  385
##              Bizkaia                 Burgos              Cáceres
##                  385                    385                  385
##                Cádiz              Cantabria  Castellón/Castelló
##                  385                    385                  385
##                Ceuta            Ciudad Real              Córdoba
##                  378                    385                  385
##            Coruña, A                 Cuenca             Gipuzkoa
##                  385                    385                  385
##               Girona                Granada          Guadalajara
```

```
##                 385                    385                    385
##              Huelva                 Huesca                   Jaén
##                 385                    385                    385
##                León                 Lleida                   Lugo
##                 385                    385                    385
##              Madrid                 Málaga                Melilla
##                 385                    385                    379
##              Murcia                Navarra                Ourense
##                 385                    385                    385
##            Palencia             Palmas, Las             Pontevedra
##                 385                    385                    385
##           Rioja, La              Salamanca Santa Cruz de Tenerife
##                 385                    385                    385
##             Segovia                Sevilla                  Soria
##                 385                    385                    385
##           Tarragona                 Teruel                 Toledo
##                 385                    385                    385
##    Valencia/València             Valladolid                 Zamora
##                 385                    385                    385
##            Zaragoza
##                 385
```

```r
table(Google$iso_3166_2_code)
```

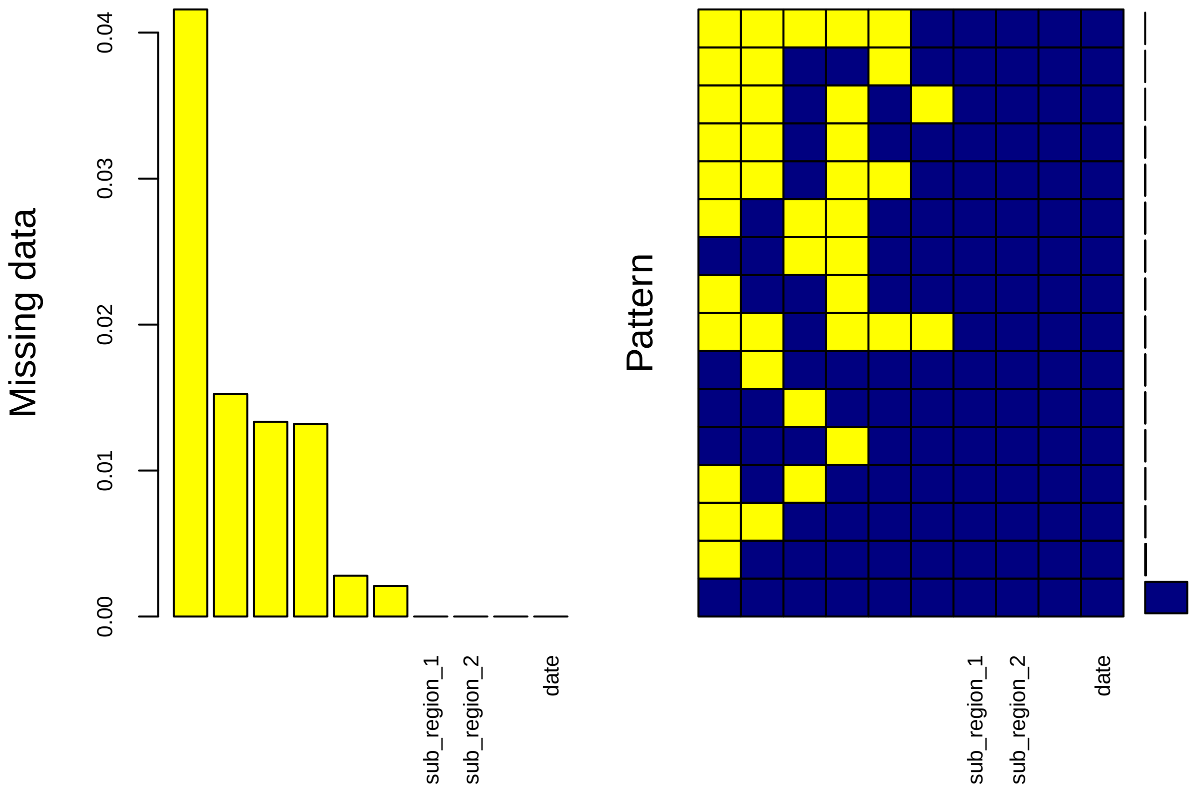
```
##
##   A  AB  AL  AV   B  BA  BI  BU   C  CA  CC  CE  CO  CR  CS  CU  GC  GI  GR  GU
## 385 385 385 385 385 385 385 385 385 385 385 378 385 385 385 385 385 385 385 385
##   H  HU   J   L  LE  LO  LU   M  MA  ML  MU  NA   O  OR   P  PM  PO   S  SA  SE
## 385 385 385 385 385 385 385 385 385 379 385 385 385 385 385 385 385 385 385 385
##  SG  SO  SS   T  TE  TF  TO   V  VA  VI   Z  ZA
## 385 385 385 385 385 385 385 385 385 385 385 385
```

```r
#unique(Google$sub_region_2)
#unique(EM3$Zonas.de.movilidad)
```

2.1.8 Google review missing values & impute

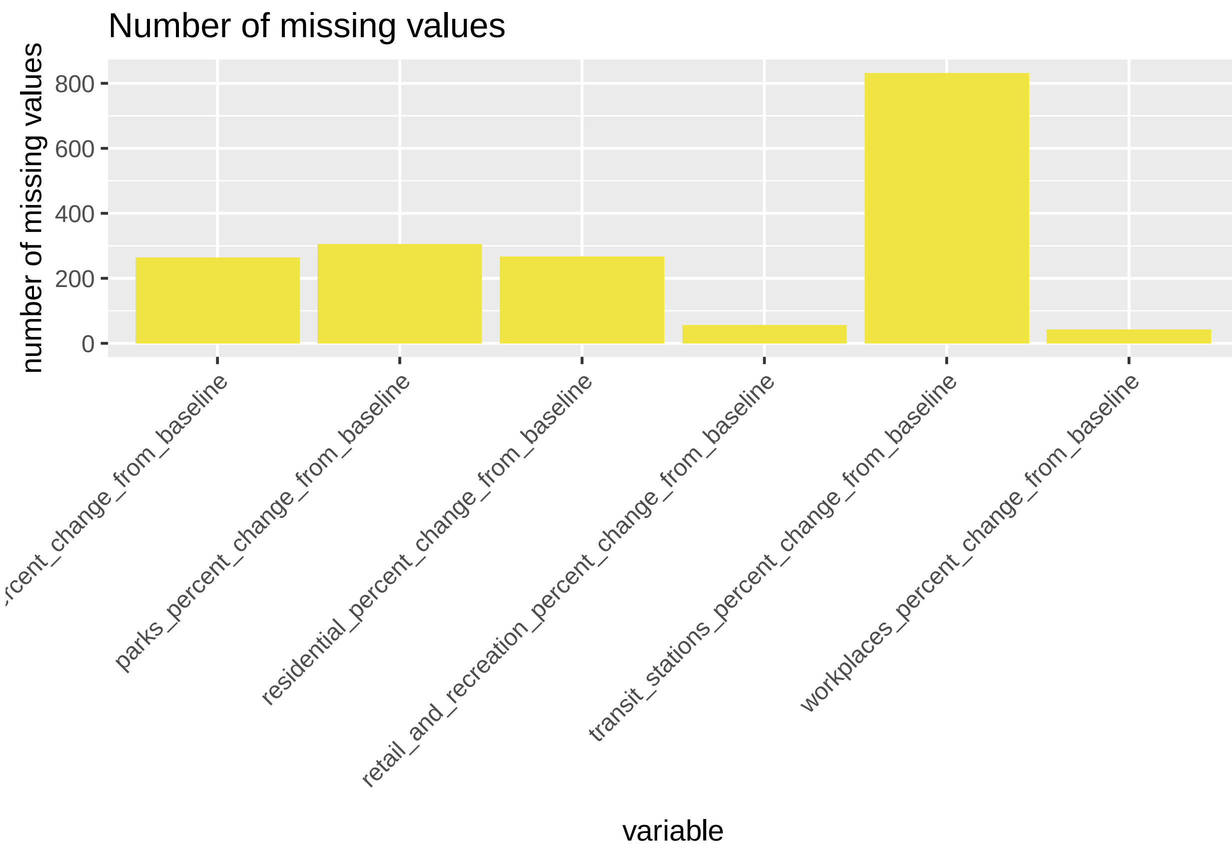
We check missing values.

```r
aggr(Google, col=c('navyblue','yellow'),
     numbers=TRUE, sortVars=TRUE,
     labels=names(Google), cex.axis=.7,
     gap=3, ylab=c("Missing data","Pattern"))
```



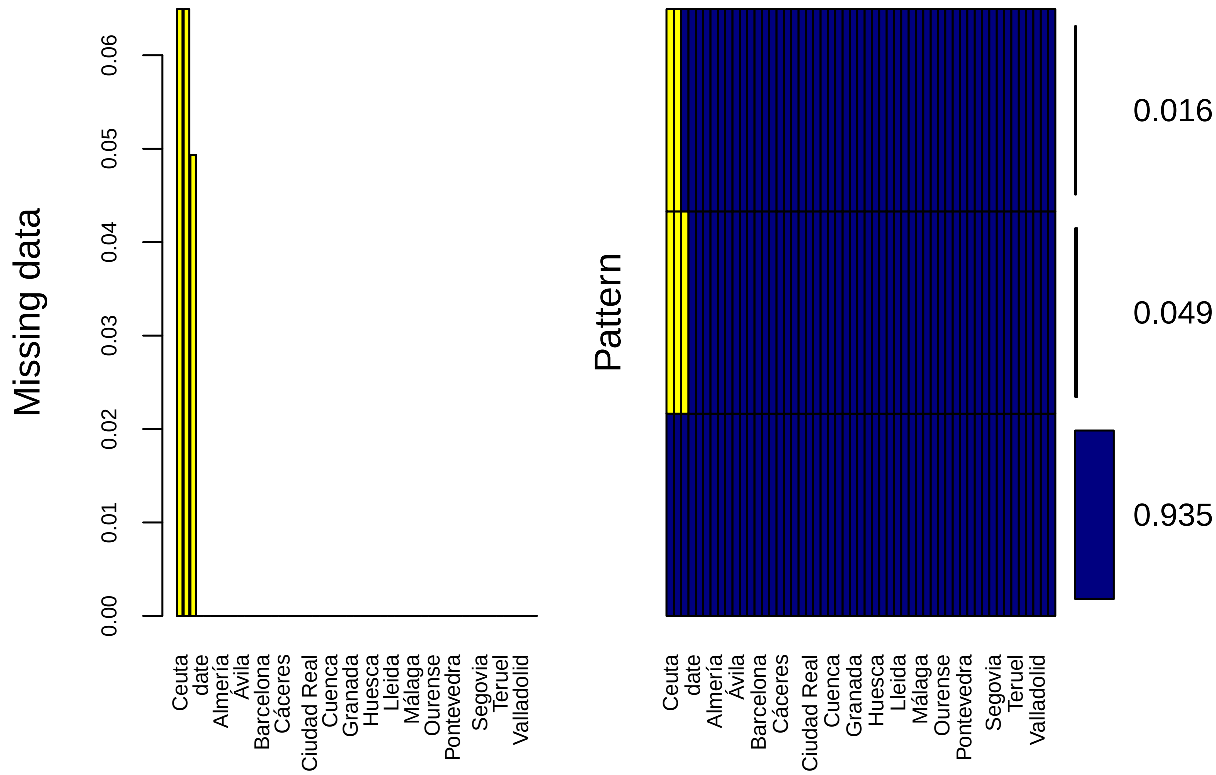

```
##
##  Variables sorted by number of missings:
##                                            Variable       Count
##       transit_stations_percent_change_from_baseline 0.041585445
##                  parks_percent_change_from_baseline 0.015244664
##            residential_percent_change_from_baseline 0.013345329
##    grocery_and_pharmacy_percent_change_from_baseline 0.013195382
##  retail_and_recreation_percent_change_from_baseline 0.002799020
##             workplaces_percent_change_from_baseline 0.002099265
##                                        sub_region_1 0.000000000
##                                        sub_region_2 0.000000000
##                                    iso_3166_2_code 0.000000000
##                                                date 0.000000000
```

```r
Google %>%
    gather(key = "key", value = "val") %>%
    mutate(is.missing = is.na(val)) %>%
    group_by(key, is.missing) %>%
    summarise(num.missing = n()) %>%
    filter(is.missing==T) %>%
    select(-is.missing) %>%
    arrange(desc(num.missing)) %>%
    ggplot() +
    geom_bar(aes(x=key, y=num.missing), stat = 'identity',fill="#F0E442") +
    labs(x='variable', y="number of missing values",
         title='Number of missing values') +
    theme(axis.text.x = element_text(angle = 45, hjust = 1))
```



We generate 6 new dataframes from the 6 features stated in order to imput missing values using the approach "imputeTS".

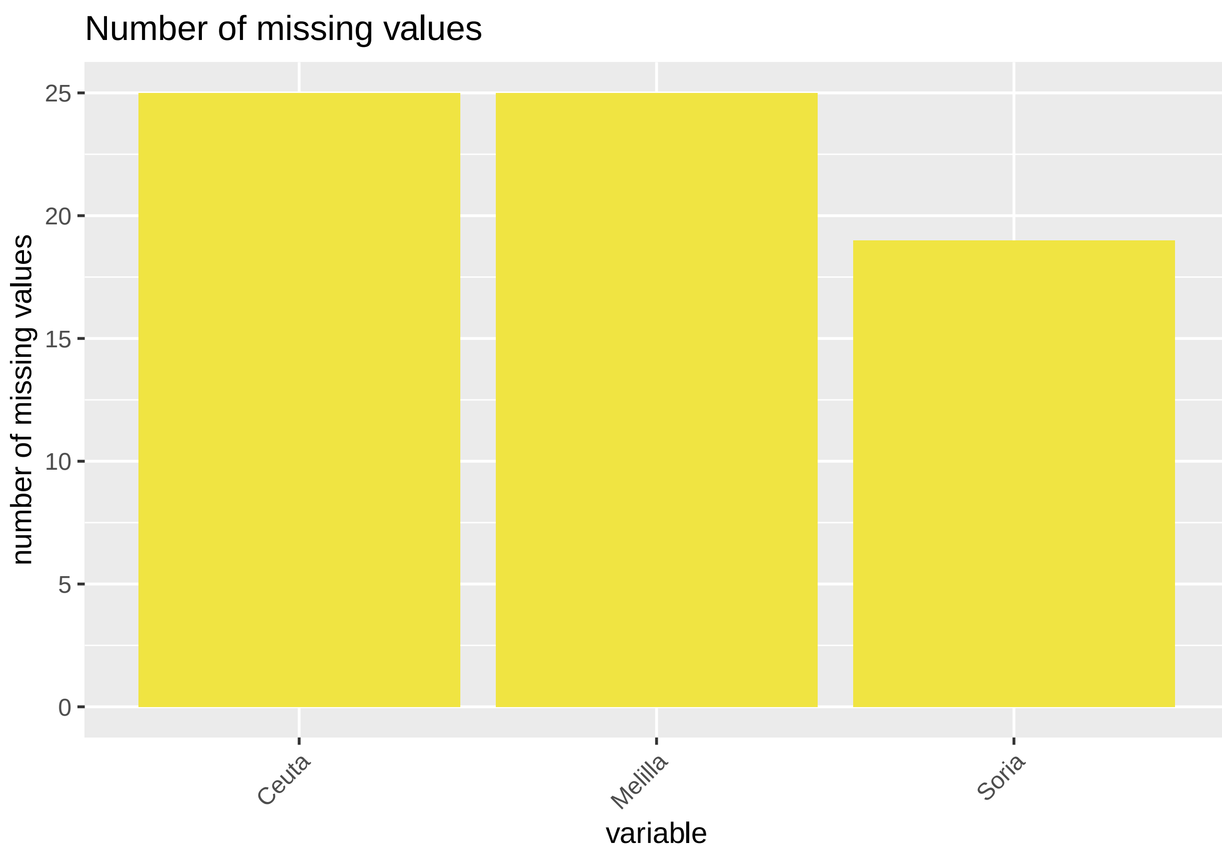
```
# Transpose dataframe
Google_retail<-Google[c(2,4,5)]
Google_t_retail<-dcast(Google_retail, date~sub_region_2, fill=NA)

# Visualize missing values
aggr(Google_t_retail, col=c('navyblue','yellow'),
     numbers=TRUE, sortVars=TRUE,
     labels=names(Google_t_retail), cex.axis=.7,
     gap=3, ylab=c("Missing data","Pattern"))
```



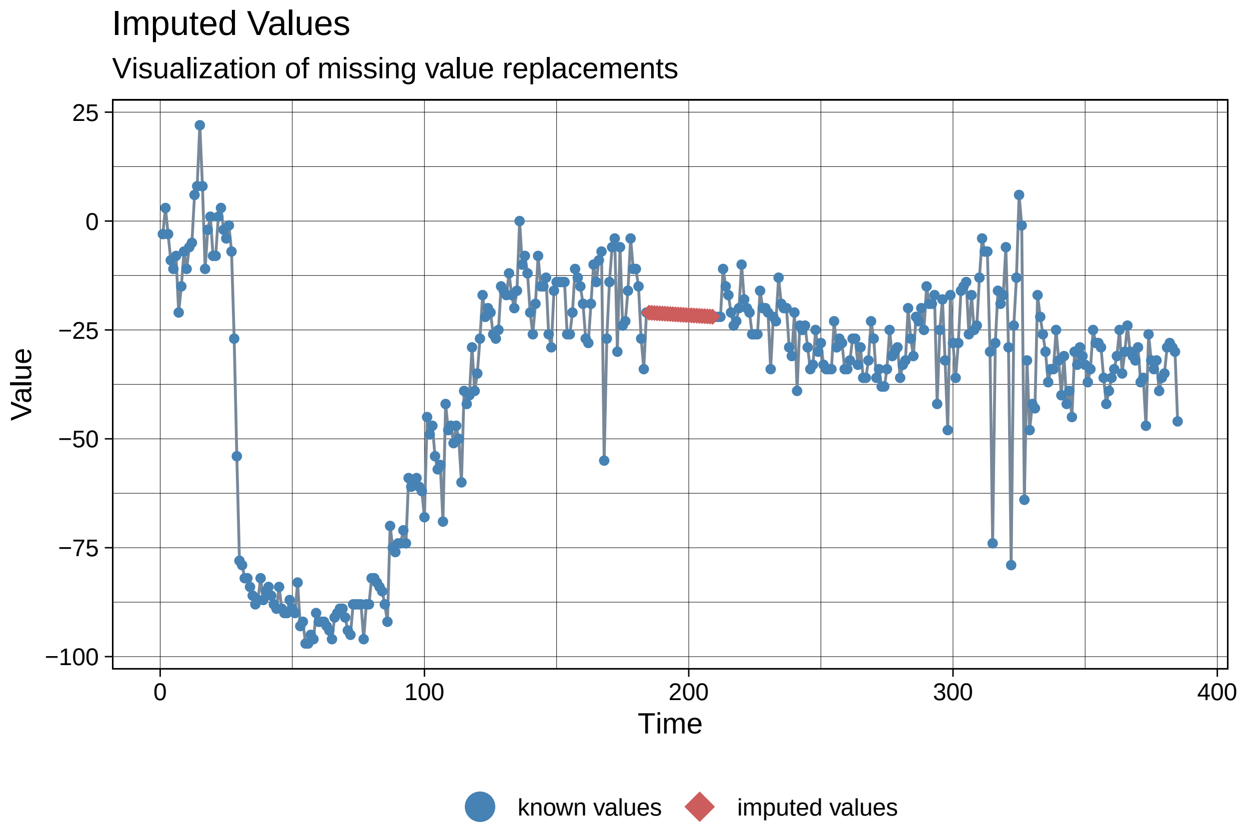

```
##
## Variables sorted by number of missings:
##              Variable      Count
##                 Ceuta 0.06493506
##               Melilla 0.06493506
##                 Soria 0.04935065
##                  date 0.00000000
##              Albacete 0.00000000
##      Alicante/Alacant 0.00000000
##               Almería 0.00000000
##           Araba/Álava 0.00000000
##              Asturias 0.00000000
##                 Ávila 0.00000000
##               Badajoz 0.00000000
##        Balears, Illes 0.00000000
##             Barcelona 0.00000000
##               Bizkaia 0.00000000
##                Burgos 0.00000000
##               Cáceres 0.00000000
##                 Cádiz 0.00000000
##             Cantabria 0.00000000
##   Castellón/Castelló 0.00000000
##           Ciudad Real 0.00000000
##               Córdoba 0.00000000
##             Coruña, A 0.00000000
##                Cuenca 0.00000000
```

```
##                 Gipuzkoa 0.00000000
##                   Girona 0.00000000
##                  Granada 0.00000000
##              Guadalajara 0.00000000
##                   Huelva 0.00000000
##                   Huesca 0.00000000
##                     Jaén 0.00000000
##                     León 0.00000000
##                   Lleida 0.00000000
##                     Lugo 0.00000000
##                   Madrid 0.00000000
##                   Málaga 0.00000000
##                   Murcia 0.00000000
##                  Navarra 0.00000000
##                  Ourense 0.00000000
##                 Palencia 0.00000000
##              Palmas, Las 0.00000000
##               Pontevedra 0.00000000
##                Rioja, La 0.00000000
##                Salamanca 0.00000000
##   Santa Cruz de Tenerife 0.00000000
##                  Segovia 0.00000000
##                  Sevilla 0.00000000
##                Tarragona 0.00000000
##                   Teruel 0.00000000
##                   Toledo 0.00000000
##        Valencia/València 0.00000000
##               Valladolid 0.00000000
##                   Zamora 0.00000000
##                 Zaragoza 0.00000000
```

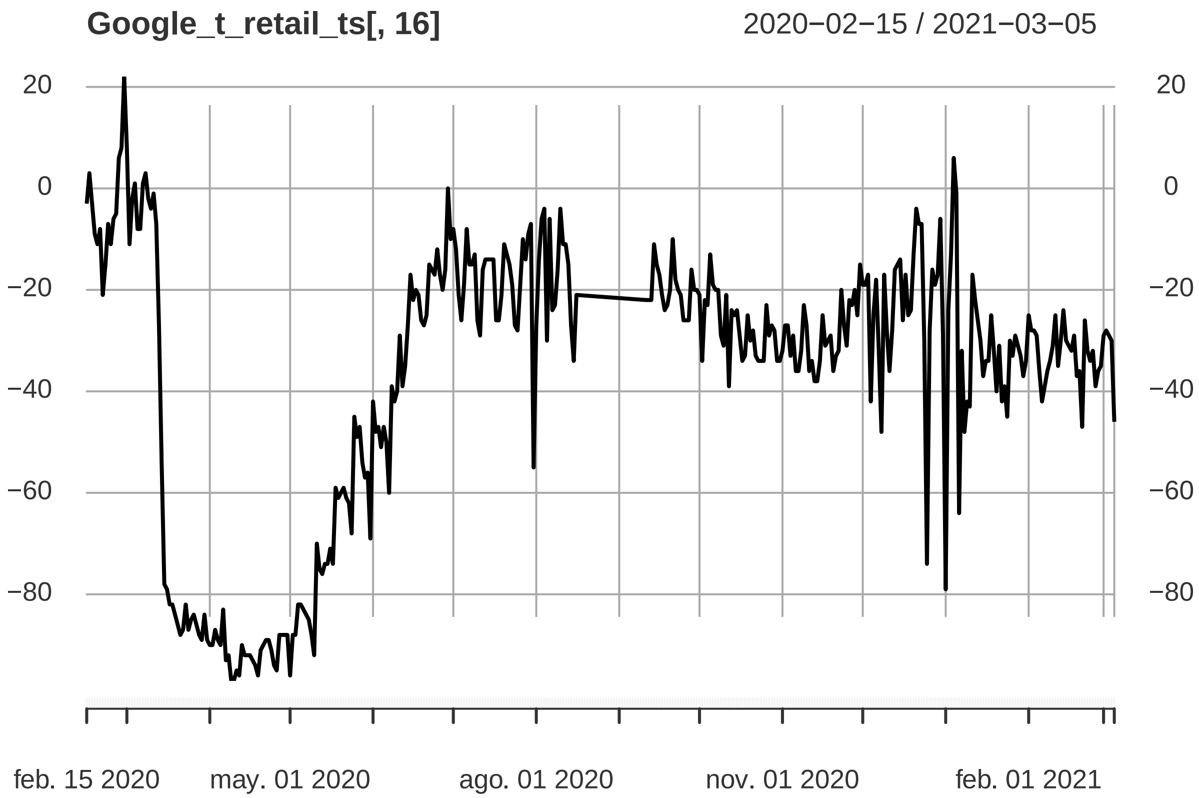
```r
Google_t_retail %>%
    gather(key = "key", value = "val") %>%
    mutate(is.missing = is.na(val)) %>%
    group_by(key, is.missing) %>%
    summarise(num.missing = n()) %>%
    filter(is.missing==T) %>%
    select(-is.missing) %>%
    arrange(desc(num.missing)) %>%
    ggplot() +
    geom_bar(aes(x=key, y=num.missing), stat = 'identity',fill="#F0E442") +
    labs(x='variable', y="number of missing values",
         title='Number of missing values') +
    theme(axis.text.x = element_text(angle = 45, hjust = 1))
```



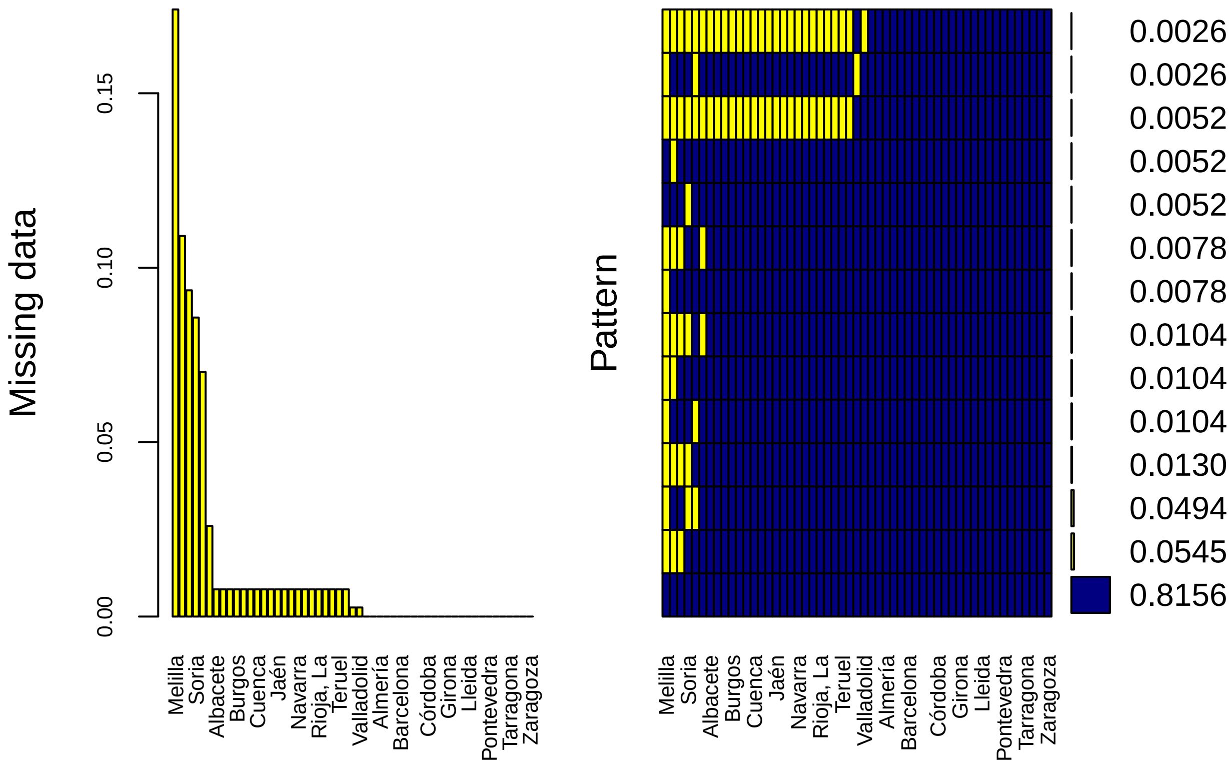

```r
# Convert dataframe to ts object
Google_t_retail_ts<-xts(Google_t_retail[-1],Google_t_retail$date)

# Impute the missing values with na_seadec (i.e Ceuta)
imp5 <- na_seadec(Google_t_retail_ts[,16])
ggplot_na_imputations(Google_t_retail_ts[,16], imp5)
```




```r
# We select na_seadec for the dataset
Google_t_retail_ts <- na_seadec(Google_t_retail_ts)
plot(Google_t_retail_ts[,16])
```



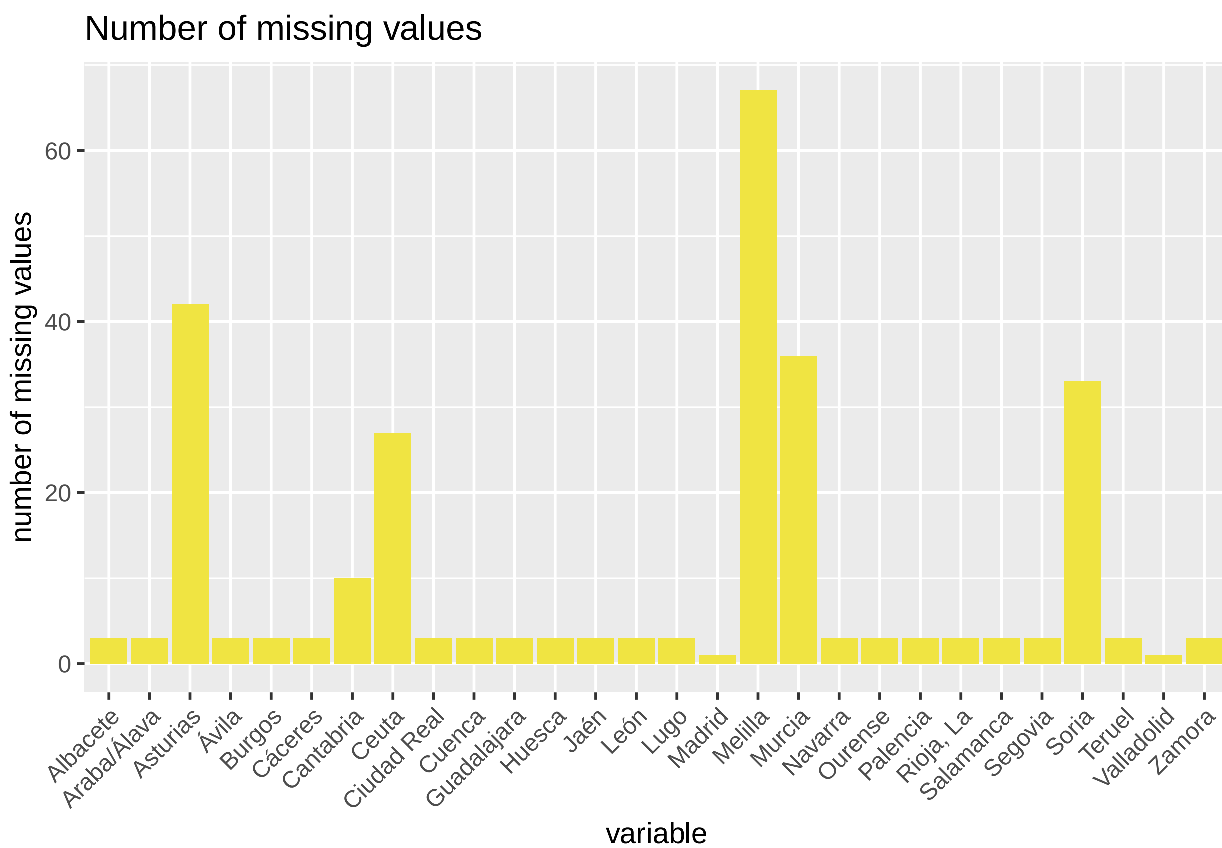

```r
# We convert the time series object to a dataframe
Google_retail <- ts_df(Google_t_retail_ts)

names(Google_retail)[names(Google_retail) == "id"] <- "sub_region_2"
names(Google_retail)[names(Google_retail) == "time"] <- "Date"
names(Google_retail)[names(Google_retail) == "value"] <- "retail_and_recreation_percent_change_from_bas

####################################################################
# Transpose dataframe
Google_grocery<-Google[c(2,4,6)]
Google_t_grocery<-dcast(Google_grocery, date~sub_region_2, fill=NA)

# Visualize missing values
aggr(Google_t_grocery, col=c('navyblue','yellow'),
     numbers=TRUE, sortVars=TRUE,
     labels=names(Google_t_grocery), cex.axis=.7,
     gap=3, ylab=c("Missing data","Pattern"))
```



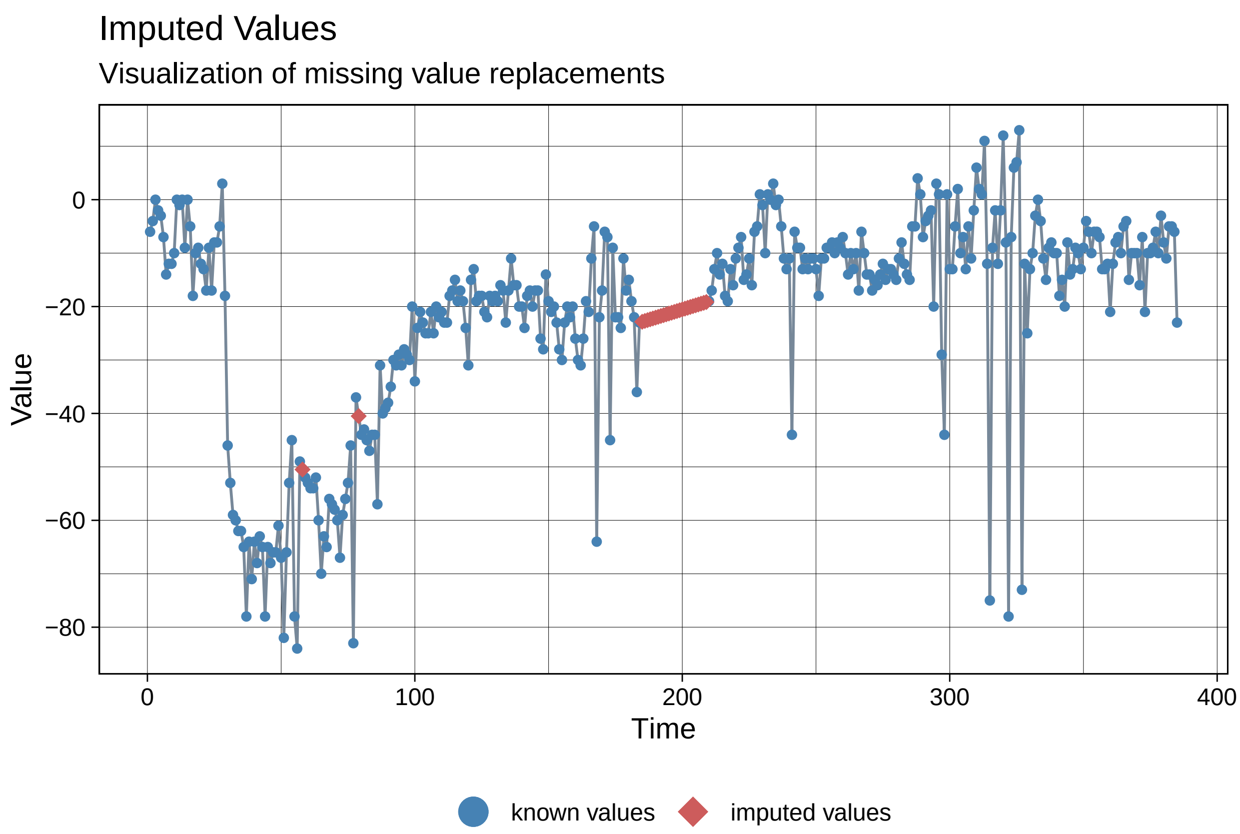

```
##
## Variables sorted by number of missings:
##             Variable       Count
##              Melilla 0.174025974
##             Asturias 0.109090909
##               Murcia 0.093506494
##                Soria 0.085714286
##                Ceuta 0.070129870
##            Cantabria 0.025974026
##             Albacete 0.007792208
##          Araba/Álava 0.007792208
##                Ávila 0.007792208
##               Burgos 0.007792208
##              Cáceres 0.007792208
##          Ciudad Real 0.007792208
##               Cuenca 0.007792208
##          Guadalajara 0.007792208
##               Huesca 0.007792208
##                 Jaén 0.007792208
##                 León 0.007792208
##                 Lugo 0.007792208
##              Navarra 0.007792208
##              Ourense 0.007792208
##             Palencia 0.007792208
##            Rioja, La 0.007792208
##            Salamanca 0.007792208
```

```
##                  Segovia 0.007792208
##                   Teruel 0.007792208
##                   Zamora 0.007792208
##                   Madrid 0.002597403
##               Valladolid 0.002597403
##                     date 0.000000000
##         Alicante/Alacant 0.000000000
##                  Almería 0.000000000
##                  Badajoz 0.000000000
##           Balears, Illes 0.000000000
##                Barcelona 0.000000000
##                  Bizkaia 0.000000000
##                    Cádiz 0.000000000
##      Castellón/Castelló 0.000000000
##                  Córdoba 0.000000000
##                Coruña, A 0.000000000
##                 Gipuzkoa 0.000000000
##                   Girona 0.000000000
##                  Granada 0.000000000
##                   Huelva 0.000000000
##                   Lleida 0.000000000
##                   Málaga 0.000000000
##              Palmas, Las 0.000000000
##               Pontevedra 0.000000000
##   Santa Cruz de Tenerife 0.000000000
##                  Sevilla 0.000000000
##                Tarragona 0.000000000
##                   Toledo 0.000000000
##        Valencia/València 0.000000000
##                 Zaragoza 0.000000000
```

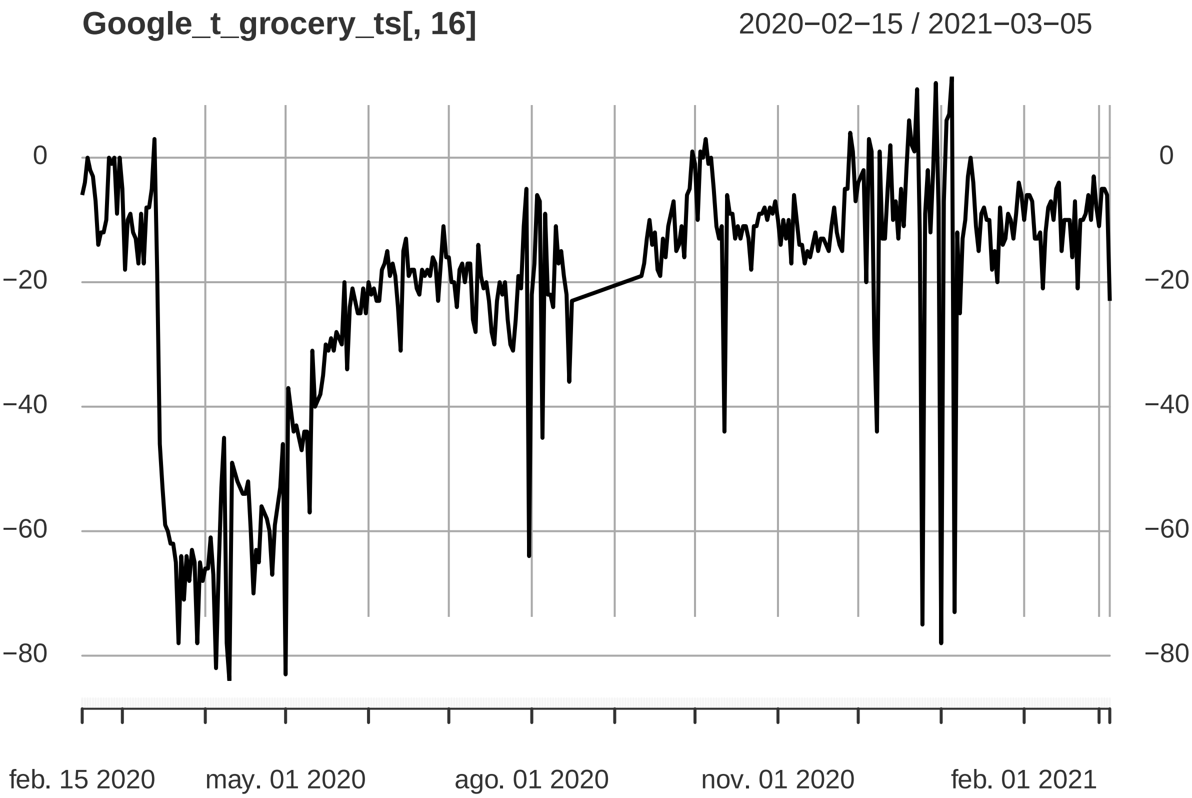
```
Google_t_grocery %>%
    gather(key = "key", value = "val") %>%
    mutate(is.missing = is.na(val)) %>%
    group_by(key, is.missing) %>%
    summarise(num.missing = n()) %>%
    filter(is.missing==T) %>%
    select(-is.missing) %>%
    arrange(desc(num.missing)) %>%
    ggplot() +
    geom_bar(aes(x=key, y=num.missing), stat = 'identity',fill="#F0E442") +
    labs(x='variable', y="number of missing values",
         title='Number of missing values') +
    theme(axis.text.x = element_text(angle = 45, hjust = 1))
```



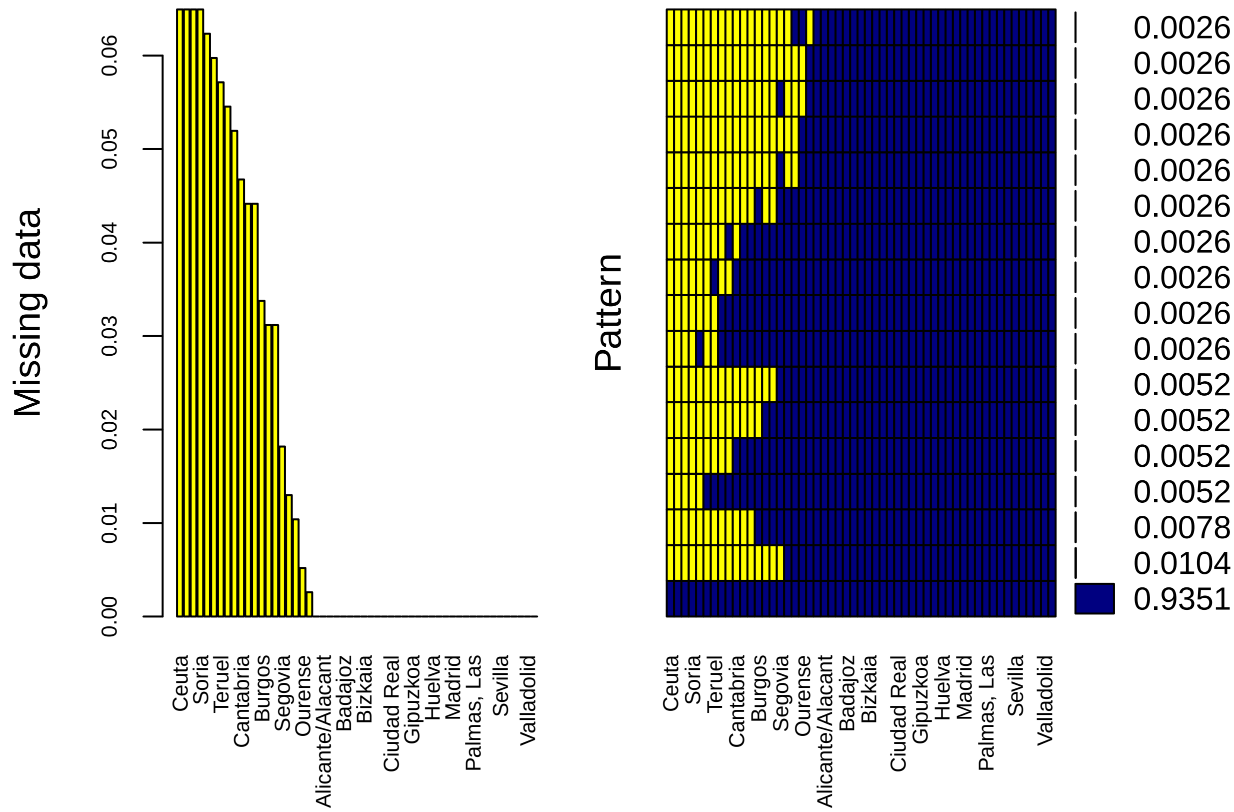

```
# Convert dataframe to ts object
Google_t_grocery_ts<-xts(Google_t_grocery[-1],Google_t_grocery$date)

# Impute the missing values with na_seadec (i.e Ceuta)
imp6 <- na_seadec(Google_t_grocery_ts[,16])
ggplot_na_imputations(Google_t_grocery_ts[,16], imp6)
```




```r
# We select na_seadec for the dataset
Google_t_grocery_ts <- na_seadec(Google_t_grocery_ts)
plot(Google_t_grocery_ts[,16])
```



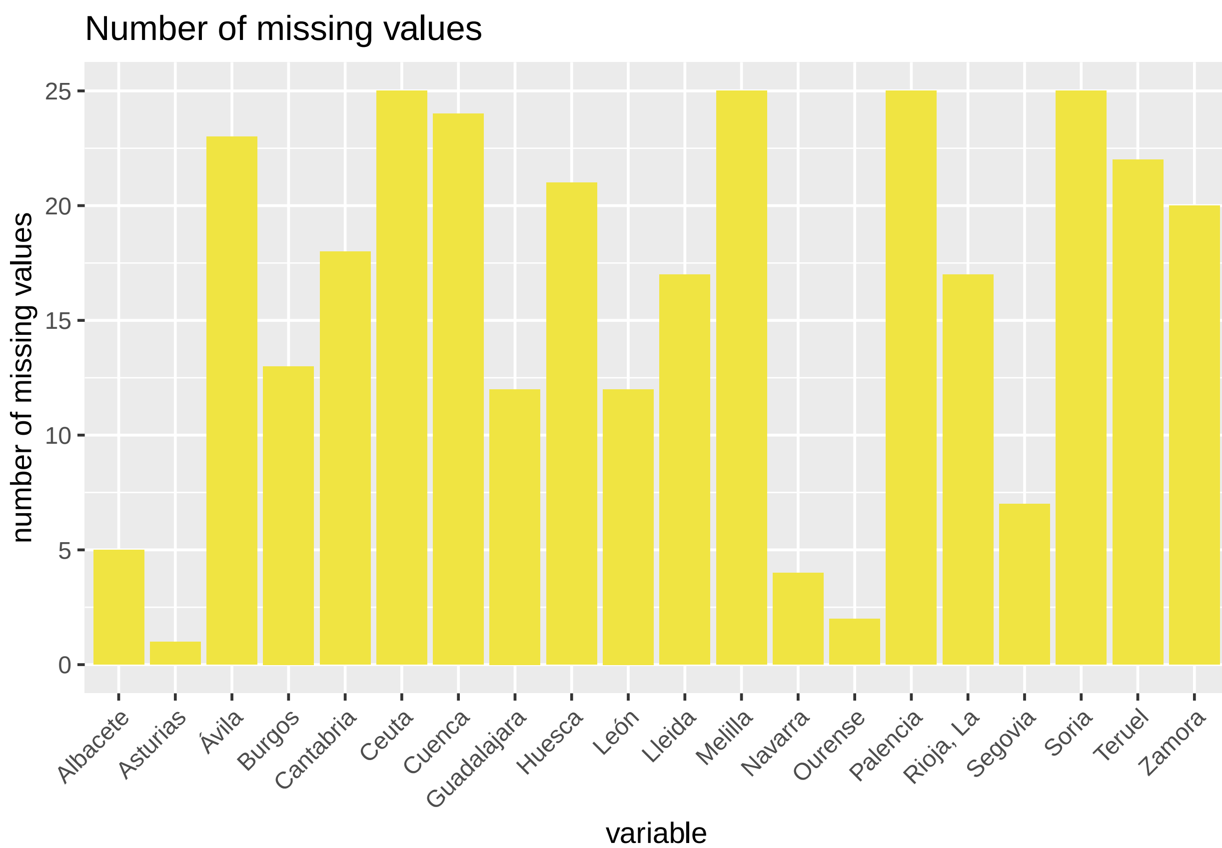

```
# We convert the time series object to a dataframe
Google_grocery <- ts_df(Google_t_grocery_ts)

names(Google_grocery)[names(Google_grocery) == "id"] <- "sub_region_2"
names(Google_grocery)[names(Google_grocery) == "time"] <- "Date"
names(Google_grocery)[names(Google_grocery) == "value"] <- "grocery_and_pharmacy_percent_change_from_ba

####################################################################
# Transpose dataframe
Google_parks<-Google[c(2,4,7)]
Google_t_parks<-dcast(Google_parks, date~sub_region_2, fill=NA)

# Visualize missing values
aggr(Google_t_parks, col=c('navyblue','yellow'),
     numbers=TRUE, sortVars=TRUE,
     labels=names(Google_t_parks), cex.axis=.7,
     gap=3, ylab=c("Missing data","Pattern"))
```



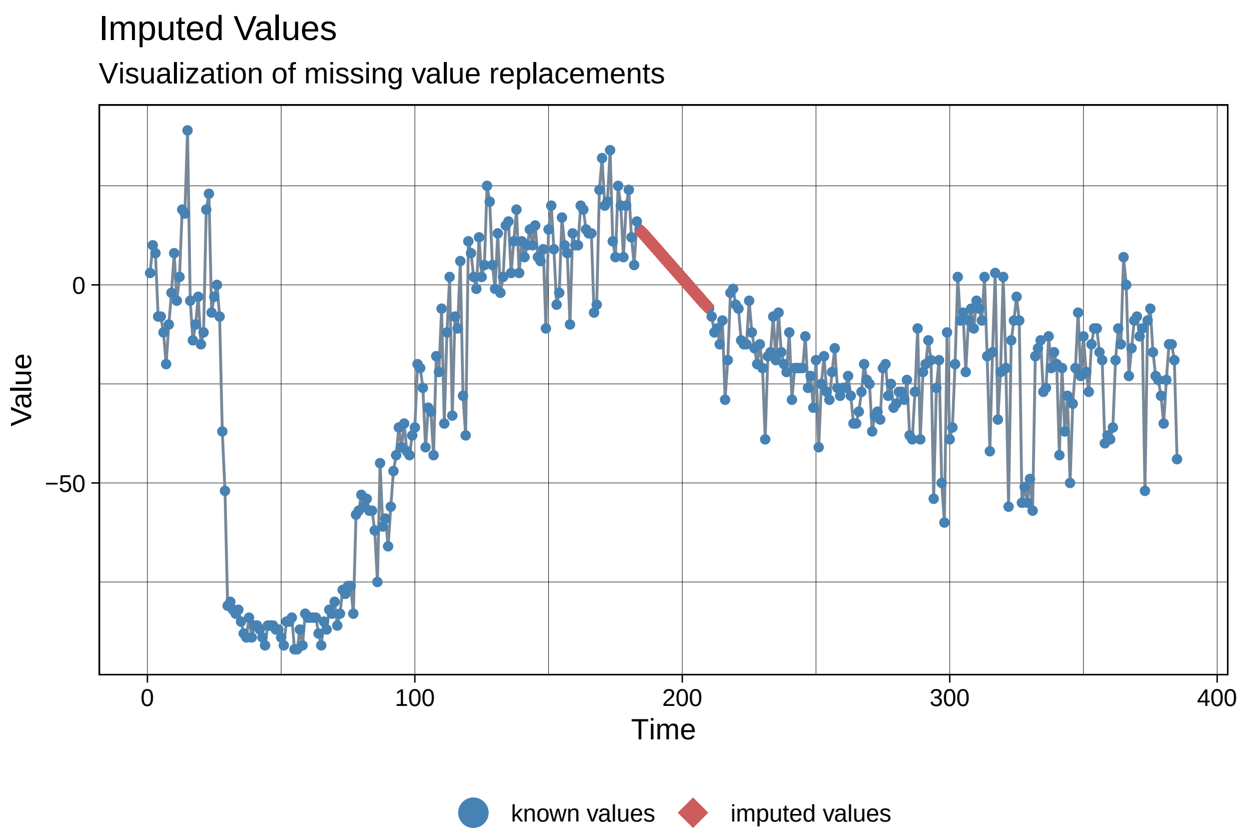

```
##
##  Variables sorted by number of missings:
##               Variable       Count
##                  Ceuta 0.064935065
##                Melilla 0.064935065
##               Palencia 0.064935065
##                  Soria 0.064935065
##                 Cuenca 0.062337662
##                  Ávila 0.059740260
##                 Teruel 0.057142857
##                 Huesca 0.054545455
##                 Zamora 0.051948052
##              Cantabria 0.046753247
##                 Lleida 0.044155844
##              Rioja, La 0.044155844
##                 Burgos 0.033766234
##            Guadalajara 0.031168831
##                   León 0.031168831
##                Segovia 0.018181818
##              Albacete 0.012987013
##                Navarra 0.010389610
##                Ourense 0.005194805
##               Asturias 0.002597403
##                   date 0.000000000
##       Alicante/Alacant 0.000000000
##                Almería 0.000000000
```

```
##              Araba/Álava 0.000000000
##                  Badajoz 0.000000000
##           Balears, Illes 0.000000000
##                Barcelona 0.000000000
##                  Bizkaia 0.000000000
##                  Cáceres 0.000000000
##                    Cádiz 0.000000000
##       Castellón/Castelló 0.000000000
##              Ciudad Real 0.000000000
##                  Córdoba 0.000000000
##                Coruña, A 0.000000000
##                 Gipuzkoa 0.000000000
##                   Girona 0.000000000
##                  Granada 0.000000000
##                   Huelva 0.000000000
##                     Jaén 0.000000000
##                     Lugo 0.000000000
##                   Madrid 0.000000000
##                   Málaga 0.000000000
##                   Murcia 0.000000000
##              Palmas, Las 0.000000000
##               Pontevedra 0.000000000
##                Salamanca 0.000000000
##   Santa Cruz de Tenerife 0.000000000
##                  Sevilla 0.000000000
##                Tarragona 0.000000000
##                   Toledo 0.000000000
##        Valencia/València 0.000000000
##               Valladolid 0.000000000
##                 Zaragoza 0.000000000
```

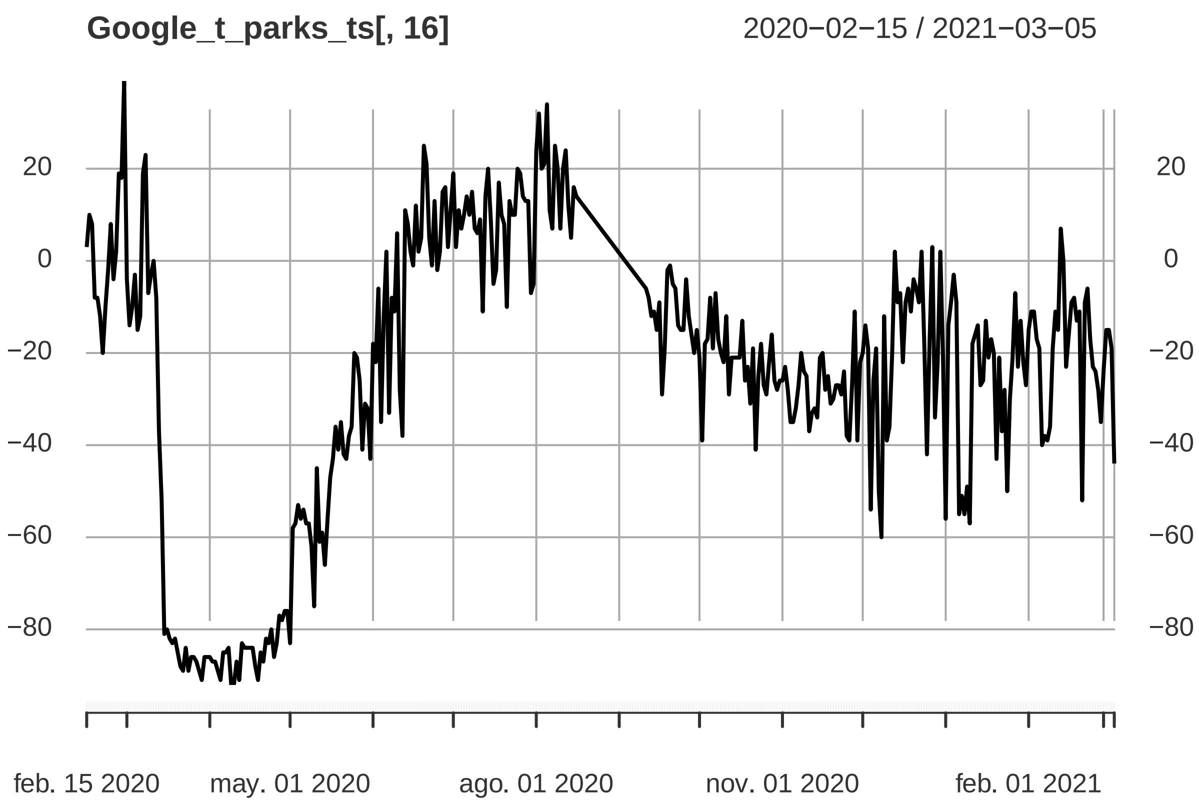
```
Google_t_parks %>%
    gather(key = "key", value = "val") %>%
    mutate(is.missing = is.na(val)) %>%
    group_by(key, is.missing) %>%
    summarise(num.missing = n()) %>%
    filter(is.missing==T) %>%
    select(-is.missing) %>%
    arrange(desc(num.missing)) %>%
    ggplot() +
    geom_bar(aes(x=key, y=num.missing), stat = 'identity',fill="#F0E442") +
    labs(x='variable', y="number of missing values",
         title='Number of missing values') +
    theme(axis.text.x = element_text(angle = 45, hjust = 1))
```



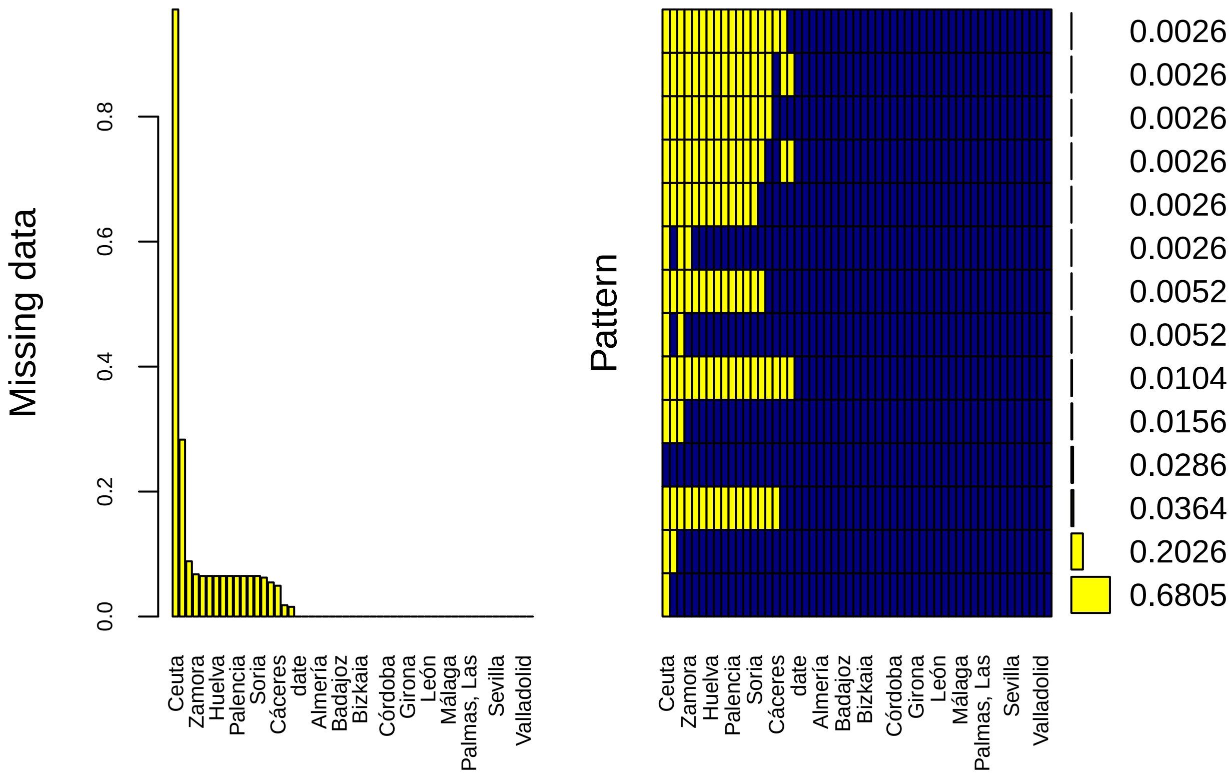

```
# Convert dataframe to ts object
Google_t_parks_ts<-xts(Google_t_parks[-1],Google_t_parks$date)

# Impute the missing values with na_seadec (i.e Ceuta)
imp7 <- na_seadec(Google_t_parks_ts[,16])
ggplot_na_imputations(Google_t_parks_ts[,16], imp7)
```




```r
# We select na_seadec for the dataset
Google_t_parks_ts <- na_seadec(Google_t_parks_ts)
plot(Google_t_parks_ts[,16])
```



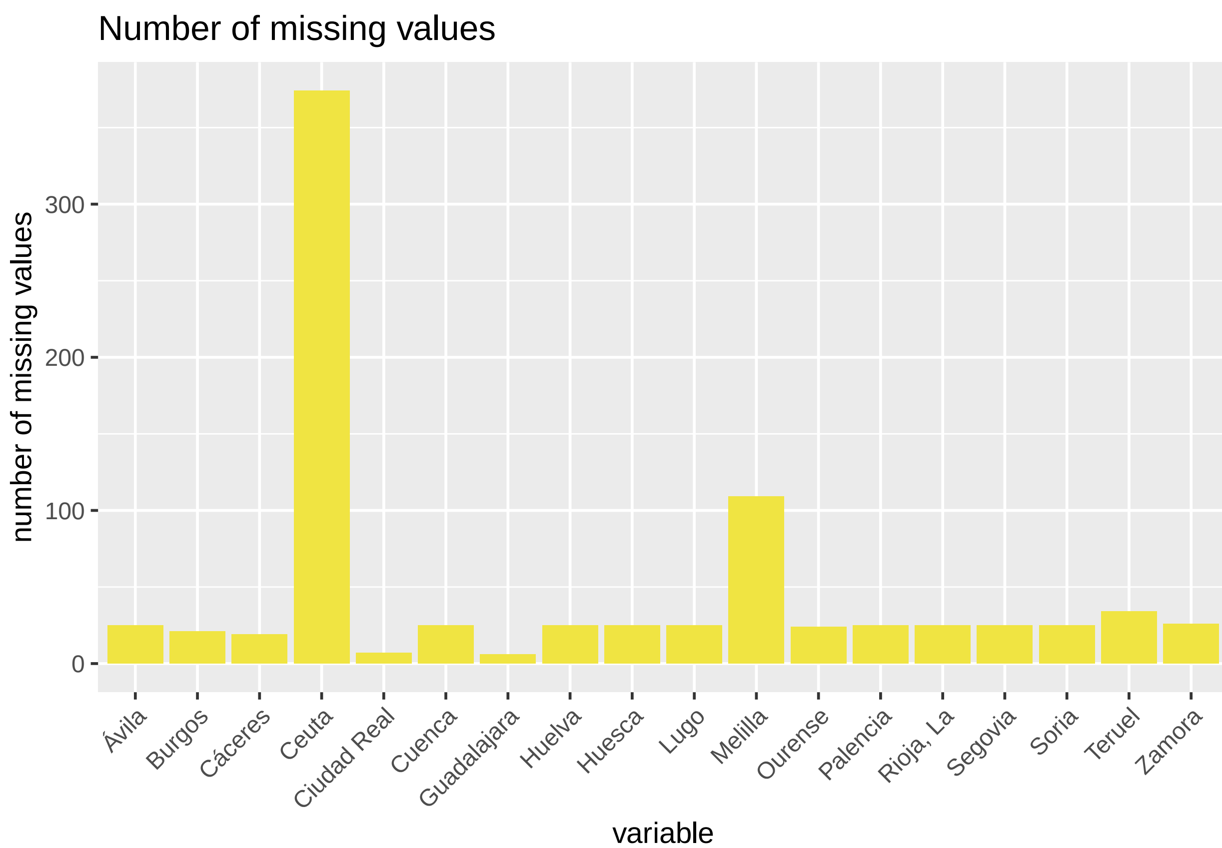

```r
# We convert the time series object to a dataframe
Google_parks <- ts_df(Google_t_parks_ts)

names(Google_parks)[names(Google_parks) == "id"] <- "sub_region_2"
names(Google_parks)[names(Google_parks) == "time"] <- "Date"
names(Google_parks)[names(Google_parks) == "value"] <- "parks_percent_change_from_baseline"

###################################################################
# Transpose dataframe
Google_transit<-Google[c(2,4,8)]
Google_t_transit<-dcast(Google_transit, date~sub_region_2, fill=NA)

# Visualize missing values
aggr(Google_t_transit, col=c('navyblue','yellow'),
     numbers=TRUE, sortVars=TRUE,
     labels=names(Google_t_transit), cex.axis=.7,
     gap=3, ylab=c("Missing data","Pattern"))
```



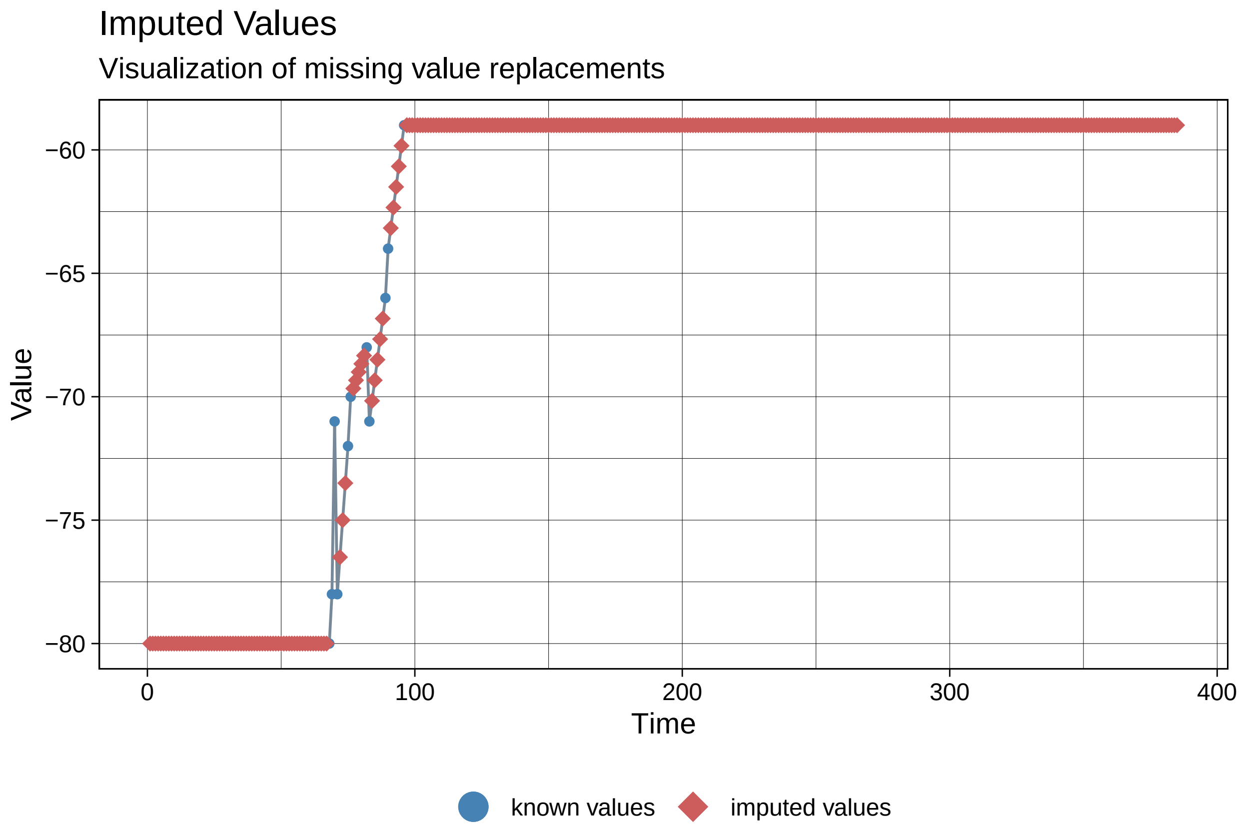

```
##
##  Variables sorted by number of missings:
##              Variable      Count
##                 Ceuta 0.97142857
##               Melilla 0.28311688
##                Teruel 0.08831169
##                Zamora 0.06753247
##                 Ávila 0.06493506
##                Cuenca 0.06493506
##                Huelva 0.06493506
##                Huesca 0.06493506
##                  Lugo 0.06493506
##              Palencia 0.06493506
##             Rioja, La 0.06493506
##               Segovia 0.06493506
##                 Soria 0.06493506
##               Ourense 0.06233766
##                Burgos 0.05454545
##               Cáceres 0.04935065
##           Ciudad Real 0.01818182
##           Guadalajara 0.01558442
##                  date 0.00000000
##              Albacete 0.00000000
##      Alicante/Alacant 0.00000000
##               Almería 0.00000000
##           Araba/Álava 0.00000000
```

```
##                 Asturias 0.00000000
##                  Badajoz 0.00000000
##           Balears, Illes 0.00000000
##                Barcelona 0.00000000
##                  Bizkaia 0.00000000
##                    Cádiz 0.00000000
##                Cantabria 0.00000000
##       Castellón/Castelló 0.00000000
##                  Córdoba 0.00000000
##                Coruña, A 0.00000000
##                 Gipuzkoa 0.00000000
##                   Girona 0.00000000
##                  Granada 0.00000000
##                     Jaén 0.00000000
##                     León 0.00000000
##                   Lleida 0.00000000
##                   Madrid 0.00000000
##                   Málaga 0.00000000
##                   Murcia 0.00000000
##                  Navarra 0.00000000
##               Palmas, Las 0.00000000
##               Pontevedra 0.00000000
##                Salamanca 0.00000000
##   Santa Cruz de Tenerife 0.00000000
##                  Sevilla 0.00000000
##                Tarragona 0.00000000
##                   Toledo 0.00000000
##        Valencia/València 0.00000000
##               Valladolid 0.00000000
##                 Zaragoza 0.00000000
```

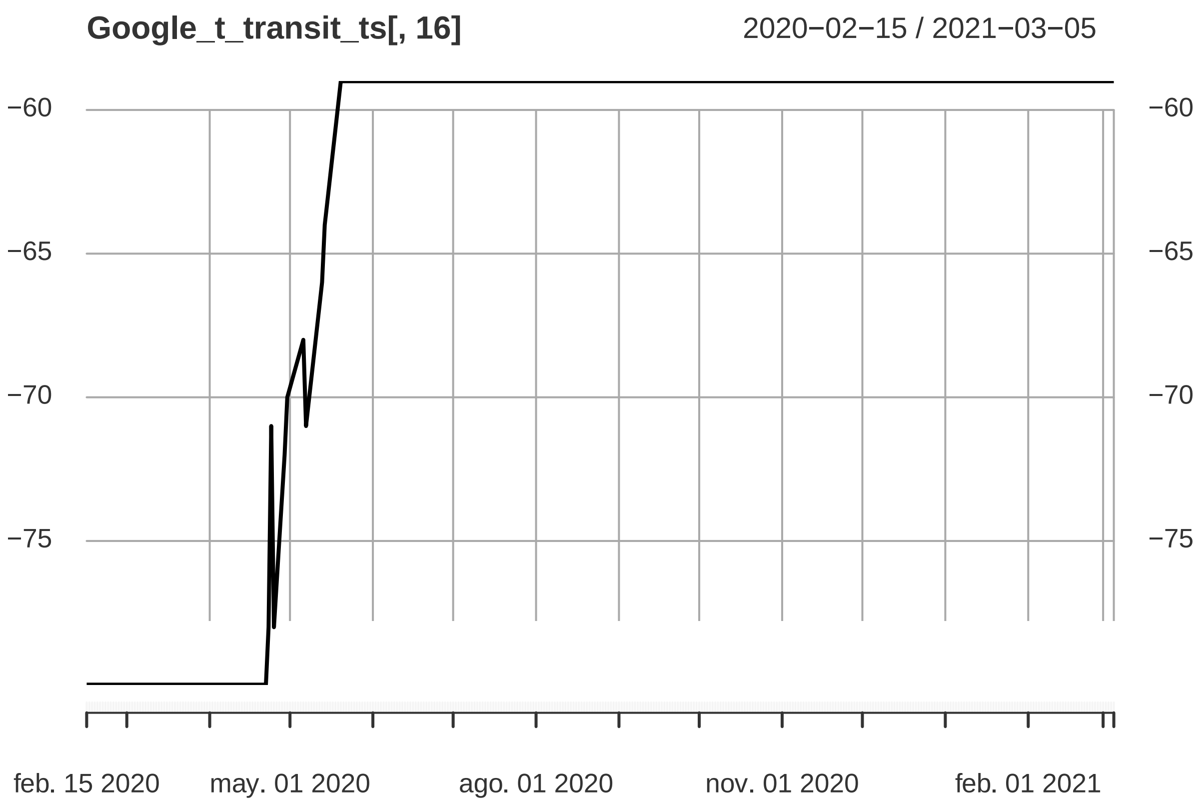
```r
Google_t_transit %>%
    gather(key = "key", value = "val") %>%
    mutate(is.missing = is.na(val)) %>%
    group_by(key, is.missing) %>%
    summarise(num.missing = n()) %>%
    filter(is.missing==T) %>%
    select(-is.missing) %>%
    arrange(desc(num.missing)) %>%
    ggplot() +
    geom_bar(aes(x=key, y=num.missing), stat = 'identity',fill="#F0E442") +
    labs(x='variable', y="number of missing values",
         title='Number of missing values') +
    theme(axis.text.x = element_text(angle = 45, hjust = 1))
```



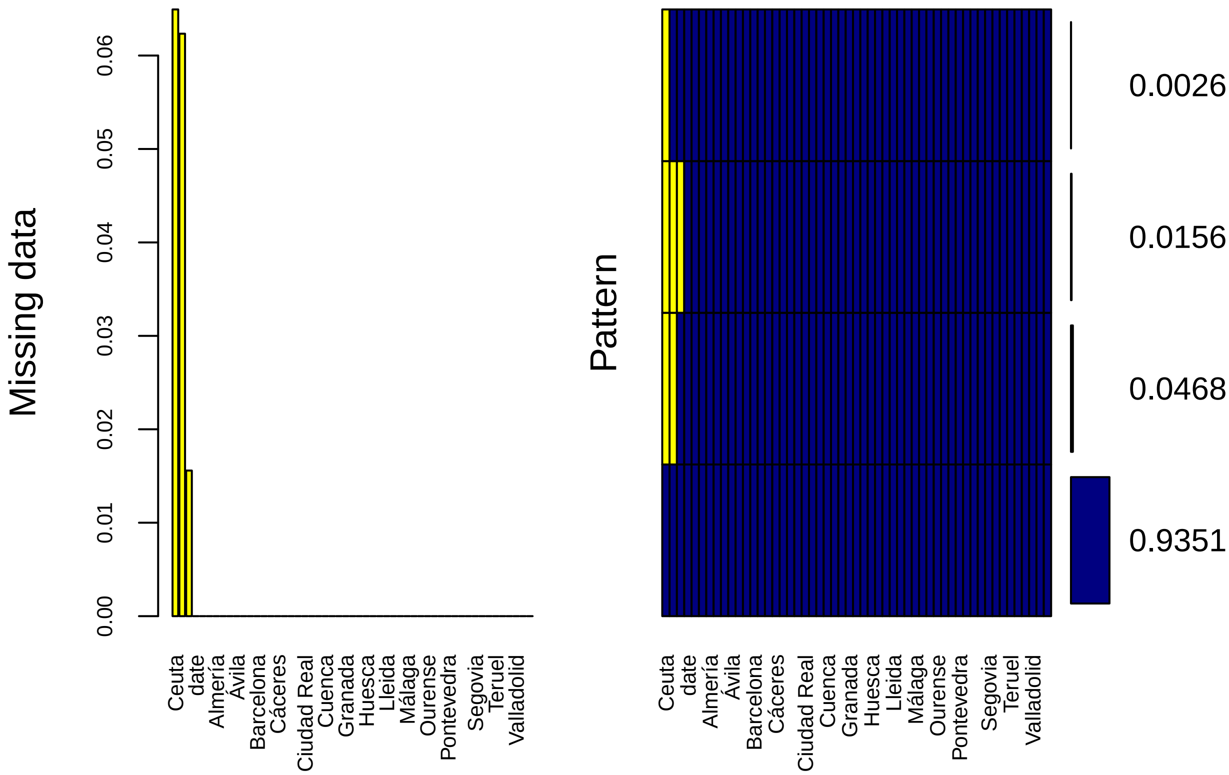

```r
# Convert dataframe to ts object
Google_t_transit_ts<-xts(Google_t_transit[-1],Google_t_transit$date)

# Impute the missing values with na_seadec (i.e Ceuta)
imp8 <- na_seadec(Google_t_transit_ts[,16])
ggplot_na_imputations(Google_t_transit_ts[,16], imp8)
```




```r
# We select na_seadec for the dataset
Google_t_transit_ts <- na_seadec(Google_t_transit_ts)
plot(Google_t_transit_ts[,16])
```



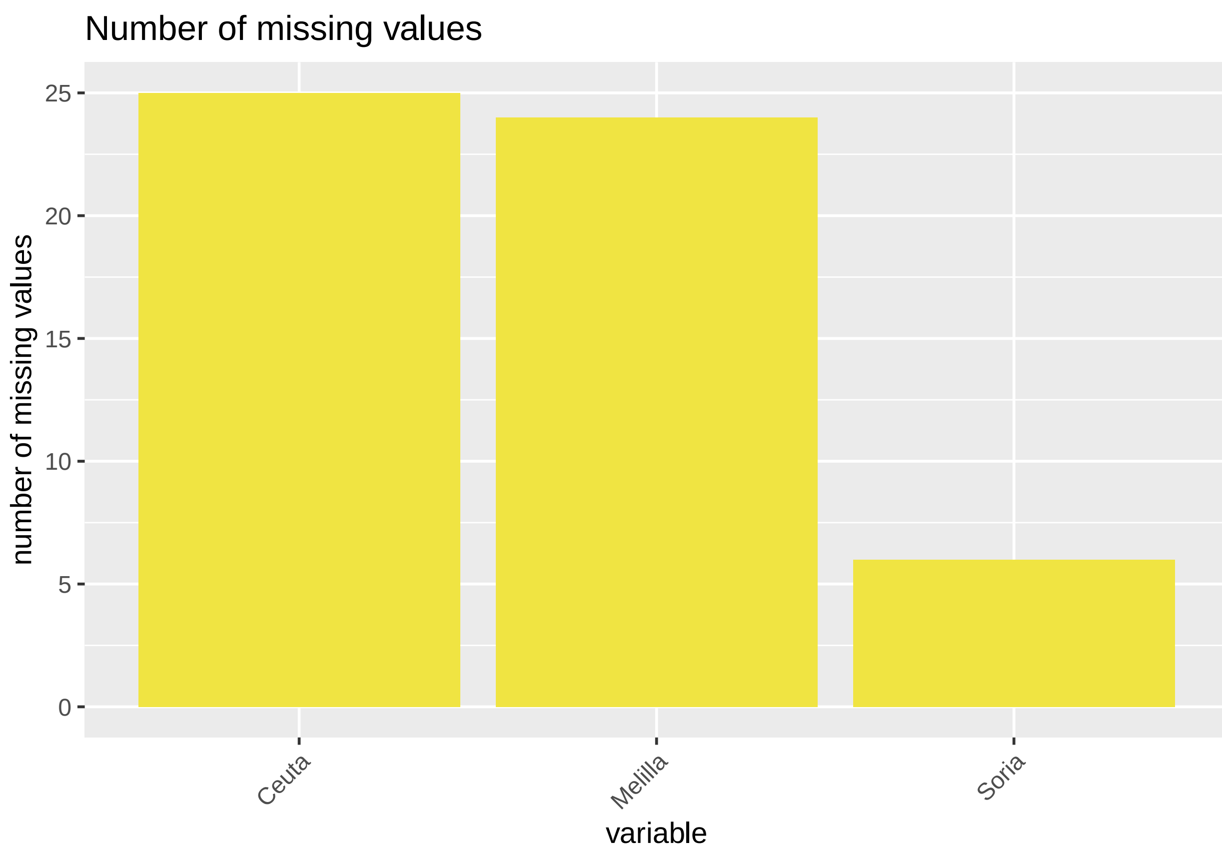

```
# We convert the time series object to a dataframe
Google_transit <- ts_df(Google_t_transit_ts)

names(Google_transit)[names(Google_transit) == "id"] <- "sub_region_2"
names(Google_transit)[names(Google_transit) == "time"] <- "Date"
names(Google_transit)[names(Google_transit) == "value"] <- "transit_stations_percent_change_from_baseli

##################################################################
# Transpose dataframe
Google_workplaces<-Google[c(2,4,9)]
Google_t_workplaces<-dcast(Google_workplaces, date~sub_region_2, fill=NA)

# Visualize missing values
aggr(Google_t_workplaces, col=c('navyblue','yellow'),
     numbers=TRUE, sortVars=TRUE,
     labels=names(Google_t_workplaces), cex.axis=.7,
     gap=3, ylab=c("Missing data","Pattern"))
```



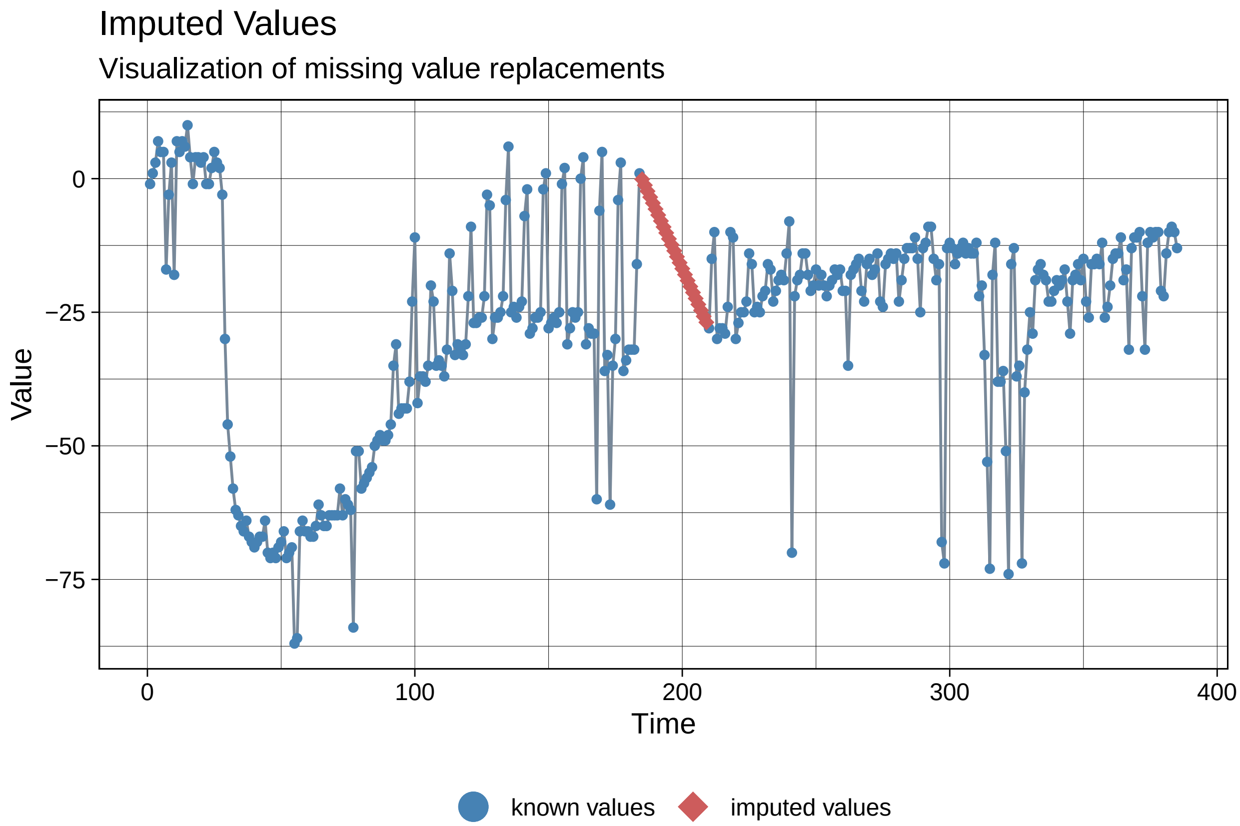

```
##
## Variables sorted by number of missings:
##             Variable      Count
##                Ceuta 0.06493506
##              Melilla 0.06233766
##                Soria 0.01558442
##                 date 0.00000000
##            Albacete 0.00000000
##    Alicante/Alacant 0.00000000
##             Almería 0.00000000
##         Araba/Álava 0.00000000
##            Asturias 0.00000000
##               Ávila 0.00000000
##             Badajoz 0.00000000
##      Balears, Illes 0.00000000
##           Barcelona 0.00000000
##             Bizkaia 0.00000000
##              Burgos 0.00000000
##             Cáceres 0.00000000
##               Cádiz 0.00000000
##           Cantabria 0.00000000
##  Castellón/Castelló 0.00000000
##         Ciudad Real 0.00000000
##             Córdoba 0.00000000
##           Coruña, A 0.00000000
##              Cuenca 0.00000000
```

```
##                Gipuzkoa 0.00000000
##                  Girona 0.00000000
##                 Granada 0.00000000
##             Guadalajara 0.00000000
##                  Huelva 0.00000000
##                  Huesca 0.00000000
##                    Jaén 0.00000000
##                    León 0.00000000
##                  Lleida 0.00000000
##                    Lugo 0.00000000
##                  Madrid 0.00000000
##                  Málaga 0.00000000
##                  Murcia 0.00000000
##                 Navarra 0.00000000
##                 Ourense 0.00000000
##                Palencia 0.00000000
##             Palmas, Las 0.00000000
##              Pontevedra 0.00000000
##               Rioja, La 0.00000000
##               Salamanca 0.00000000
##  Santa Cruz de Tenerife 0.00000000
##                 Segovia 0.00000000
##                 Sevilla 0.00000000
##               Tarragona 0.00000000
##                  Teruel 0.00000000
##                  Toledo 0.00000000
##       Valencia/València 0.00000000
##              Valladolid 0.00000000
##                  Zamora 0.00000000
##                Zaragoza 0.00000000
```

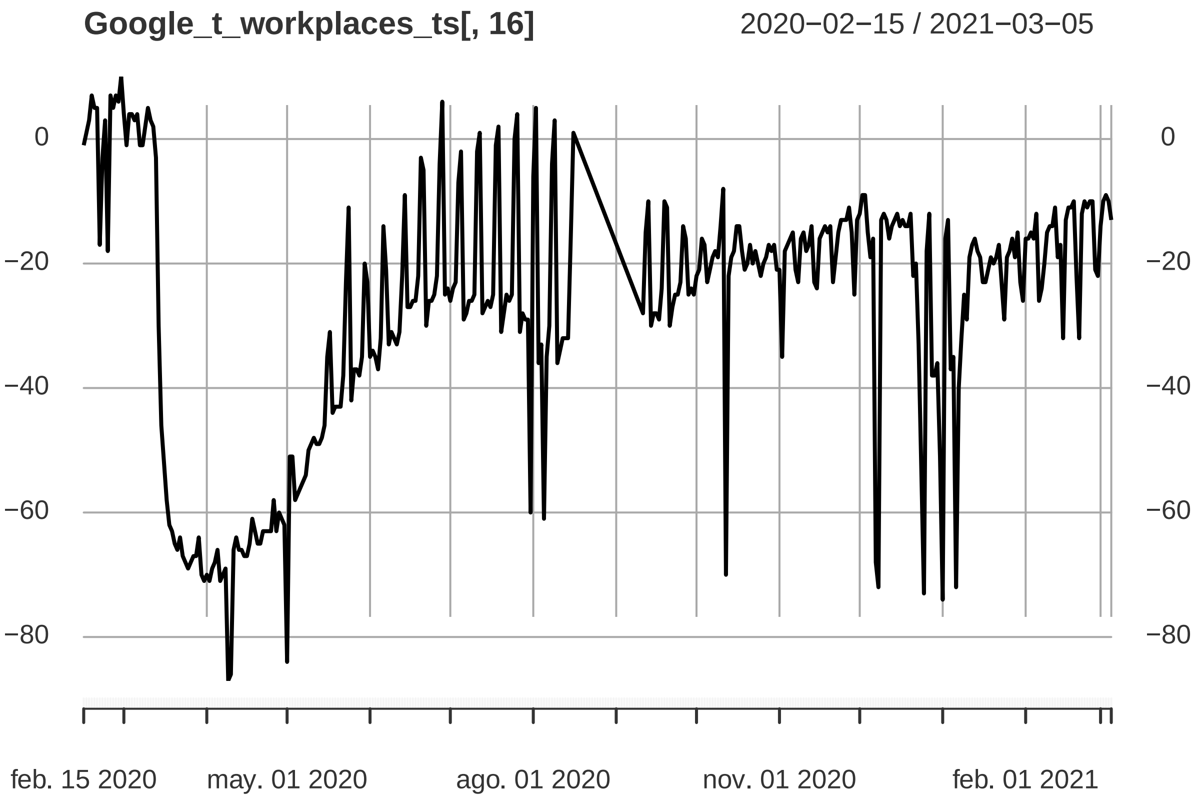
```
Google_t_workplaces %>%
    gather(key = "key", value = "val") %>%
    mutate(is.missing = is.na(val)) %>%
    group_by(key, is.missing) %>%
    summarise(num.missing = n()) %>%
    filter(is.missing==T) %>%
    select(-is.missing) %>%
    arrange(desc(num.missing)) %>%
    ggplot() +
    geom_bar(aes(x=key, y=num.missing), stat = 'identity',fill="#F0E442") +
    labs(x='variable', y="number of missing values",
         title='Number of missing values') +
    theme(axis.text.x = element_text(angle = 45, hjust = 1))
```



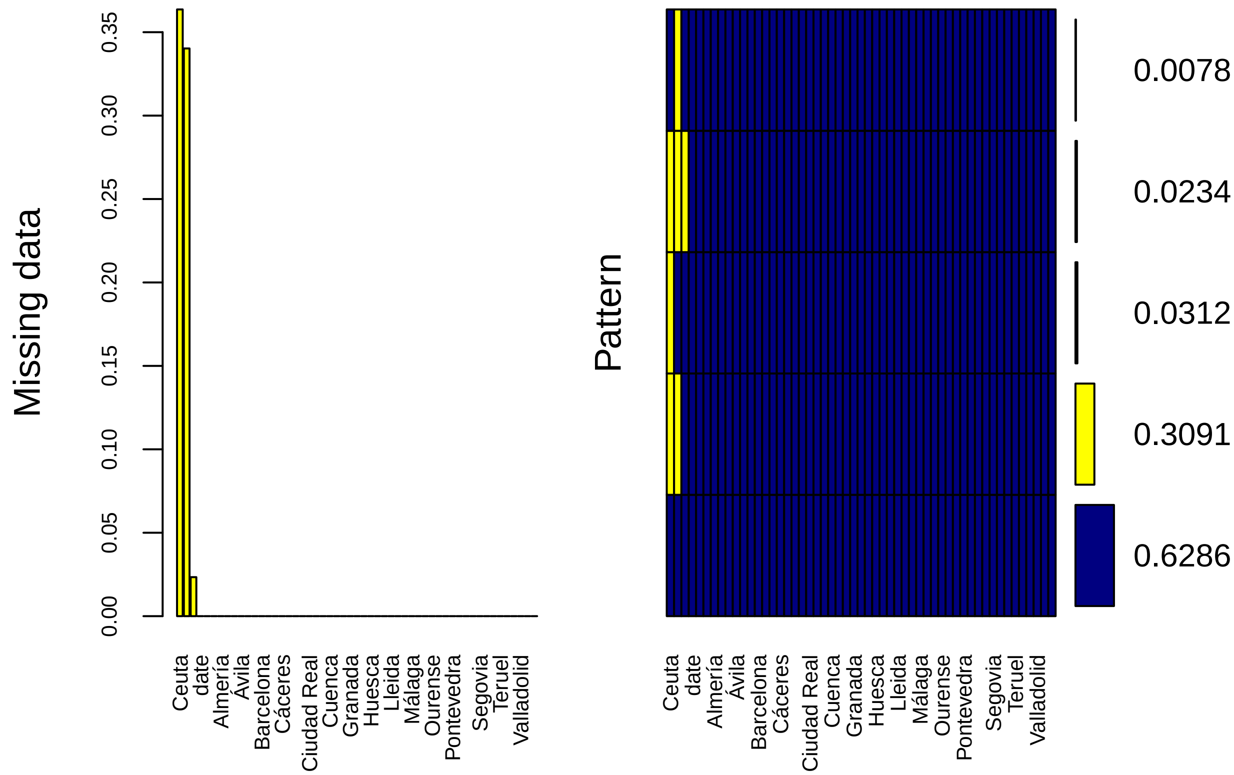

```
# Convert dataframe to ts object
Google_t_workplaces_ts<-xts(Google_t_workplaces[-1],Google_t_workplaces$date)

# Impute the missing values with na_seadec (i.e Ceuta)
imp9 <- na_seadec(Google_t_workplaces_ts[,16])
ggplot_na_imputations(Google_t_workplaces_ts[,16], imp9)
```




```
# We select na_seadec for the dataset
Google_t_workplaces_ts <- na_seadec(Google_t_workplaces_ts)
plot(Google_t_workplaces_ts[,16])
```




```
# We convert the time series object to a dataframe
Google_workplaces <- ts_df(Google_t_workplaces_ts)

names(Google_workplaces)[names(Google_workplaces) == "id"] <- "sub_region_2"
names(Google_workplaces)[names(Google_workplaces) == "time"] <- "Date"
names(Google_workplaces)[names(Google_workplaces) == "value"] <- "workplaces_percent_change_from_baseli

###################################################################
# Transpose dataframe
Google_residential<-Google[c(2,4,10)]
Google_t_residential<-dcast(Google_residential, date~sub_region_2, fill=NA)

# Visualize missing values
aggr(Google_t_residential, col=c('navyblue','yellow'),
     numbers=TRUE, sortVars=TRUE,
     labels=names(Google_t_residential), cex.axis=.7,
     gap=3, ylab=c("Missing data","Pattern"))
```

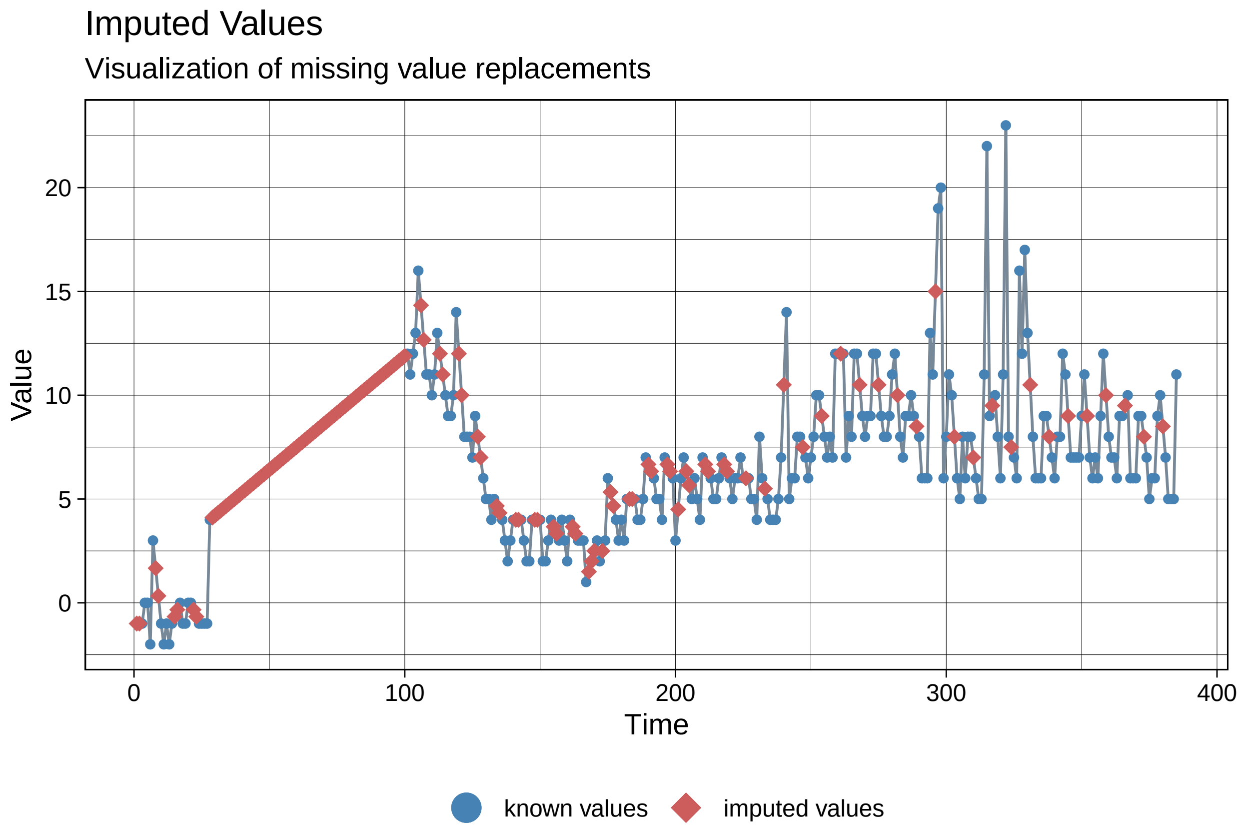



```
##
##  Variables sorted by number of missings:
##               Variable      Count
##                  Ceuta 0.36363636
##                Melilla 0.34025974
##                  Soria 0.02337662
##                   date 0.00000000
##              Albacete 0.00000000
##      Alicante/Alacant 0.00000000
##               Almería 0.00000000
##           Araba/Álava 0.00000000
##              Asturias 0.00000000
##                 Ávila 0.00000000
##               Badajoz 0.00000000
##         Balears, Illes 0.00000000
##             Barcelona 0.00000000
##               Bizkaia 0.00000000
##                Burgos 0.00000000
##               Cáceres 0.00000000
##                 Cádiz 0.00000000
##             Cantabria 0.00000000
##   Castellón/Castelló 0.00000000
##           Ciudad Real 0.00000000
##               Córdoba 0.00000000
##             Coruña, A 0.00000000
##                Cuenca 0.00000000
```

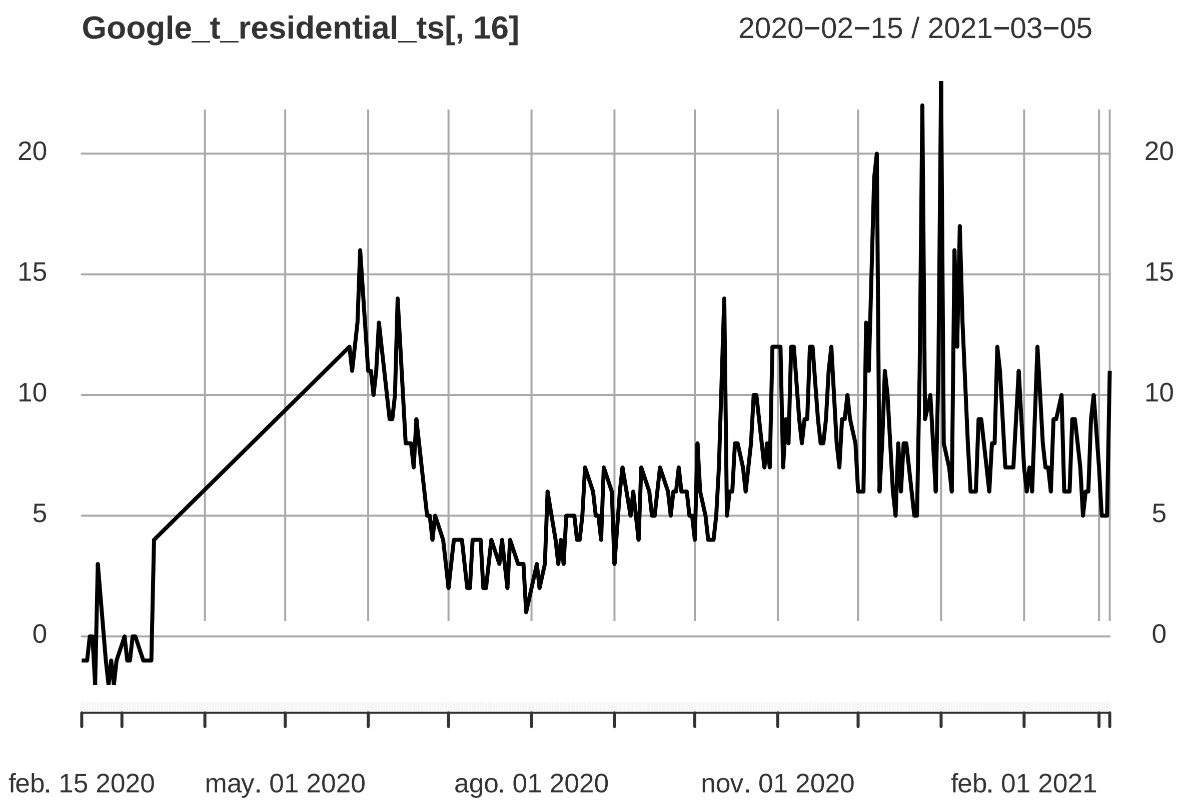
```
##                Gipuzkoa 0.00000000
##                  Girona 0.00000000
##                 Granada 0.00000000
##             Guadalajara 0.00000000
##                  Huelva 0.00000000
##                  Huesca 0.00000000
##                    Jaén 0.00000000
##                    León 0.00000000
##                  Lleida 0.00000000
##                    Lugo 0.00000000
##                  Madrid 0.00000000
##                  Málaga 0.00000000
##                  Murcia 0.00000000
##                 Navarra 0.00000000
##                 Ourense 0.00000000
##                Palencia 0.00000000
##             Palmas, Las 0.00000000
##              Pontevedra 0.00000000
##               Rioja, La 0.00000000
##               Salamanca 0.00000000
##  Santa Cruz de Tenerife 0.00000000
##                 Segovia 0.00000000
##                 Sevilla 0.00000000
##               Tarragona 0.00000000
##                  Teruel 0.00000000
##                  Toledo 0.00000000
##       Valencia/València 0.00000000
##              Valladolid 0.00000000
##                  Zamora 0.00000000
##                Zaragoza 0.00000000
```

```
Google_t_residential %>%
    gather(key = "key", value = "val") %>%
    mutate(is.missing = is.na(val)) %>%
    group_by(key, is.missing) %>%
    summarise(num.missing = n()) %>%
    filter(is.missing==T) %>%
    select(-is.missing) %>%
    arrange(desc(num.missing)) %>%
    ggplot() +
    geom_bar(aes(x=key, y=num.missing), stat = 'identity',fill="#F0E442") +
    labs(x='variable', y="number of missing values",
         title='Number of missing values') +
    theme(axis.text.x = element_text(angle = 45, hjust = 1))
```


```
# Convert dataframe to ts object
Google_t_residential_ts<-xts(Google_t_residential[-1],Google_t_residential$date)

# Impute the missing values with na_seadec (i.e Ceuta)
imp10 <- na_seadec(Google_t_residential_ts[,16])
ggplot_na_imputations(Google_t_residential_ts[,16], imp10)
```




```
# We select na_seadec for the dataset
Google_t_residential_ts <- na_seadec(Google_t_residential_ts)
plot(Google_t_residential_ts[,16])
```




```r
# We convert the time series object to a dataframe
Google_residential <- ts_df(Google_t_residential_ts)

names(Google_residential)[names(Google_residential) == "id"] <- "sub_region_2"
names(Google_residential)[names(Google_residential) == "time"] <- "Date"
names(Google_residential)[names(Google_residential) == "value"] <- "residential_percent_change_from_base
```

Now we merge the previous dataframes into new one with the imputed vaules and we add the ISO code for the province.

```r
# New dataframe Google_b
Google_b <- merge(Google_retail, Google_grocery) %>%
              merge(Google_parks) %>%
              merge(Google_transit) %>%
              merge(Google_workplaces) %>%
              merge(Google_residential)

Google_b$iso_code <- NA
Google_b$iso_code<-Google[match(Google_b$sub_region_2, Google$sub_region_2),3]
rm("Google")
Google<-Google_b
rm("Google_b")
head(Google,5)
```

```
##   sub_region_2       Date retail_and_recreation_percent_change_from_baseline
## 1     Albacete 2020-02-15                                                  3
## 2     Albacete 2020-02-16                                                  5
```

```
## 3     Albacete 2020-02-17                                                -2
## 4     Albacete 2020-02-18                                                -3
## 5     Albacete 2020-02-19                                                 0
##   grocery_and_pharmacy_percent_change_from_baseline
## 1                                                -5
## 2                                                 1
## 3                                                 3
## 4                                                -1
## 5                                                 1
##   parks_percent_change_from_baseline
## 1                                 35
## 2                                 40
## 3                                  7
## 4                                 -4
## 5                                  7
##   transit_stations_percent_change_from_baseline
## 1                                            13
## 2                                            18
## 3                                            20
## 4                                             6
## 5                                             9
##   workplaces_percent_change_from_baseline
## 1                                       1
## 2                                       0
## 3                                       5
## 4                                       4
## 5                                       4
##   residential_percent_change_from_baseline iso_code
## 1                                       -3       AB
## 2                                       -4       AB
## 3                                       -1       AB
## 4                                       -1       AB
## 5                                       -1       AB
```

```
table(Google$sub_region_2)
```

```
##
##              Albacete       Alicante/Alacant                Almería
##                   385                    385                    385
##           Araba/Álava               Asturias                  Ávila
##                   385                    385                    385
##               Badajoz         Balears, Illes              Barcelona
##                   385                    385                    385
##               Bizkaia                 Burgos                Cáceres
##                   385                    385                    385
##                 Cádiz              Cantabria    Castellón/Castelló
##                   385                    385                    385
##                 Ceuta            Ciudad Real                Córdoba
##                   385                    385                    385
##             Coruña, A                 Cuenca               Gipuzkoa
##                   385                    385                    385
##                Girona                Granada            Guadalajara
##                   385                    385                    385
##                Huelva                 Huesca                   Jaén
##                   385                    385                    385
```

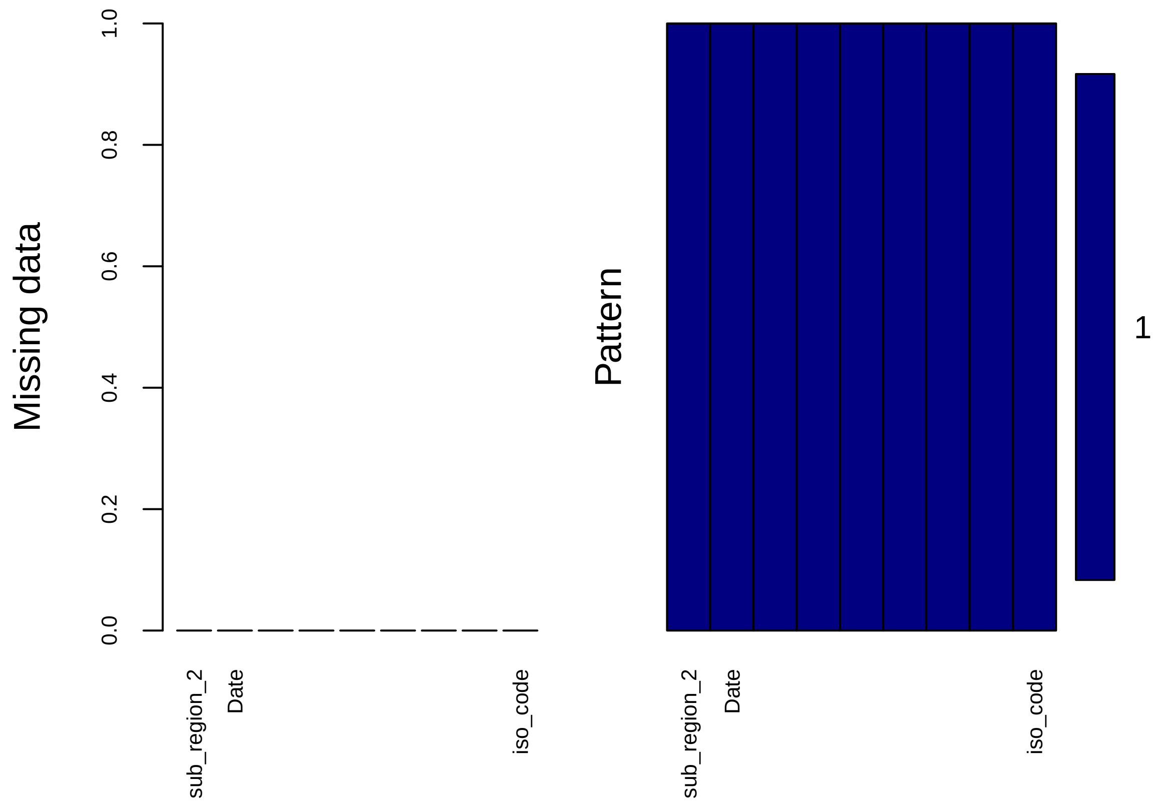
```
##                   León                 Lleida                   Lugo
##                    385                    385                    385
##                 Madrid                 Málaga                Melilla
##                    385                    385                    385
##                 Murcia                Navarra                Ourense
##                    385                    385                    385
##               Palencia            Palmas, Las             Pontevedra
##                    385                    385                    385
##              Rioja, La              Salamanca Santa Cruz de Tenerife
##                    385                    385                    385
##                Segovia                Sevilla                  Soria
##                    385                    385                    385
##              Tarragona                 Teruel                 Toledo
##                    385                    385                    385
##      Valencia/València             Valladolid                 Zamora
##                    385                    385                    385
##               Zaragoza
##                    385
```

```r
table(Google$iso_code)
```

```
##
##   A  AB  AL  AV   B  BA  BI  BU   C  CA  CC  CE  CO  CR  CS  CU  GC  GI  GR  GU
## 385 385 385 385 385 385 385 385 385 385 385 385 385 385 385 385 385 385 385 385
##   H  HU   J   L  LE  LO  LU   M  MA  ML  MU  NA   O  OR   P  PM  PO   S  SA  SE
## 385 385 385 385 385 385 385 385 385 385 385 385 385 385 385 385 385 385 385 385
##  SG  SO  SS   T  TE  TF  TO   V  VA  VI   Z  ZA
## 385 385 385 385 385 385 385 385 385 385 385 385
```

We check missing values. We should obtain zero missing values.

```r
aggr(Google, col=c('navyblue','yellow'),
     numbers=TRUE, sortVars=TRUE,
     labels=names(Google), cex.axis=.7,
     gap=3, ylab=c("Missing data","Pattern"))
```




```
##
##  Variables sorted by number of missings:
##                                            Variable Count
##                                        sub_region_2     0
##                                                Date     0
##  retail_and_recreation_percent_change_from_baseline     0
##   grocery_and_pharmacy_percent_change_from_baseline     0
##                  parks_percent_change_from_baseline     0
##       transit_stations_percent_change_from_baseline     0
##             workplaces_percent_change_from_baseline     0
##            residential_percent_change_from_baseline     0
##                                            iso_code     0
```

```
Google %>%
    gather(key = "key", value = "val") %>%
    mutate(is.missing = is.na(val)) %>%
    group_by(key, is.missing) %>%
    summarise(num.missing = n()) %>%
    filter(is.missing==T) %>%
    select(-is.missing) %>%
    arrange(desc(num.missing)) %>%
    ggplot() +
    geom_bar(aes(x=key, y=num.missing), stat = 'identity',fill="#F0E442") +
    labs(x='variable', y="number of missing values",
         title='Number of missing values') +
    theme(axis.text.x = element_text(angle = 45, hjust = 1))
```

2.1.9 CNE review

The CSV files are provided per “imputed date” (fecha)”:

- **cases_technic_province.csv** - Number of cases by diagnostic technique and province (of residence)
- **cases_hosp_uci_def_sexo_edad_provres.csv** - Number of hospitalizations, number of ICU admissions and number of deaths by sex, age and province of residence.

```r
head(str(CNE_tecnica, vec.len=3))
```

```
## 'data.frame':    23426 obs. of  8 variables:
##  $ provincia_iso               : chr  "A" "AB" "AL" ...
##  $ fecha                       : chr  "2020-01-01" "2020-01-01" "2020-01-01" ...
##  $ num_casos                   : int  0 0 0 0 0 0 0 0 ...
##  $ num_casos_prueba_pcr        : int  0 0 0 0 0 0 0 0 ...
##  $ num_casos_prueba_test_ac    : int  0 0 0 0 0 0 0 0 ...
##  $ num_casos_prueba_ag         : int  0 0 0 0 0 0 0 0 ...
##  $ num_casos_prueba_elisa      : int  0 0 0 0 0 0 0 0 ...
##  $ num_casos_prueba_desconocida: int  0 0 0 0 0 0 0 0 ...
```

```
## NULL
```

```r
summary(CNE_tecnica)
```

```
##  provincia_iso         fecha             num_casos      num_casos_prueba_pcr
##  Length:23426       Length:23426       Min.   :   0.0   Min.   :   0.0
##  Class :character   Class :character   1st Qu.:   2.0   1st Qu.:   2.0
##  Mode  :character   Mode  :character   Median :  32.0   Median :  26.0
```

```
##                                         Mean   : 136.9   Mean   : 109.6
##                                         3rd Qu.: 120.0   3rd Qu.: 100.0
##                                         Max.   :6972.0   Max.   :6546.0
##  num_casos_prueba_test_ac num_casos_prueba_ag num_casos_prueba_elisa
##  Min.   : 0.0000          Min.   :   0.00     Min.   : 0.0000
##  1st Qu.: 0.0000          1st Qu.:   0.00     1st Qu.: 0.0000
##  Median : 0.0000          Median :   0.00     Median : 0.0000
##  Mean   : 0.2037          Mean   :  26.21     Mean   : 0.1602
##  3rd Qu.: 0.0000          3rd Qu.:   9.00     3rd Qu.: 0.0000
##  Max.   :32.0000          Max.   :3267.00     Max.   :71.0000
##  num_casos_prueba_desconocida
##  Min.   :  0.0000
##  1st Qu.:  0.0000
##  Median :  0.0000
##  Mean   :  0.7122
##  3rd Qu.:  0.0000
##  Max.   :505.0000
```

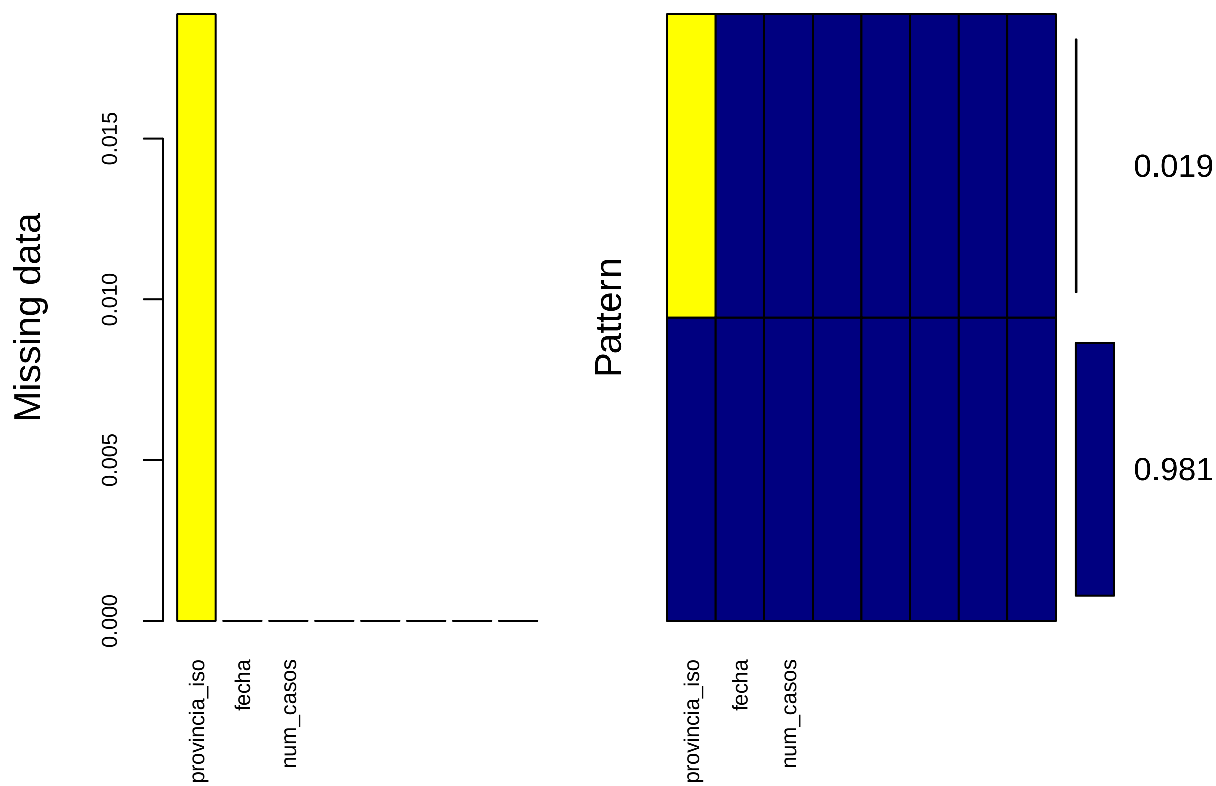
```
table(CNE_tecnica$provincia_iso)
```

```
##
##   A  AB  AL  AV   B  BA  BI  BU   C  CA  CC  CE  CO  CR  CS  CU  GC  GI  GR  GU
## 442 442 442 442 442 442 442 442 442 442 442 442 442 442 442 442 442 442 442 442
##   H  HU   J   L  LE  LO  LU   M  MA  ML  MU  NC   O  OR   P  PM  PO   S  SA  SE
## 442 442 442 442 442 442 442 442 442 442 442 442 442 442 442 442 442 442 442 442
##  SG  SO  SS   T  TE  TF  TO   V  VA  VI   Z  ZA
## 442 442 442 442 442 442 442 442 442 442 442 442
```

2.1.10 CNE review missing values & impute

We check missing values for CNE_tecnica. In this case we omit the NA values.

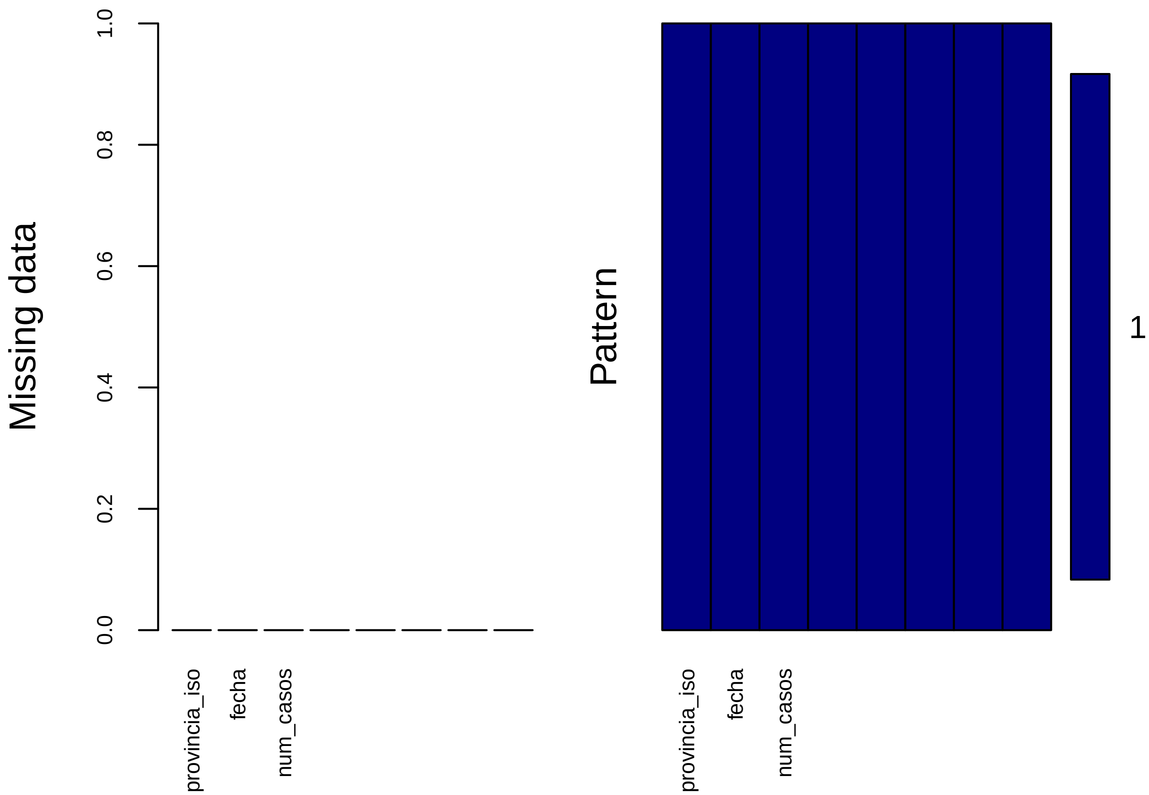
```
aggr(CNE_tecnica, col=c('navyblue','yellow'),
     numbers=TRUE, sortVars=TRUE,
     labels=names(CNE_tecnica), cex.axis=.7,
     gap=3, ylab=c("Missing data","Pattern"))
```




```
##
##  Variables sorted by number of missings:
##                     Variable      Count
##                provincia_iso 0.01886792
##                        fecha 0.00000000
##                    num_casos 0.00000000
##         num_casos_prueba_pcr 0.00000000
##     num_casos_prueba_test_ac 0.00000000
##          num_casos_prueba_ag 0.00000000
##       num_casos_prueba_elisa 0.00000000
##  num_casos_prueba_desconocida 0.00000000
```

```
CNE_tecnica %>%
    gather(key = "key", value = "val") %>%
    mutate(is.missing = is.na(val)) %>%
    group_by(key, is.missing) %>%
    summarise(num.missing = n()) %>%
    filter(is.missing==T) %>%
    select(-is.missing) %>%
    arrange(desc(num.missing)) %>%
    ggplot() +
    geom_bar(aes(x=key, y=num.missing), stat = 'identity',fill="#F0E442") +
    labs(x='variable', y="number of missing values",
         title='Number of missing values') +
    theme(axis.text.x = element_text(angle = 45, hjust = 1))
```


```
##################################
CNE_tecnica <- na.omit(CNE_tecnica)
##################################

aggr(CNE_tecnica, col=c('navyblue','yellow'),
     numbers=TRUE, sortVars=TRUE,
     labels=names(CNE_tecnica), cex.axis=.7,
     gap=3, ylab=c("Missing data","Pattern"))
```




```
##
##  Variables sorted by number of missings:
##                     Variable Count
##                provincia_iso     0
##                        fecha     0
##                    num_casos     0
##         num_casos_prueba_pcr     0
##     num_casos_prueba_test_ac     0
##          num_casos_prueba_ag     0
##       num_casos_prueba_elisa     0
##  num_casos_prueba_desconocida     0
```

```
CNE_tecnica %>%
    gather(key = "key", value = "val") %>%
    mutate(is.missing = is.na(val)) %>%
    group_by(key, is.missing) %>%
    summarise(num.missing = n()) %>%
    filter(is.missing==T) %>%
    select(-is.missing) %>%
    arrange(desc(num.missing)) %>%
    ggplot() +
    geom_bar(aes(x=key, y=num.missing), stat = 'identity',fill="#F0E442") +
    labs(x='variable', y="number of missing values",
         title='Number of missing values') +
    theme(axis.text.x = element_text(angle = 45, hjust = 1))
```


```r
head(str(CNE_casos,vec.len=3))
```

```
## 'data.frame':    702780 obs. of  8 variables:
##  $ provincia_iso: chr  "A" "A" "A" ...
##  $ sexo         : chr  "H" "H" "H" ...
##  $ grupo_edad   : chr  "0-9" "10-19" "20-29" ...
##  $ fecha        : chr  "2020-01-01" "2020-01-01" "2020-01-01" ...
##  $ num_casos    : int  0 0 0 0 0 0 0 0 ...
##  $ num_hosp     : int  0 0 0 0 0 0 0 0 ...
##  $ num_uci      : int  0 0 0 0 0 0 0 0 ...
##  $ num_def      : int  0 0 0 0 0 0 0 0 ...
```

```
## NULL
```

```r
summary(CNE_casos)
```

```
##  provincia_iso          sexo              grupo_edad           fecha
##  Length:702780      Length:702780      Length:702780      Length:702780
##  Class :character   Class :character   Class :character   Class :character
##  Mode  :character   Mode  :character   Mode  :character   Mode  :character
##
##
##
##    num_casos          num_hosp           num_uci            num_def
##  Min.   :  0.000   Min.   :  0.0000   Min.   : 0.00000   Min.   :  0.0000
##  1st Qu.:  0.000   1st Qu.:  0.0000   1st Qu.: 0.00000   1st Qu.:  0.0000
##  Median :  0.000   Median :  0.0000   Median : 0.00000   Median :  0.0000
##  Mean   :  4.562   Mean   :  0.4611   Mean   : 0.04117   Mean   :  0.1036
```

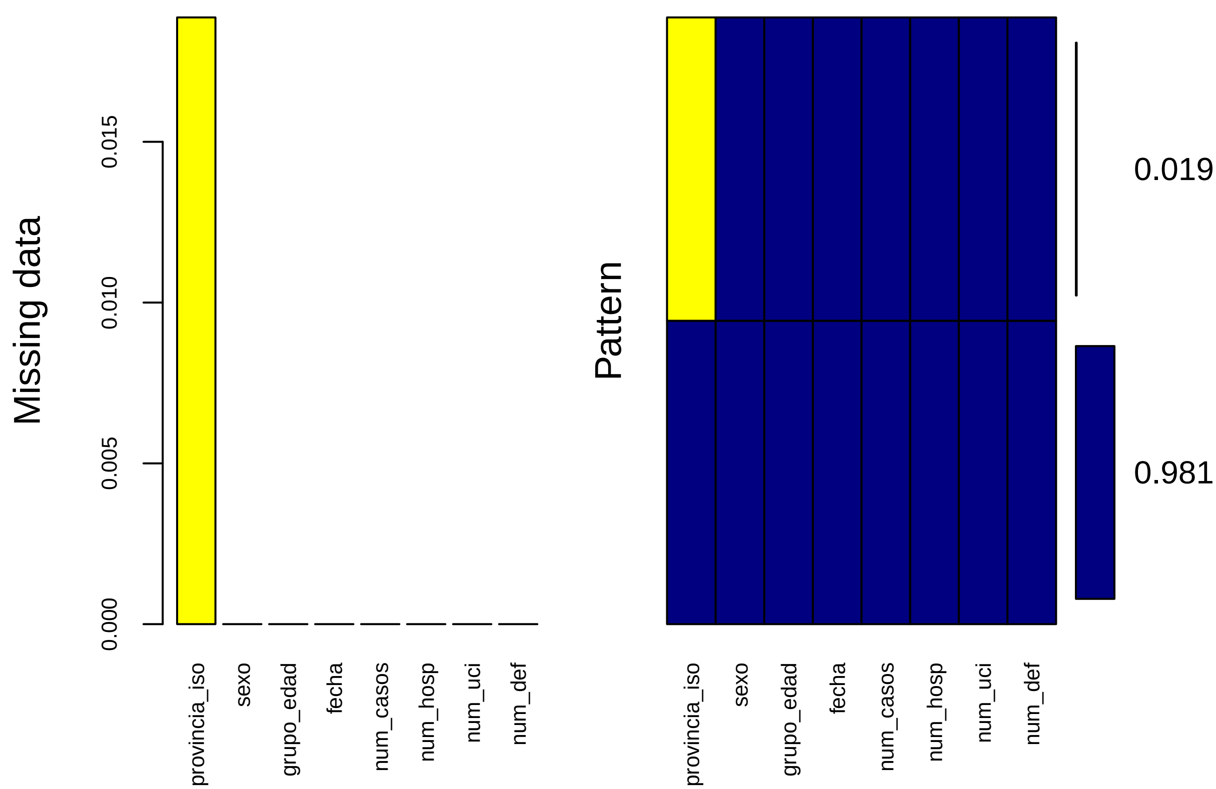
```
##  3rd Qu.:  2.000   3rd Qu.:  0.0000   3rd Qu.: 0.00000   3rd Qu.:  0.0000
##  Max.   :771.000   Max.   :269.0000   Max.   :35.00000   Max.   :100.0000
```

```r
table(CNE_casos$provincia_iso)
```

```
## 
##     A    AB    AL    AV     B    BA    BI    BU     C    CA    CC    CE    CO 
## 13260 13260 13260 13260 13260 13260 13260 13260 13260 13260 13260 13260 13260 
##    CR    CS    CU    GC    GI    GR    GU     H    HU     J     L    LE    LO 
## 13260 13260 13260 13260 13260 13260 13260 13260 13260 13260 13260 13260 13260 
##    LU     M    MA    ML    MU    NC     O    OR     P    PM    PO     S    SA 
## 13260 13260 13260 13260 13260 13260 13260 13260 13260 13260 13260 13260 13260 
##    SE    SG    SO    SS     T    TE    TF    TO     V    VA    VI     Z    ZA 
## 13260 13260 13260 13260 13260 13260 13260 13260 13260 13260 13260 13260 13260
```

We check missing values for CNE_casos. In this case also we omit the NA values.

```r
aggr(CNE_casos, col=c('navyblue','yellow'),
     numbers=TRUE, sortVars=TRUE,
     labels=names(CNE_casos), cex.axis=.7,
     gap=3, ylab=c("Missing data","Pattern"))
```



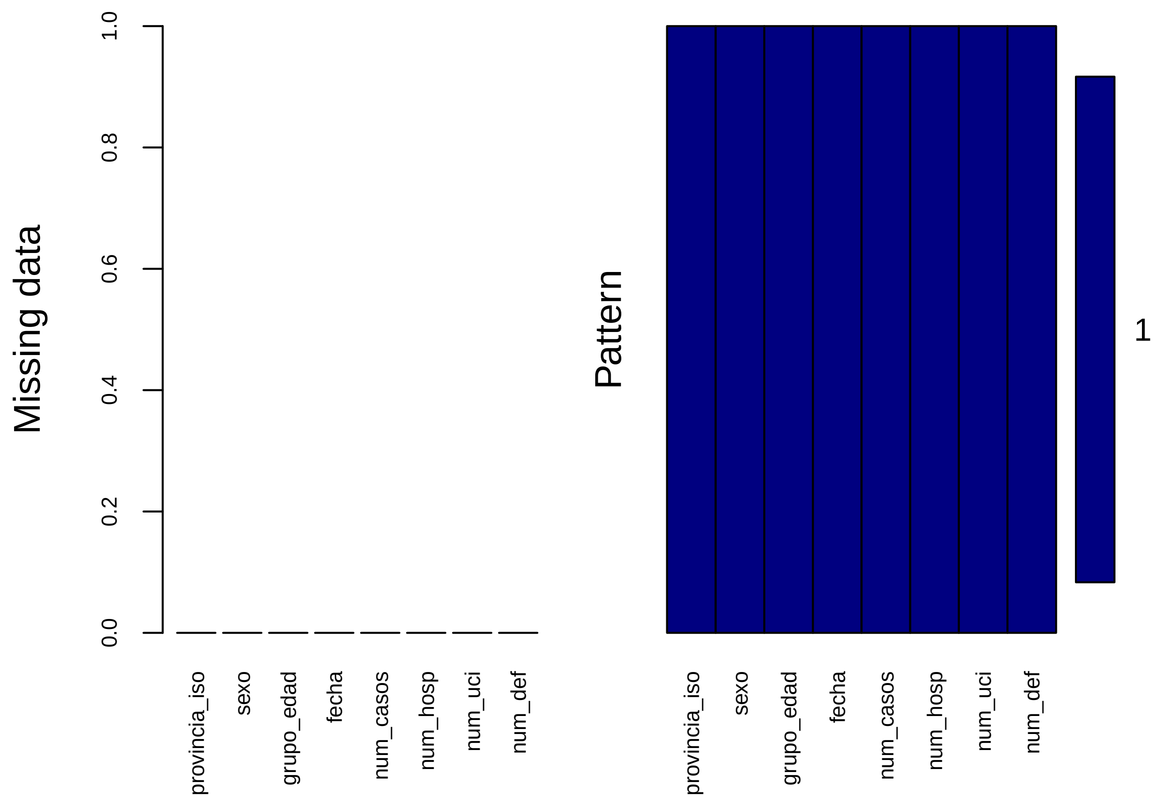

```
## 
##  Variables sorted by number of missings: 
##       Variable      Count
##   provincia_iso 0.01886792
##           sexo 0.00000000
##     grupo_edad 0.00000000
```

```
##          fecha 0.00000000
##      num_casos 0.00000000
##       num_hosp 0.00000000
##        num_uci 0.00000000
##        num_def 0.00000000
```

```
CNE_casos %>%
    gather(key = "key", value = "val") %>%
    mutate(is.missing = is.na(val)) %>%
    group_by(key, is.missing) %>%
    summarise(num.missing = n()) %>%
    filter(is.missing==T) %>%
    select(-is.missing) %>%
    arrange(desc(num.missing)) %>%
    ggplot() +
    geom_bar(aes(x=key, y=num.missing), stat = 'identity',fill="#F0E442") +
    labs(x='variable', y="number of missing values",
         title='Number of missing values') +
    theme(axis.text.x = element_text(angle = 45, hjust = 1))
```


```
##############################
CNE_casos <- na.omit(CNE_casos)
##############################

aggr(CNE_casos, col=c('navyblue','yellow'),
     numbers=TRUE, sortVars=TRUE,
     labels=names(CNE_casos), cex.axis=.7,
```

```r
    gap=3, ylab=c("Missing data","Pattern"))
```




```
##
##  Variables sorted by number of missings:
##       Variable Count
##  provincia_iso     0
##           sexo     0
##     grupo_edad     0
##          fecha     0
##      num_casos     0
##       num_hosp     0
##        num_uci     0
##        num_def     0
```

```r
CNE_casos %>%
    gather(key = "key", value = "val") %>%
    mutate(is.missing = is.na(val)) %>%
    group_by(key, is.missing) %>%
    summarise(num.missing = n()) %>%
    filter(is.missing==T) %>%
    select(-is.missing) %>%
    arrange(desc(num.missing)) %>%
    ggplot() +
    geom_bar(aes(x=key, y=num.missing), stat = 'identity',fill="#F0E442") +
    labs(x='variable', y="number of missing values",
         title='Number of missing values') +
```

```r
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
```

2.1.11 CNE data transformation

We are going to **transform / eliminate**:

- A - "Fecha" column is transformed (in both datasets) from "character" to "date".
- B - "Grupo_edad" and "Sexo" columns are eliminated from dataset "CNE_casos" due to they are not adding value (mobility does not include this variable).
- C - We change NC iso code to NA (Navarra) in both dataframes.

```r
# Transform / eliminate A
CNE_tecnica$fecha <- as.Date(CNE_tecnica$fecha ,format="%Y-%m-%d")
CNE_casos$fecha <- as.Date(CNE_casos$fecha ,format="%Y-%m-%d")

# Transform / eliminate B
CNE_casos<-within(CNE_casos, rm(grupo_edad, sexo))

# Iso code update for Navarra C
CNE_tecnica$provincia_iso[CNE_tecnica$provincia_iso=="NC"] <- "NA"
CNE_casos$provincia_iso[CNE_casos$provincia_iso=="NC"] <- "NA"

head(CNE_tecnica,5)
```

```
##   provincia_iso      fecha num_casos num_casos_prueba_pcr
## 1             A 2020-01-01         0                    0
## 2            AB 2020-01-01         0                    0
```

```
## 3            AL 2020-01-01         0                    0
## 4            AV 2020-01-01         0                    0
## 5             B 2020-01-01         0                    0
##   num_casos_prueba_test_ac num_casos_prueba_ag num_casos_prueba_elisa
## 1                        0                   0                      0
## 2                        0                   0                      0
## 3                        0                   0                      0
## 4                        0                   0                      0
## 5                        0                   0                      0
##   num_casos_prueba_desconocida
## 1                            0
## 2                            0
## 3                            0
## 4                            0
## 5                            0
```

```
head(CNE_casos,5)
```

```
##   provincia_iso      fecha num_casos num_hosp num_uci num_def
## 1             A 2020-01-01         0        0       0       0
## 2             A 2020-01-01         0        0       0       0
## 3             A 2020-01-01         0        0       0       0
## 4             A 2020-01-01         0        0       0       0
## 5             A 2020-01-01         0        0       0       0
```

We check both dataframes offers the same total results.

```
CNE_tecnica %>%
  group_by(provincia_iso) %>%
  summarise_at(vars(num_casos), sum)
```

```
## # A tibble: 52 x 2
##    provincia_iso num_casos
##    <chr>             <int>
##  1 A                143555
##  2 AB                26916
##  3 AL                47032
##  4 AV                11084
##  5 B                382992
##  6 BA                45886
##  7 BI                80588
##  8 BU                29808
##  9 C                 51272
## 10 CA                70428
## # ... with 42 more rows
```

```
CNE_casos %>%
  group_by(provincia_iso) %>%
  summarise_at(vars(num_casos), sum)
```

```
## # A tibble: 52 x 2
##    provincia_iso num_casos
##    <chr>             <int>
##  1 A                143555
##  2 AB                26916
##  3 AL                47032
##  4 AV                11084
```

```
##   5 B                    382992
##   6 BA                    45886
##   7 BI                    80588
##   8 BU                    29808
##   9 C                     51272
##  10 CA                    70428
## # ... with 42 more rows
```

2.2 Datasets combinations

We proceed to **combine** the different data sets into one.

2.2.1 CNE_tec_cas

- CNE_casos_g, a groupped dataframe due to the columns eliminated in previous step (grupo_edad, sexo)
- CNE_tec_cas -> CNE_tecnica + CNE_casos_g

Here we merge by columns "provincia_iso","fecha".

```r
# CNE_casos_g
CNE_casos_g = CNE_casos %>%
  group_by(provincia_iso, fecha) %>%
  summarise_at(vars(num_casos, num_hosp, num_uci, num_def), sum)
head(CNE_casos_g,5)
```

```
## # A tibble: 5 x 6
## # Groups:   provincia_iso [1]
##   provincia_iso fecha      num_casos num_hosp num_uci num_def
##   <chr>         <date>         <int>    <int>   <int>   <int>
## 1 A             2020-01-01         0        1       0       0
## 2 A             2020-01-02         0        0       0       0
## 3 A             2020-01-03         0        0       0       0
## 4 A             2020-01-04         0        0       0       0
## 5 A             2020-01-05         0        1       0       0
```

```r
# New dataframe CNE_tec_cas
CNE_tec_cas<-merge(CNE_tecnica,
                   CNE_casos_g, by.x=c("provincia_iso","fecha"),
                   by.y=c("provincia_iso","fecha"))

# We check both dataframes offers the same total results
CNE_tecnica %>%
  group_by(provincia_iso) %>%
  summarise_at(vars(num_casos), sum)
```

```
## # A tibble: 52 x 2
##    provincia_iso num_casos
##    <chr>             <int>
##  1 A                143555
##  2 AB                26916
##  3 AL                47032
##  4 AV                11084
##  5 B                382992
##  6 BA                45886
##  7 BI                80588
##  8 BU                29808
```

```
##  9 C                   51272
## 10 CA                  70428
## # ... with 42 more rows
```

```r
CNE_casos_g %>%
  group_by(provincia_iso) %>%
  summarise_at(vars(num_casos), sum)
```

```
## # A tibble: 52 x 2
##    provincia_iso num_casos
##    <chr>             <int>
##  1 A                143555
##  2 AB                26916
##  3 AL                47032
##  4 AV                11084
##  5 B                382992
##  6 BA                45886
##  7 BI                80588
##  8 BU                29808
##  9 C                 51272
## 10 CA                70428
## # ... with 42 more rows
```

```r
head(CNE_tec_cas,5)
```

```
##   provincia_iso      fecha num_casos.x num_casos_prueba_pcr
## 1             A 2020-01-01           0                    0
## 2             A 2020-01-02           0                    0
## 3             A 2020-01-03           0                    0
## 4             A 2020-01-04           0                    0
## 5             A 2020-01-05           0                    0
##   num_casos_prueba_test_ac num_casos_prueba_ag num_casos_prueba_elisa
## 1                        0                   0                      0
## 2                        0                   0                      0
## 3                        0                   0                      0
## 4                        0                   0                      0
## 5                        0                   0                      0
##   num_casos_prueba_desconocida num_casos.y num_hosp num_uci num_def
## 1                            0           0        1       0       0
## 2                            0           0        0       0       0
## 3                            0           0        0       0       0
## 4                            0           0        0       0       0
## 5                            0           0        1       0       0
```

```r
table(CNE_tec_cas$provincia_iso)
```

```
## 
##   A  AB  AL  AV   B  BA  BI  BU   C  CA  CC  CE  CO  CR  CS  CU  GC  GI  GR  GU 
## 442 442 442 442 442 442 442 442 442 442 442 442 442 442 442 442 442 442 442 442 
##   H  HU   J   L  LE  LO  LU   M  MA  ML  MU  NA   O  OR   P  PM  PO   S  SA  SE 
## 442 442 442 442 442 442 442 442 442 442 442 442 442 442 442 442 442 442 442 442 
##  SG  SO  SS   T  TE  TF  TO   V  VA  VI   Z  ZA 
## 442 442 442 442 442 442 442 442 442 442 442 442
```

2.2.2 GOG_CNE

- GOG_CNE -> CNE_tec_cas + Google

Here we merge by columns “provincia_iso” / “fecha” and “iso_3166_2_code” / “date”.

```
# New dataframe GOG_CNE
GOG_CNE<-merge(CNE_tec_cas,
               Google,
               by.x=c("provincia_iso","fecha"),
               by.y=c("iso_code","Date"))
head(GOG_CNE,5)
```

```
##   provincia_iso      fecha num_casos.x num_casos_prueba_pcr
## 1             A 2020-02-15           1                    1
## 2             A 2020-02-16           1                    1
## 3             A 2020-02-17           1                    1
## 4             A 2020-02-18           1                    1
## 5             A 2020-02-19           1                    1
##   num_casos_prueba_test_ac num_casos_prueba_ag num_casos_prueba_elisa
## 1                        0                   0                      0
## 2                        0                   0                      0
## 3                        0                   0                      0
## 4                        0                   0                      0
## 5                        0                   0                      0
##   num_casos_prueba_desconocida num_casos.y num_hosp num_uci num_def
## 1                            0           0        1       0       0
## 2                            0           0        0       0       0
## 3                            0           0        1       0       0
## 4                            0           0        1       0       0
## 5                            0           0        2       1       0
##       sub_region_2 retail_and_recreation_percent_change_from_baseline
## 1 Alicante/Alacant                                                  3
## 2 Alicante/Alacant                                                 -2
## 3 Alicante/Alacant                                                  0
## 4 Alicante/Alacant                                                 -5
## 5 Alicante/Alacant                                                  1
##   grocery_and_pharmacy_percent_change_from_baseline
## 1                                                -1
## 2                                                 1
## 3                                                 2
## 4                                                -2
## 5                                                 1
##   parks_percent_change_from_baseline
## 1                                 34
## 2                                  8
## 3                                  9
## 4                                -14
## 5                                 10
##   transit_stations_percent_change_from_baseline
## 1                                             7
## 2                                             5
## 3                                             7
## 4                                            -2
## 5                                             3
##   workplaces_percent_change_from_baseline
## 1                                       0
## 2                                      -2
## 3                                       3
```

```
## 4                                        2
## 5                                        3
##   residential_percent_change_from_baseline
## 1                                       -1
## 2                                       -1
## 3                                        0
## 4                                        1
## 5                                        0
```

```r
table(GOG_CNE$provincia_iso)
```

```
## 
##   A  AB  AL  AV   B  BA  BI  BU   C  CA  CC  CE  CO  CR  CS  CU  GC  GI  GR  GU 
## 385 385 385 385 385 385 385 385 385 385 385 385 385 385 385 385 385 385 385 385 
##   H  HU   J   L  LE  LO  LU   M  MA  ML  MU  NA   O  OR   P  PM  PO   S  SA  SE 
## 385 385 385 385 385 385 385 385 385 385 385 385 385 385 385 385 385 385 385 385 
##  SG  SO  SS   T  TE  TF  TO   V  VA  VI   Z  ZA 
## 385 385 385 385 385 385 385 385 385 385 385 385
```

2.2.3 Total

- Total -> GOG_CNE + EM3

Here we merge by columns "sub_region_2" / "fecha" and "Zonas.de.movilidad" / "Periodo". With this dataset we have 21 features for study.

```r
# New dataframe Total
Total<-merge(GOG_CNE,
             EM3,
             by.x=c("sub_region_2","fecha"),
             by.y=c("Zonas.de.movilidad","Periodo"))
head(Total,5)
```

```
##   sub_region_2      fecha provincia_iso num_casos.x num_casos_prueba_pcr
## 1     Albacete 2020-03-16            AB         137                  132
## 2     Albacete 2020-03-17            AB         128                  123
## 3     Albacete 2020-03-18            AB         114                  107
## 4     Albacete 2020-03-19            AB         149                  133
## 5     Albacete 2020-03-20            AB         131                  121
##   num_casos_prueba_test_ac num_casos_prueba_ag num_casos_prueba_elisa
## 1                        5                   0                      0
## 2                        5                   0                      0
## 3                        7                   0                      0
## 4                       16                   0                      0
## 5                       10                   0                      0
##   num_casos_prueba_desconocida num_casos.y num_hosp num_uci num_def
## 1                            0          65       43       3       7
## 2                            0          29       40       4       2
## 3                            0          26       24       7       7
## 4                            0          22       40       5       7
## 5                            0          85       63       4       6
##   retail_and_recreation_percent_change_from_baseline
## 1                                                -81
## 2                                                -84
## 3                                                -83
## 4                                                -93
```

```
## 5                                               -87
##   grocery_and_pharmacy_percent_change_from_baseline
## 1                                              -32
## 2                                              -41
## 3                                              -32
## 4                                              -92
## 5                                              -34
##   parks_percent_change_from_baseline
## 1                                -73
## 2                                -74
## 3                                -70
## 4                                -80
## 5                                -74
##   transit_stations_percent_change_from_baseline
## 1                                           -66
## 2                                           -72
## 3                                           -70
## 4                                           -86
## 5                                           -76
##   workplaces_percent_change_from_baseline
## 1                                     -51
## 2                                     -56
## 3                                     -58
## 4                                     -85
## 5                                     -68
##   residential_percent_change_from_baseline Total
## 1                                       22 9.900
## 2                                       23 9.705
## 3                                       23 9.510
## 4                                       35 9.130
## 5                                       32 8.750
```

```r
head(str(Total,vec.len=1))
```

```
## 'data.frame':    15080 obs. of  20 variables:
##  $ sub_region_2                                      : chr  "Albacete" ...
##  $ fecha                                             : Date, format: "2020-03-16" ...
##  $ provincia_iso                                     : chr  "AB" ...
##  $ num_casos.x                                       : int  137 128 ...
##  $ num_casos_prueba_pcr                              : int  132 123 ...
##  $ num_casos_prueba_test_ac                          : int  5 5 ...
##  $ num_casos_prueba_ag                               : int  0 0 ...
##  $ num_casos_prueba_elisa                            : int  0 0 ...
##  $ num_casos_prueba_desconocida                      : int  0 0 ...
##  $ num_casos.y                                       : int  65 29 ...
##  $ num_hosp                                          : int  43 40 ...
##  $ num_uci                                           : int  3 4 ...
##  $ num_def                                           : int  7 2 ...
##  $ retail_and_recreation_percent_change_from_baseline: num  -81 -84 ...
##  $ grocery_and_pharmacy_percent_change_from_baseline : num  -32 -41 ...
##  $ parks_percent_change_from_baseline                : num  -73 -74 ...
##  $ transit_stations_percent_change_from_baseline     : num  -66 -72 ...
##  $ workplaces_percent_change_from_baseline           : num  -51 -56 ...
##  $ residential_percent_change_from_baseline          : num  22 23 ...
##  $ Total                                             : num  9.9 ...
```

```
## NULL
```

```r
summary(Total)
```

```
##  sub_region_2           fecha            provincia_iso       num_casos.x
##  Length:15080       Min.   :2020-03-16   Length:15080       Min.   :   0
##  Class :character   1st Qu.:2020-05-27   Class :character   1st Qu.:   5
##  Mode  :character   Median :2020-08-07   Mode  :character   Median :  39
##                     Mean   :2020-08-07                      Mean   : 126
##                     3rd Qu.:2020-10-19                      3rd Qu.: 120
##                     Max.   :2020-12-30                      Max.   :6565
##  num_casos_prueba_pcr num_casos_prueba_test_ac num_casos_prueba_ag
##  Min.   :   0.0       Min.   : 0.0000          Min.   :   0.00
##  1st Qu.:   5.0       1st Qu.: 0.0000          1st Qu.:   0.00
##  Median :  35.0       Median : 0.0000          Median :   0.00
##  Mean   : 110.2       Mean   : 0.2832          Mean   :  15.19
##  3rd Qu.: 105.0       3rd Qu.: 0.0000          3rd Qu.:   4.00
##  Max.   :6546.0       Max.   :32.0000          Max.   :1465.00
##  num_casos_prueba_elisa num_casos_prueba_desconocida  num_casos.y
##  Min.   : 0.0000        Min.   : 0.0000              Min.   :   0
##  1st Qu.: 0.0000        1st Qu.: 0.0000              1st Qu.:   6
##  Median : 0.0000        Median : 0.0000              Median :  37
##  Mean   : 0.1989        Mean   : 0.1317              Mean   : 127
##  3rd Qu.: 0.0000        3rd Qu.: 0.0000              3rd Qu.: 117
##  Max.   :71.0000        Max.   :65.0000              Max.   :7724
##     num_hosp           num_uci            num_def
##  Min.   :   0.00   Min.   :  0.000   Min.   :  0.000
##  1st Qu.:   1.00   1st Qu.:  0.000   1st Qu.:  0.000
##  Median :   4.00   Median :  0.000   Median :  1.000
##  Mean   :  14.86   Mean   :  1.281   Mean   :  3.437
##  3rd Qu.:  12.00   3rd Qu.:  1.000   3rd Qu.:  3.000
##  Max.   :1930.00   Max.   :135.000   Max.   :334.000
##  retail_and_recreation_percent_change_from_baseline
##  Min.   :-97.00
##  1st Qu.:-57.00
##  Median :-30.00
##  Mean   :-37.29
##  3rd Qu.:-17.00
##  Max.   : 71.00
##  grocery_and_pharmacy_percent_change_from_baseline
##  Min.   :-96.00
##  1st Qu.:-24.00
##  Median : -6.00
##  Mean   :-11.75
##  3rd Qu.:  4.00
##  Max.   :194.00
##  parks_percent_change_from_baseline
##  Min.   :-94.000
##  1st Qu.:-30.000
##  Median : -2.000
##  Mean   :  5.809
##  3rd Qu.: 30.000
##  Max.   :543.000
##  transit_stations_percent_change_from_baseline
##  Min.   :-100.00
```

```
##  1st Qu.: -53.00
##  Median : -31.00
##  Mean   : -35.19
##  3rd Qu.: -17.00
##  Max.   :  74.00
##  workplaces_percent_change_from_baseline
##  Min.   :-92.00
##  1st Qu.:-43.00
##  Median :-26.00
##  Mean   :-29.08
##  3rd Qu.:-13.00
##  Max.   : 55.00
##  residential_percent_change_from_baseline     Total
##  Min.   :-10.00                           Min.   : 1.95
##  1st Qu.:  4.00                           1st Qu.:11.36
##  Median :  7.00                           Median :14.39
##  Mean   : 10.14                           Mean   :14.20
##  3rd Qu.: 14.00                           3rd Qu.:17.11
##  Max.   : 48.00                           Max.   :29.00
```

```r
table(Total$sub_region_2)
```

```
## 
##                Albacete        Alicante/Alacant                 Almería 
##                     290                     290                     290 
##             Araba/Álava                Asturias                   Ávila 
##                     290                     290                     290 
##                 Badajoz          Balears, Illes               Barcelona 
##                     290                     290                     290 
##                 Bizkaia                  Burgos                 Cáceres 
##                     290                     290                     290 
##                   Cádiz               Cantabria     Castellón/Castelló 
##                     290                     290                     290 
##                   Ceuta             Ciudad Real                 Córdoba 
##                     290                     290                     290 
##               Coruña, A                  Cuenca                Gipuzkoa 
##                     290                     290                     290 
##                  Girona                 Granada             Guadalajara 
##                     290                     290                     290 
##                  Huelva                  Huesca                    Jaén 
##                     290                     290                     290 
##                    León                  Lleida                    Lugo 
##                     290                     290                     290 
##                  Madrid                  Málaga                 Melilla 
##                     290                     290                     290 
##                  Murcia                 Navarra                 Ourense 
##                     290                     290                     290 
##                Palencia             Palmas, Las              Pontevedra 
##                     290                     290                     290 
##               Rioja, La               Salamanca Santa Cruz de Tenerife 
##                     290                     290                     290 
##                 Segovia                 Sevilla                   Soria 
##                     290                     290                     290 
##               Tarragona                  Teruel                  Toledo 
##                     290                     290                     290 
```

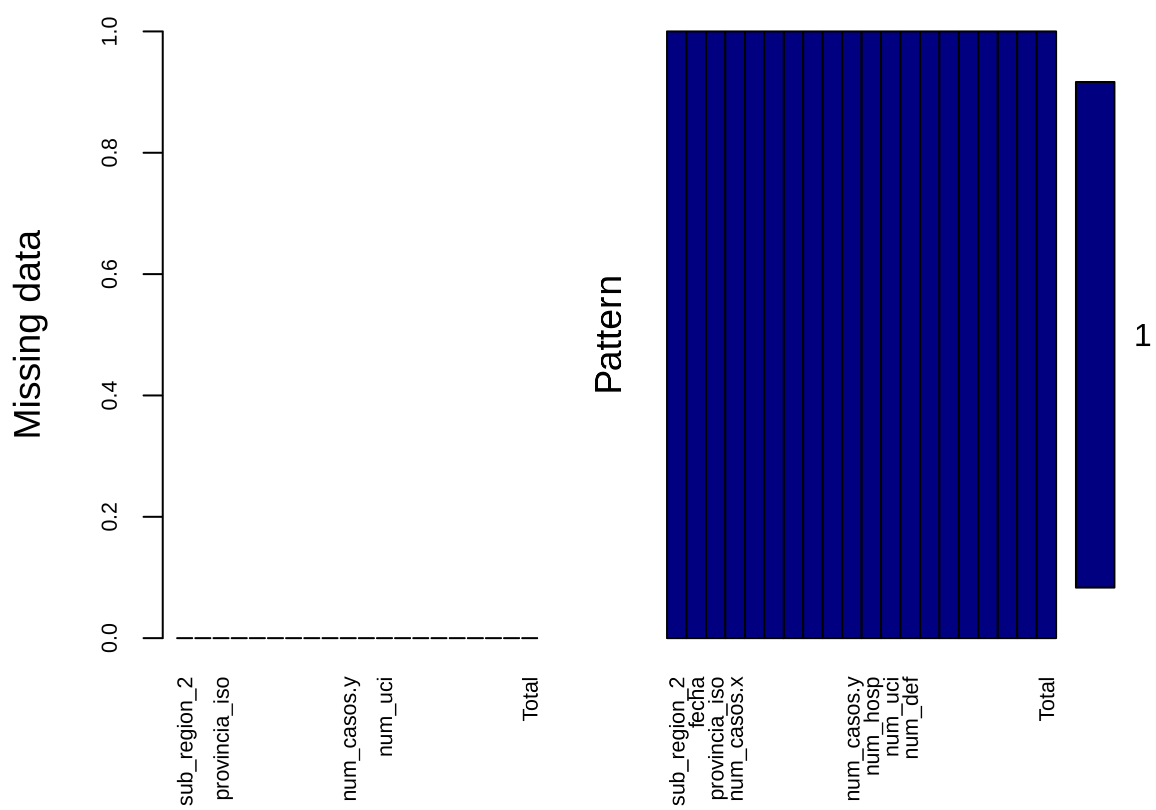
```
##      Valencia/València              Valladolid                  Zamora
##                    290                     290                     290
##               Zaragoza
##                    290
```

```r
table(Total$provincia_iso)
```

```
##
##    A  AB  AL  AV   B  BA  BI  BU   C  CA  CC  CE  CO  CR  CS  CU  GC  GI  GR  GU
## 290 290 290 290 290 290 290 290 290 290 290 290 290 290 290 290 290 290 290 290
##    H  HU   J   L  LE  LO  LU   M  MA  ML  MU  NA   O  OR   P  PM  PO   S  SA  SE
## 290 290 290 290 290 290 290 290 290 290 290 290 290 290 290 290 290 290 290 290
##   SG  SO  SS   T  TE  TF  TO   V  VA  VI   Z  ZA
## 290 290 290 290 290 290 290 290 290 290 290 290
```

We check the missing values. We should have zero missing values

```r
aggr(Total, col=c('navyblue','yellow'),
     numbers=TRUE, sortVars=TRUE,
     labels=names(Total), cex.axis=.7,
     gap=3, ylab=c("Missing data","Pattern"))
```




```
##
##  Variables sorted by number of missings:
##                                          Variable Count
##                                      sub_region_2     0
##                                             fecha     0
##                                     provincia_iso     0
```

```
##                                             num_casos.x     0
##                                    num_casos_prueba_pcr     0
##                                num_casos_prueba_test_ac     0
##                                     num_casos_prueba_ag     0
##                                  num_casos_prueba_elisa     0
##                            num_casos_prueba_desconocida     0
##                                             num_casos.y     0
##                                                num_hosp     0
##                                                 num_uci     0
##                                                 num_def     0
##  retail_and_recreation_percent_change_from_baseline     0
##   grocery_and_pharmacy_percent_change_from_baseline     0
##                  parks_percent_change_from_baseline     0
##       transit_stations_percent_change_from_baseline     0
##             workplaces_percent_change_from_baseline     0
##            residential_percent_change_from_baseline     0
##                                                   Total     0
```

```
Total %>%
    gather(key = "key", value = "val") %>%
    mutate(is.missing = is.na(val)) %>%
    group_by(key, is.missing) %>%
    summarise(num.missing = n()) %>%
    filter(is.missing==T) %>%
    select(-is.missing) %>%
    arrange(desc(num.missing)) %>%
    ggplot() +
    geom_bar(aes(x=key, y=num.missing), stat = 'identity',fill="#F0E442") +
    labs(x='variable', y="number of missing values",
         title='Number of missing values') +
    theme(axis.text.x = element_text(angle = 45, hjust = 1))
```


```r
# Review results
# Discrepancies due to different time-frames when merge CNE dataframes (see previous checks)
Total %>%
  group_by(provincia_iso) %>%
  summarise_at(vars(num_casos.x,num_casos.y), sum)
```

```
## # A tibble: 52 x 3
##    provincia_iso num_casos.x num_casos.y
##    <chr>               <int>       <int>
##  1 A                   56493       55068
##  2 AB                  16459       16626
##  3 AL                  21488       21372
##  4 AV                   6525        6681
##  5 B                  257034      261208
##  6 BA                  23165       22612
##  7 BI                  56867       57728
##  8 BU                  22742       22978
##  9 C                   25641       25604
## 10 CA                  31593       31225
## # ... with 42 more rows
```

```r
# CSV file generation
head(Total,5)
```

```
##   sub_region_2      fecha provincia_iso num_casos.x num_casos_prueba_pcr
## 1     Albacete 2020-03-16            AB         137                  132
## 2     Albacete 2020-03-17            AB         128                  123
```

```
## 3     Albacete 2020-03-18            AB         114                    107
## 4     Albacete 2020-03-19            AB         149                    133
## 5     Albacete 2020-03-20            AB         131                    121
##   num_casos_prueba_test_ac num_casos_prueba_ag num_casos_prueba_elisa
## 1                        5                   0                      0
## 2                        5                   0                      0
## 3                        7                   0                      0
## 4                       16                   0                      0
## 5                       10                   0                      0
##   num_casos_prueba_desconocida num_casos.y num_hosp num_uci num_def
## 1                            0          65       43       3       7
## 2                            0          29       40       4       2
## 3                            0          26       24       7       7
## 4                            0          22       40       5       7
## 5                            0          85       63       4       6
##   retail_and_recreation_percent_change_from_baseline
## 1                                                -81
## 2                                                -84
## 3                                                -83
## 4                                                -93
## 5                                                -87
##   grocery_and_pharmacy_percent_change_from_baseline
## 1                                               -32
## 2                                               -41
## 3                                               -32
## 4                                               -92
## 5                                               -34
##   parks_percent_change_from_baseline
## 1                                -73
## 2                                -74
## 3                                -70
## 4                                -80
## 5                                -74
##   transit_stations_percent_change_from_baseline
## 1                                           -66
## 2                                           -72
## 3                                           -70
## 4                                           -86
## 5                                           -76
##   workplaces_percent_change_from_baseline
## 1                                     -51
## 2                                     -56
## 3                                     -58
## 4                                     -85
## 5                                     -68
##   residential_percent_change_from_baseline Total
## 1                                       22 9.900
## 2                                       23 9.705
## 3                                       23 9.510
## 4                                       35 9.130
## 5                                       32 8.750
```

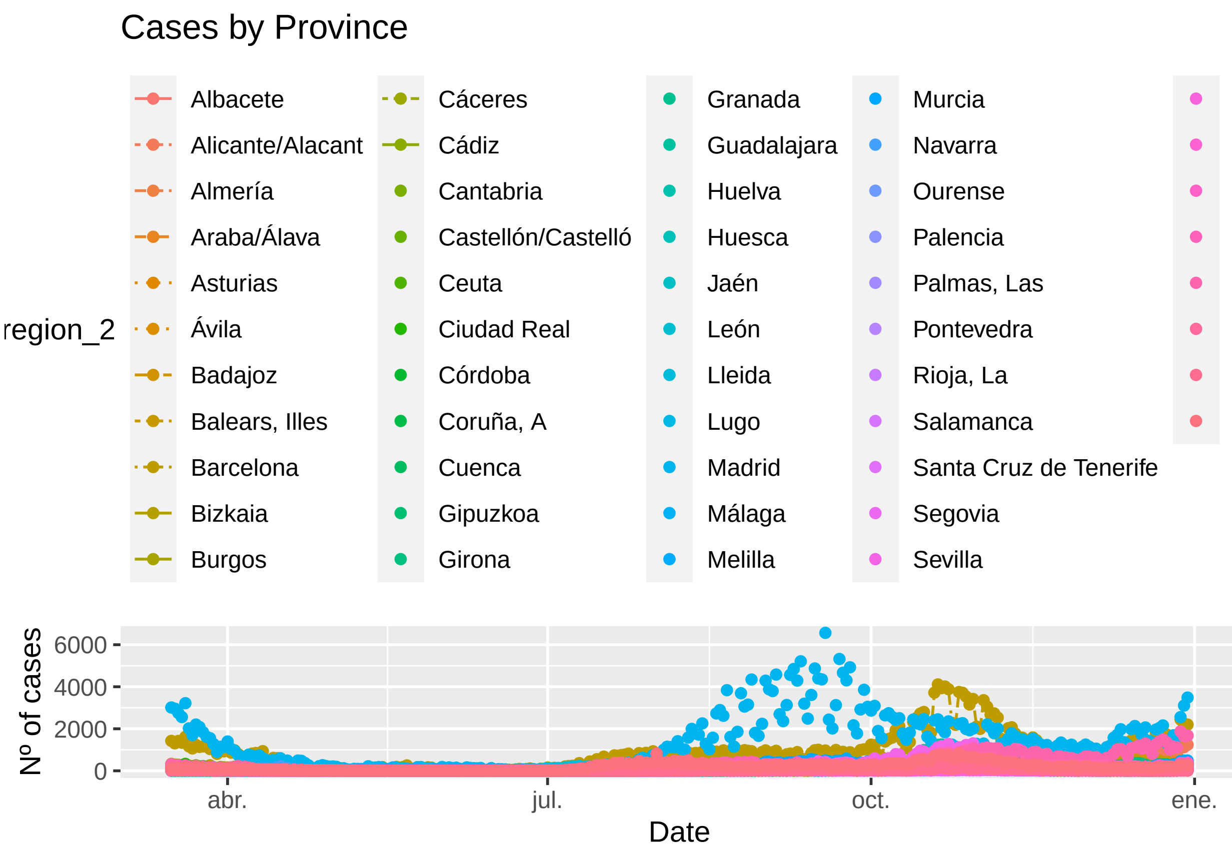
```
write.csv2(Total,"D:\\UOC Master Data Science\\_ M2.882 - TFM - Área 5\\UOC - Guia - PECS\\Pec3\\Total.c
```

2.3 Visual analysis

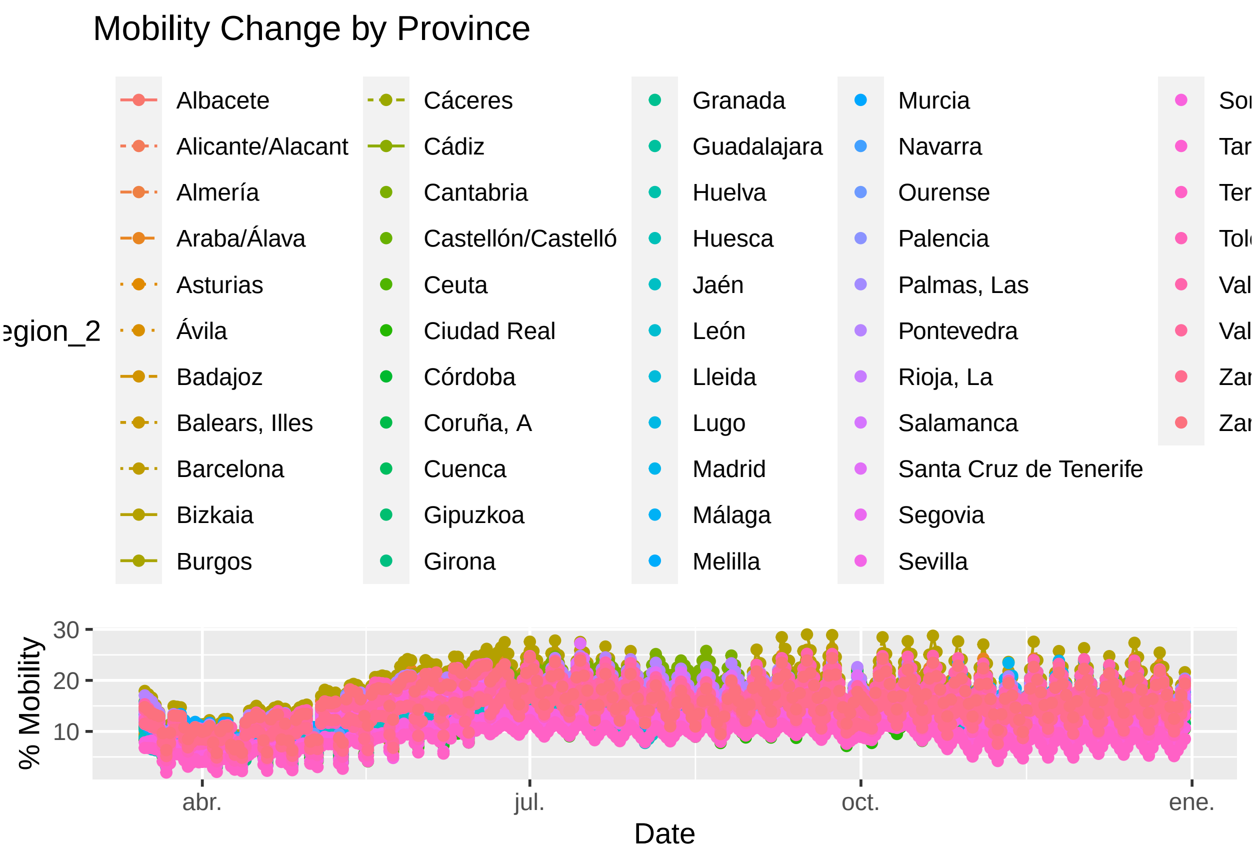
2.3.1 Dataframe plots

We have generated some plots from the **dataframe** object generated.

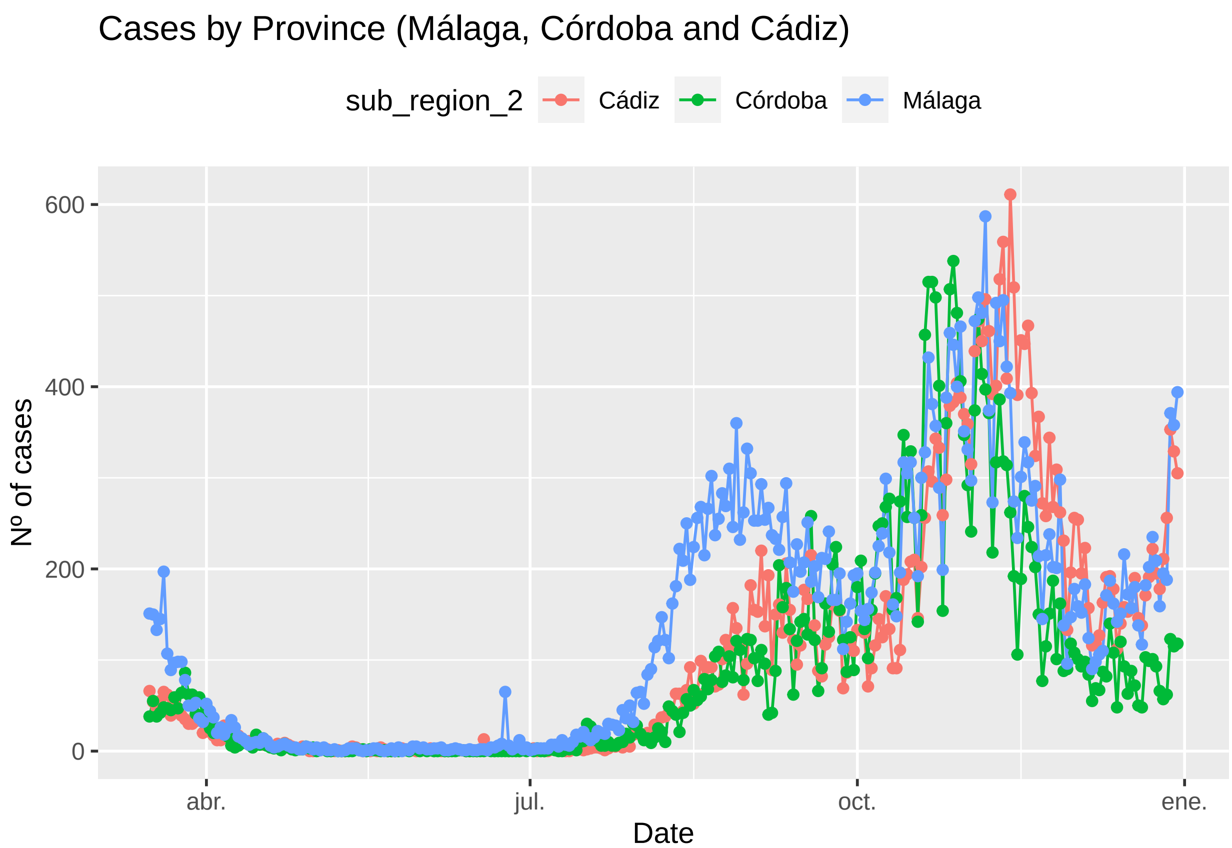
```
# Line plots
# All num_casos.x
ggplot(Total, aes(x=fecha, y=num_casos.x, group=sub_region_2)) +
  geom_line(aes(linetype=sub_region_2, color=sub_region_2))+
  geom_point(aes(color=sub_region_2))+
  theme(legend.position="top") +
  labs(title="Cases by Province",
        x ="Date", y = "Nº of cases")
```



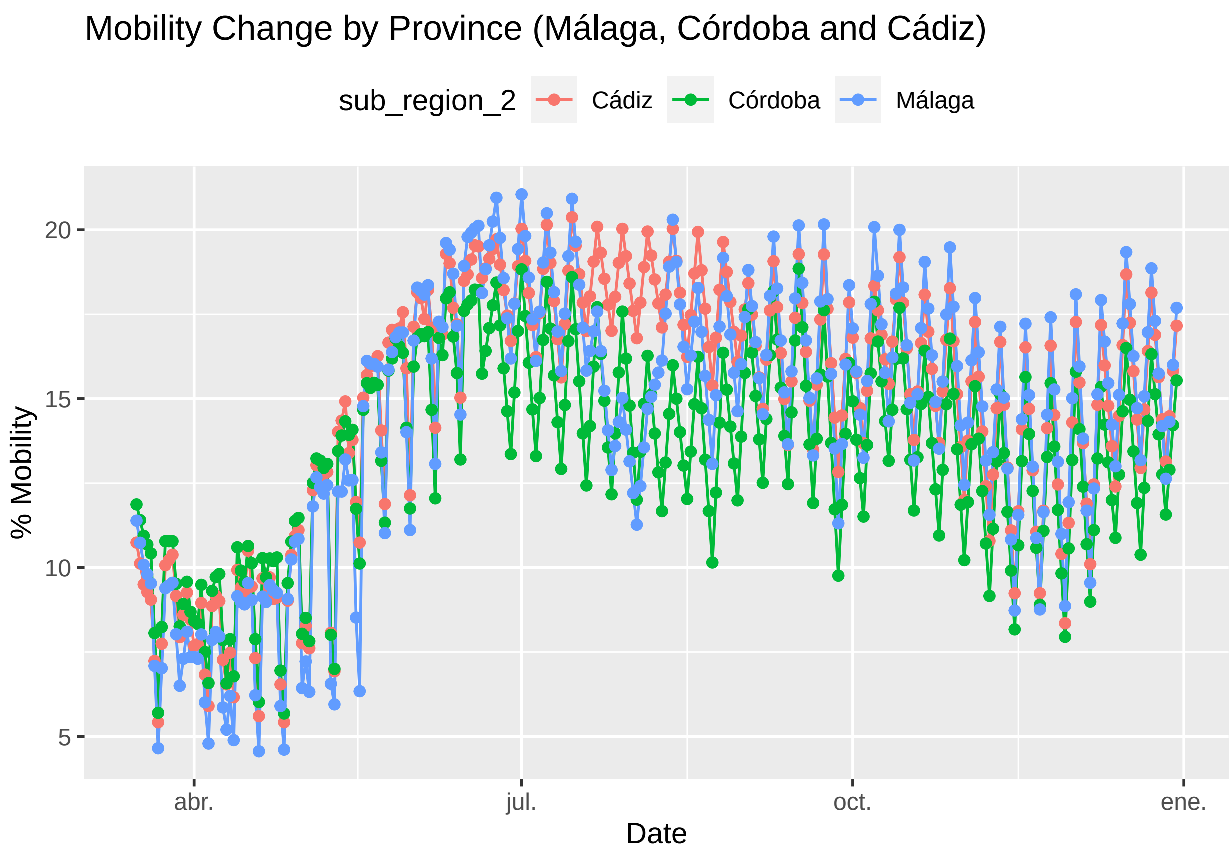

```
# All Total (mobility)
ggplot(Total, aes(x=fecha, y=Total, group=sub_region_2)) +
  geom_line(aes(linetype=sub_region_2, color=sub_region_2))+
  geom_point(aes(color=sub_region_2))+
  theme(legend.position="top") +
  labs(title="Mobility Change by Province",
        x ="Date", y = "% Mobility")
```




```r
# Mal, Cor and Cad - num_casos.x
Total %>%
  filter(sub_region_2 == "Málaga" | sub_region_2 == "Cádiz" |
         sub_region_2 == "Córdoba") %>%
  ggplot(aes(x=fecha, y=num_casos.x))+
    geom_line(aes(color=sub_region_2))+
    geom_point(aes(color=sub_region_2))+
    theme(legend.position="top") +
    labs(title="Cases by Province (Málaga, Córdoba and Cádiz)",
      x ="Date", y = "Nº of cases")
```



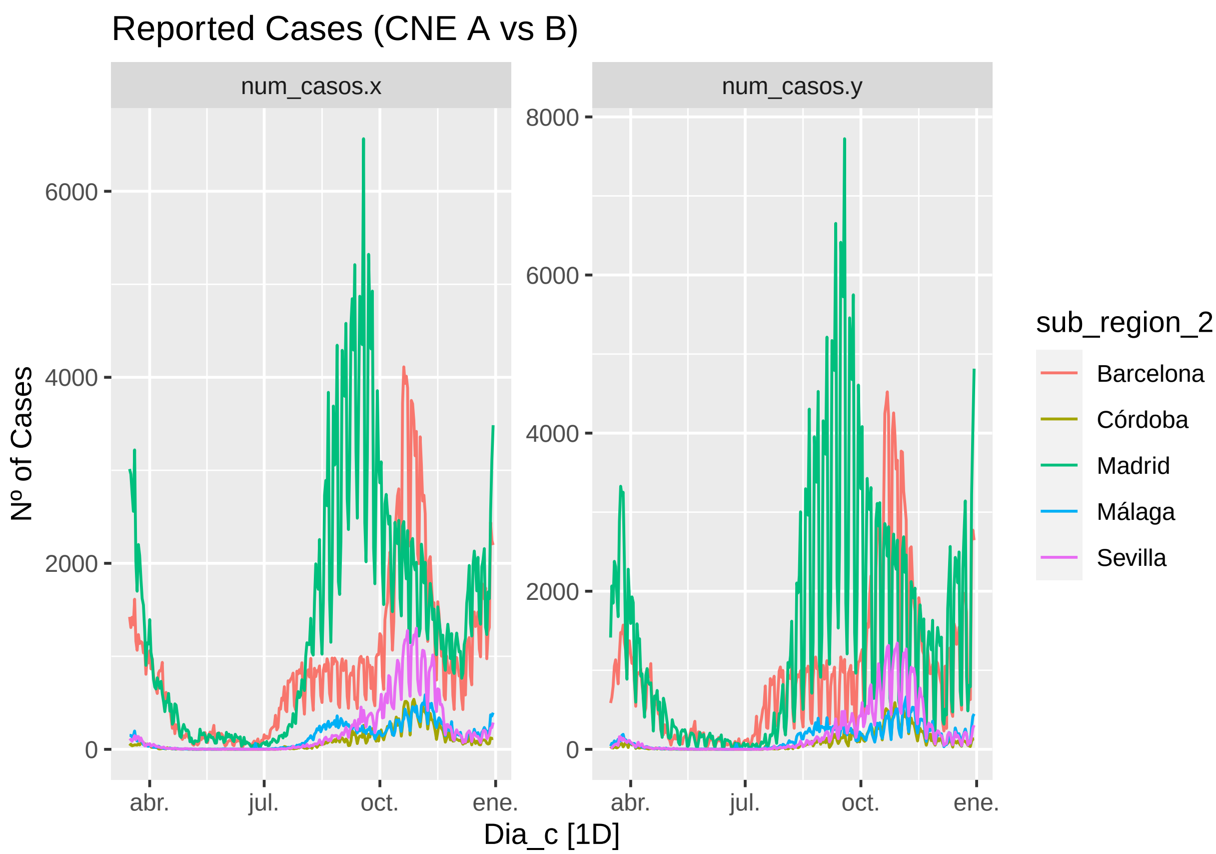

```
# Mal, Cor and Cad - Total (mobility)
Total %>%
  filter(sub_region_2 == "Málaga" | sub_region_2 == "Cádiz" |
         sub_region_2 == "Córdoba") %>%
  ggplot(aes(x=fecha, y=Total))+
    geom_line(aes(color=sub_region_2))+
    geom_point(aes(color=sub_region_2))+
    theme(legend.position="top") +
  labs(title="Mobility Change by Province (Málaga, Córdoba and Cádiz)",
       x ="Date", y = "% Mobility")
```



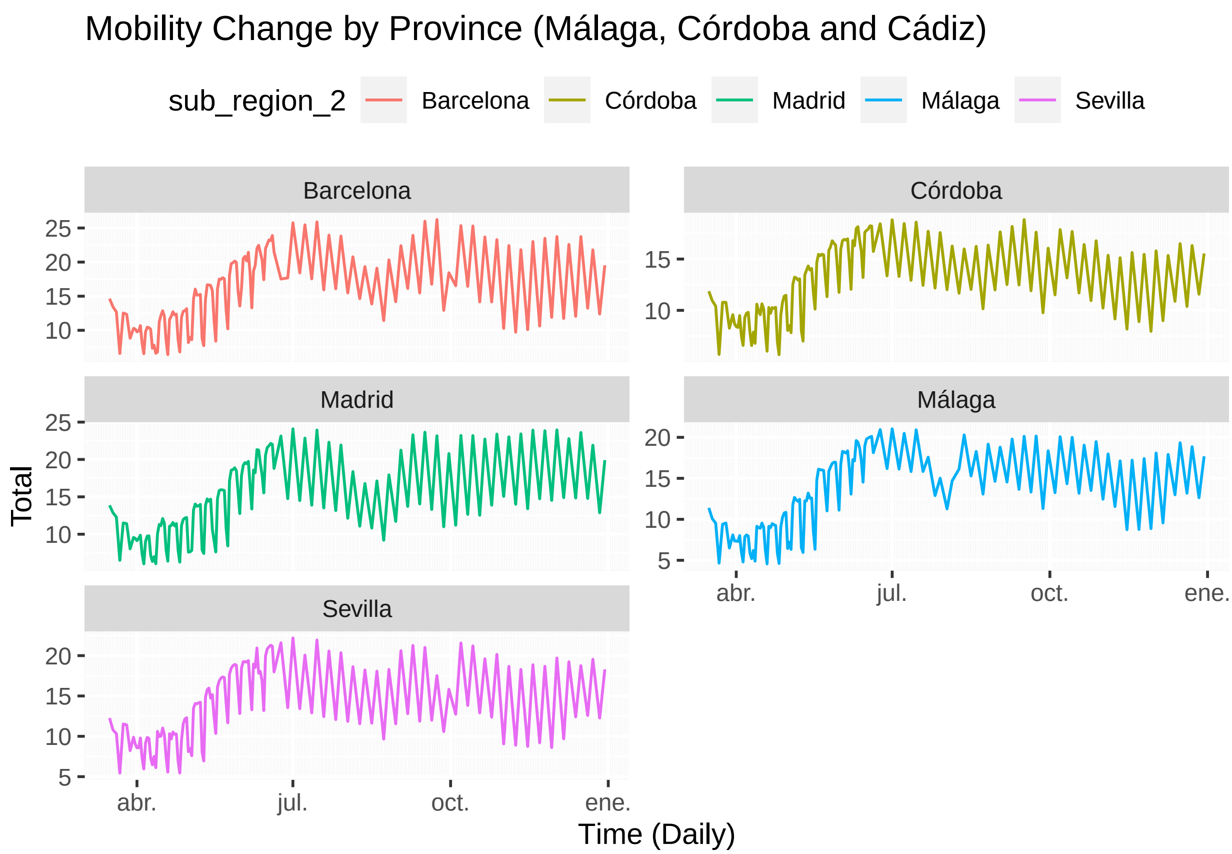
2.3.2 Time-series plots

We have generated some plots from the **time-series** object generated.

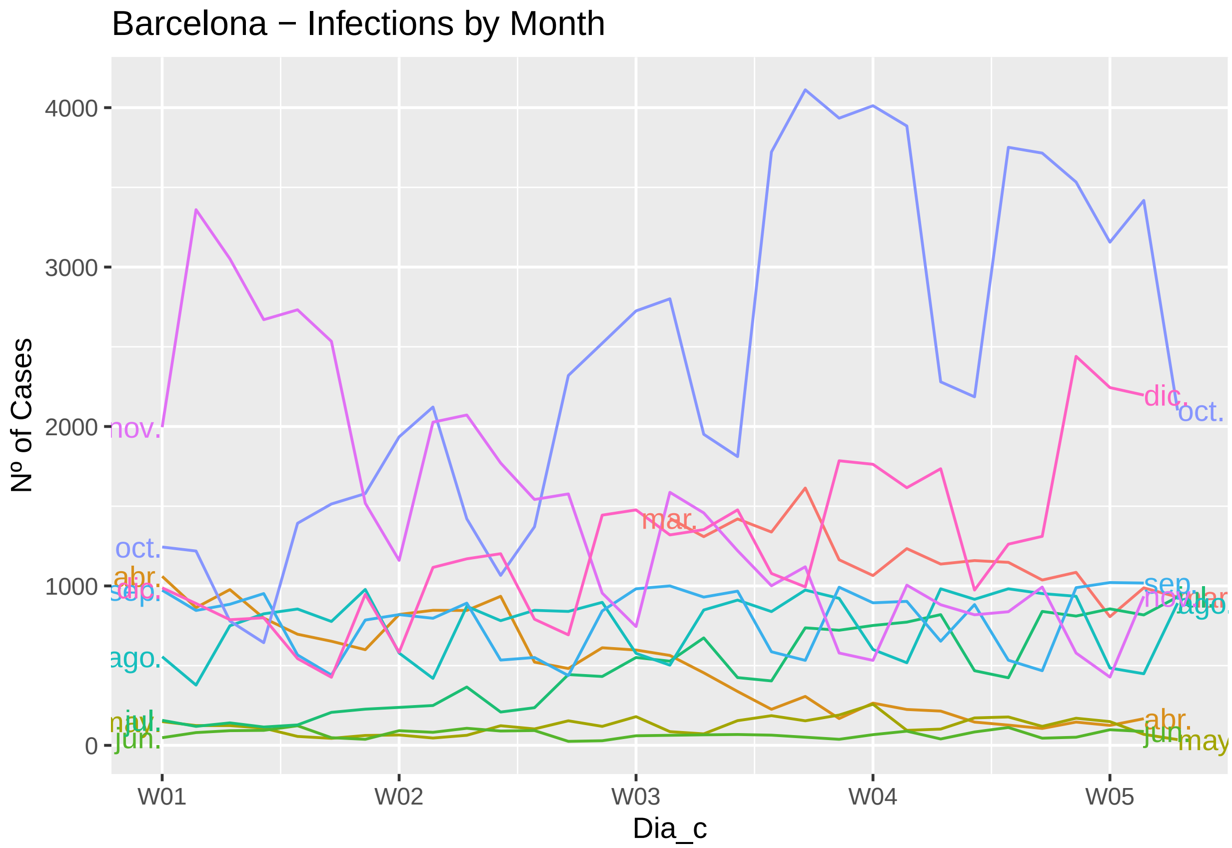
```
# Convert dataframe to ts object
Total_ts <- Total[-3] %>%
  mutate(Dia_c = as_date(fecha)) %>%
  select(-fecha) %>%
  as_tsibble(key = c(sub_region_2),
             index = Dia_c)

# Filter for Bar, Mad, Mal, Cor and, Cad
Total_ts %>% filter(sub_region_2 == "Barcelona" | sub_region_2 == "Madrid" |
                    sub_region_2 == "Málaga" | sub_region_2 == "Sevilla" |
                    sub_region_2 == "Córdoba") -> Total_ts_b

# Plots
# A num_casos.x,num_casos.y
autoplot(Total_ts_b, vars(num_casos.x,num_casos.y)) +
  labs(y = "Nº of Cases",
       title = "Reported Cases (CNE A vs B)")
```




```r
# B Total (mobility)
autoplot(Total_ts_b, Total) +
  facet_wrap(~sub_region_2, scales = "free_y", ncol=2) +
  theme(legend.position = "top") +
  scale_x_date(date_minor_breaks = "1 day", name = "Time (Daily)") +
  ggtitle(label = "Mobility Change by Province (Málaga, Córdoba and Cádiz)")
```

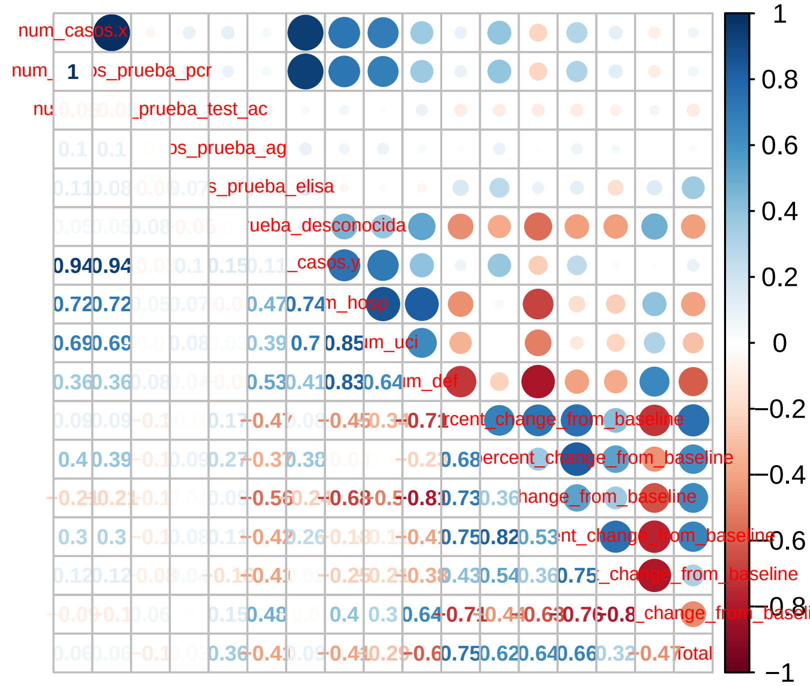



```r
# C sub_region_2 == "Barcelona" by month
Total_ts %>% filter(sub_region_2 == "Barcelona") %>%
  gg_season(num_casos.x, period = "month", labels = "both") +
  theme(legend.position = "top") +
  labs(y="Nº of Cases", title="Barcelona - Infections by Month")
```



2.3.3 Correlation plots

```
Total.res<-Total %>%
  filter(sub_region_2 == "Barcelona")
Total.res<-cor(Total.res[,c(-1,-2,-3)],method="spearman")
corrplot.mixed(Total.res,upper="circle",number.cex=.65,tl.cex=.6)
```



2.3.4 PCA

```r
pca <- prcomp(Total.res, scale = T)
summary(pca)
```

```
## Importance of components:
##                           PC1    PC2     PC3     PC4     PC5     PC6     PC7
## Standard deviation     3.1552 1.9451 1.10671 1.01898 0.79637 0.39357 0.30798
## Proportion of Variance 0.5856 0.2225 0.07205 0.06108 0.03731 0.00911 0.00558
## Cumulative Proportion  0.5856 0.8081 0.88019 0.94126 0.97857 0.98768 0.99326
##                            PC8     PC9    PC10    PC11    PC12    PC13    PC14
## Standard deviation     0.25489 0.13998 0.12930 0.07468 0.06868 0.04114 0.02780
## Proportion of Variance 0.00382 0.00115 0.00098 0.00033 0.00028 0.00010 0.00005
## Cumulative Proportion  0.99708 0.99823 0.99922 0.99955 0.99982 0.99992 0.99997
##                           PC15      PC16      PC17
## Standard deviation     0.02311 0.0004975 1.662e-17
## Proportion of Variance 0.00003 0.0000000 0.000e+00
## Cumulative Proportion  1.00000 1.0000000 1.000e+00
```

```r
pca$rotation
```

```
##                                                              PC1          PC2
## num_casos.x                                         -0.129562285 -0.464986629
## num_casos_prueba_pcr                                -0.128418565 -0.465950898
## num_casos_prueba_test_ac                            -0.088940792  0.231057951
## num_casos_prueba_ag                                 -0.001675564 -0.009243491
```

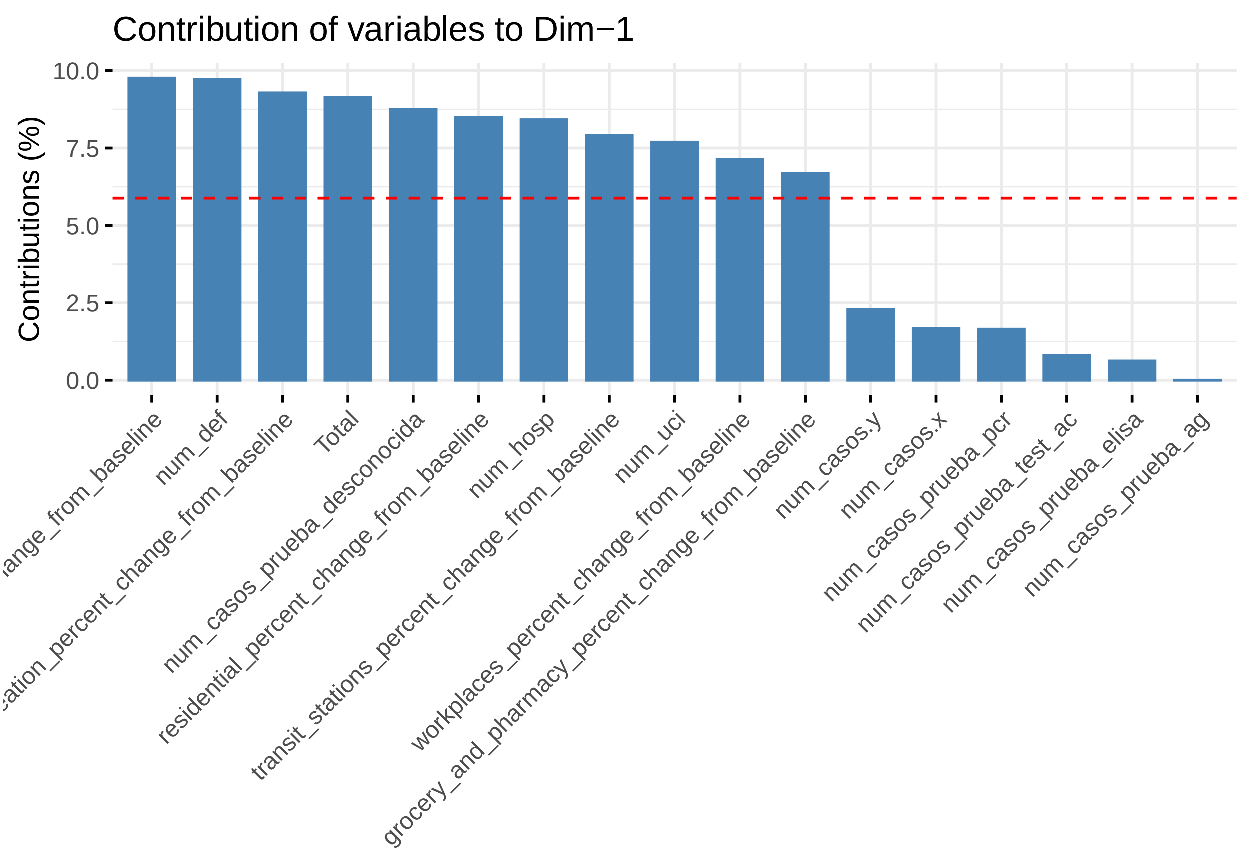
```
## num_casos_prueba_elisa                             0.078751296  0.020912483
## num_casos_prueba_desconocida                      -0.295765806  0.091860764
## num_casos.y                                       -0.151382954 -0.445490227
## num_hosp                                          -0.290069059 -0.205021107
## num_uci                                           -0.277303343 -0.239750604
## num_def                                           -0.311776607 -0.055197949
## retail_and_recreation_percent_change_from_baseline  0.304649528 -0.115160291
## grocery_and_pharmacy_percent_change_from_baseline   0.258379798 -0.275801588
## parks_percent_change_from_baseline                  0.312392677  0.010291105
## transit_stations_percent_change_from_baseline       0.281285103 -0.223780364
## workplaces_percent_change_from_baseline             0.267174369 -0.184576680
## residential_percent_change_from_baseline          -0.291342632  0.150674362
## Total                                               0.302368253 -0.083800967
##                                                            PC3          PC4
## num_casos.x                                       -0.010975904 -0.030403672
## num_casos_prueba_pcr                              -0.024925551 -0.028418976
## num_casos_prueba_test_ac                          -0.427898056 -0.235435666
## num_casos_prueba_ag                               -0.022108733  0.960265373
## num_casos_prueba_elisa                              0.813326701 -0.075903939
## num_casos_prueba_desconocida                        0.045279265 -0.062749259
## num_casos.y                                         0.035912235 -0.041920910
## num_hosp                                          -0.024325699 -0.009769069
## num_uci                                             0.011742424 -0.001199326
## num_def                                           -0.001007225  0.007393882
## retail_and_recreation_percent_change_from_baseline  0.022029205 -0.059991137
## grocery_and_pharmacy_percent_change_from_baseline   0.039488488 -0.036730856
## parks_percent_change_from_baseline                  0.007150472 -0.002771943
## transit_stations_percent_change_from_baseline     -0.084057805 -0.019455388
## workplaces_percent_change_from_baseline           -0.276591011  0.025327418
## residential_percent_change_from_baseline            0.203862386  0.009045275
## Total                                               0.151254460 -0.055345035
##                                                            PC5          PC6
## num_casos.x                                         0.116446135 -0.131228544
## num_casos_prueba_pcr                                0.109980545 -0.134501202
## num_casos_prueba_test_ac                            0.829833413  0.031884983
## num_casos_prueba_ag                                 0.252463522 -0.001392026
## num_casos_prueba_elisa                              0.401233306  0.296243799
## num_casos_prueba_desconocida                      -0.142121866  0.184113998
## num_casos.y                                         0.131204581 -0.169826745
## num_hosp                                            0.011450514  0.077745046
## num_uci                                           -0.001533074 -0.047774906
## num_def                                           -0.025641794  0.277066590
## retail_and_recreation_percent_change_from_baseline  0.053560696 -0.227365262
## grocery_and_pharmacy_percent_change_from_baseline   0.072051650  0.272608991
## parks_percent_change_from_baseline                  0.007525639 -0.365792434
## transit_stations_percent_change_from_baseline       0.011058698  0.242572903
## workplaces_percent_change_from_baseline           -0.078582419  0.594388722
## residential_percent_change_from_baseline            0.008208359 -0.079603305
## Total                                               0.091154606 -0.223129602
##                                                             PC7          PC8
## num_casos.x                                         0.0004795406  0.13151654
## num_casos_prueba_pcr                                0.0002683955  0.12133638
## num_casos_prueba_test_ac                          -0.0648539470 -0.04409771
## num_casos_prueba_ag                               -0.1028202858 -0.05195295
```

```
## num_casos_prueba_elisa                              -0.0347383093  0.26437915
## num_casos_prueba_desconocida                        -0.8605874091 -0.16548725
## num_casos.y                                         -0.0515963101 -0.02368004
## num_hosp                                             0.0209603510 -0.06447931
## num_uci                                             -0.0710126016  0.13002996
## num_def                                              0.2027103077 -0.19180284
## retail_and_recreation_percent_change_from_baseline -0.2496463511 -0.17256257
## grocery_and_pharmacy_percent_change_from_baseline   0.1376630812 -0.62167733
## parks_percent_change_from_baseline                  -0.0586673961  0.20049426
## transit_stations_percent_change_from_baseline       -0.1197545999 -0.12766849
## workplaces_percent_change_from_baseline              0.0027410329  0.30721382
## residential_percent_change_from_baseline             0.2684813767 -0.38036262
## Total                                               -0.1517274684 -0.30955866
##                                                              PC9          PC10
## num_casos.x                                         -0.227263114 -6.241636e-03
## num_casos_prueba_pcr                                -0.231300202 -9.028489e-03
## num_casos_prueba_test_ac                             0.045691432 -1.093004e-05
## num_casos_prueba_ag                                 -0.001576642 -2.135880e-03
## num_casos_prueba_elisa                               0.004092429 -6.241912e-02
## num_casos_prueba_desconocida                        -0.107479027 -3.859579e-02
## num_casos.y                                         -0.179985745  9.929420e-02
## num_hosp                                             0.115313985  7.915736e-03
## num_uci                                              0.861969505 -2.617357e-02
## num_def                                             -0.002824193 -1.631097e-02
## retail_and_recreation_percent_change_from_baseline -0.030110953 -3.774488e-01
## grocery_and_pharmacy_percent_change_from_baseline   0.075186973 -3.206029e-01
## parks_percent_change_from_baseline                   0.188608867 -2.455229e-01
## transit_stations_percent_change_from_baseline        0.180191343 -1.630827e-02
## workplaces_percent_change_from_baseline             -0.026693337  2.363506e-01
## residential_percent_change_from_baseline            -0.017660900  8.446853e-02
## Total                                                0.129903837  7.841035e-01
##                                                             PC11         PC12
## num_casos.x                                          0.150339680 -0.098740167
## num_casos_prueba_pcr                                 0.126992279 -0.079740339
## num_casos_prueba_test_ac                             0.014275417 -0.038922985
## num_casos_prueba_ag                                 -0.003610965 -0.000542660
## num_casos_prueba_elisa                              -0.031383946  0.011899542
## num_casos_prueba_desconocida                         0.096876689 -0.226649005
## num_casos.y                                         -0.124042590 -0.004188169
## num_hosp                                            -0.295504980  0.054422871
## num_uci                                              0.215675654  0.119518189
## num_def                                             -0.576851508 -0.122978678
## retail_and_recreation_percent_change_from_baseline -0.095116740  0.547116189
## grocery_and_pharmacy_percent_change_from_baseline   0.317187045 -0.183082597
## parks_percent_change_from_baseline                  -0.165315524 -0.717543438
## transit_stations_percent_change_from_baseline       -0.434761142 -0.070831989
## workplaces_percent_change_from_baseline              0.244425893 -0.064165599
## residential_percent_change_from_baseline             0.281252485 -0.203892883
## Total                                               -0.062067677 -0.006841197
##                                                             PC13          PC14
## num_casos.x                                          0.3449187655 -0.0543570547
## num_casos_prueba_pcr                                 0.3643161925 -0.0306379756
## num_casos_prueba_test_ac                             0.0042729074  0.0008274198
## num_casos_prueba_ag                                  0.0007637199 -0.0110243800
```

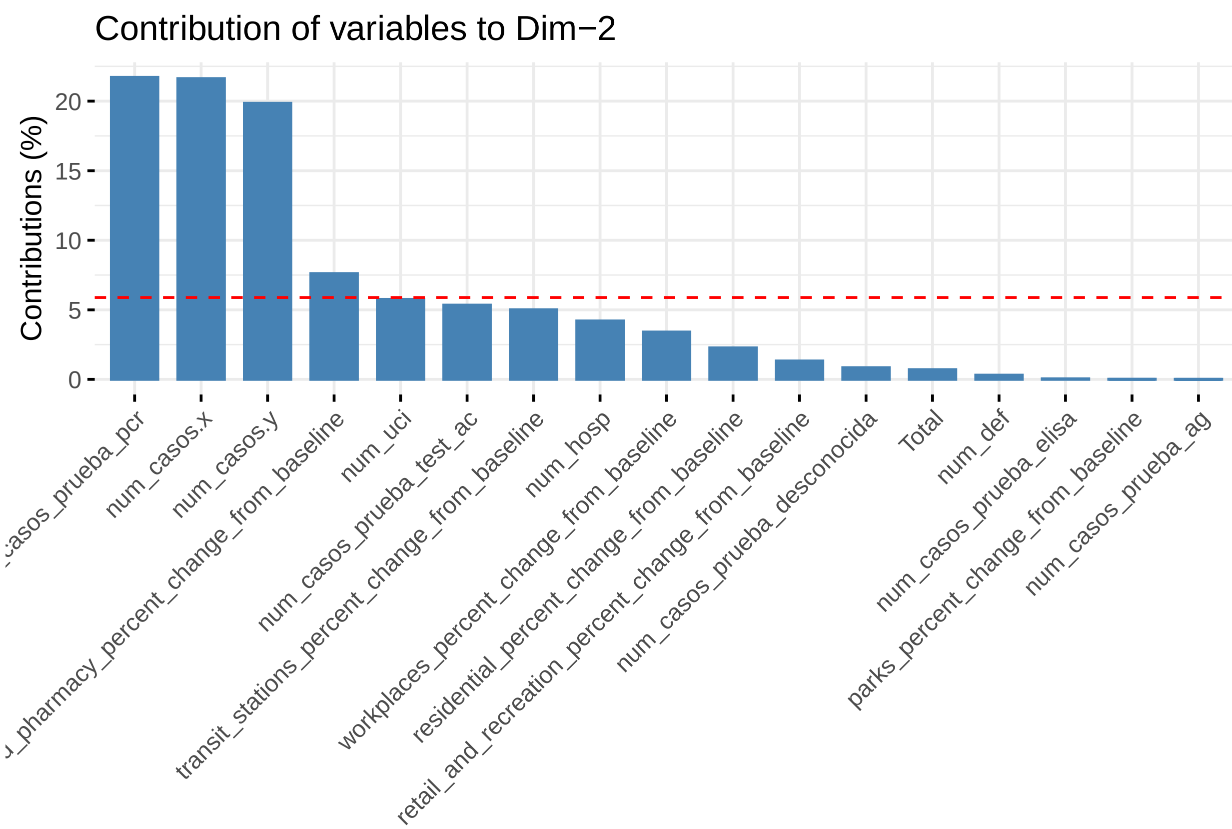
```
## num_casos_prueba_elisa                            0.0008013510 -0.0202884647
## num_casos_prueba_desconocida                      0.0054529561 -0.0221981125
## num_casos.y                                      -0.7663017380  0.2848281549
## num_hosp                                          0.0769267720 -0.3309963210
## num_uci                                          -0.0306335521  0.0234964937
## num_def                                          -0.0120730936 -0.3072889001
## retail_and_recreation_percent_change_from_baseline  0.0074835070 -0.1526510903
## grocery_and_pharmacy_percent_change_from_baseline  -0.1063887575 -0.1908139009
## parks_percent_change_from_baseline               -0.0922587915 -0.1668113179
## transit_stations_percent_change_from_baseline     0.3077286900  0.6675984100
## workplaces_percent_change_from_baseline          -0.1589063997 -0.1207464140
## residential_percent_change_from_baseline          0.0900247812  0.3291718452
## Total                                             0.0780792943 -0.2307727814
##                                                          PC15          PC16
## num_casos.x                                      -0.092101494  0.667350782
## num_casos_prueba_pcr                             -0.121611684 -0.650673761
## num_casos_prueba_test_ac                         -0.005028446  0.007775569
## num_casos_prueba_ag                              -0.002845807  0.005140801
## num_casos_prueba_elisa                            0.024084461 -0.008952581
## num_casos_prueba_desconocida                     -0.032932643  0.005804736
## num_casos.y                                       0.016372728 -0.002745862
## num_hosp                                          0.801653691 -0.007783786
## num_uci                                          -0.184854135  0.010580552
## num_def                                          -0.508148077  0.087912561
## retail_and_recreation_percent_change_from_baseline -0.045137621  0.195138926
## grocery_and_pharmacy_percent_change_from_baseline   0.002181701 -0.109298519
## parks_percent_change_from_baseline                0.066660222  0.065119772
## transit_stations_percent_change_from_baseline     0.076647486  0.013640473
## workplaces_percent_change_from_baseline           0.060173696  0.150949432
## residential_percent_change_from_baseline          0.141714061  0.214283914
## Total                                            -0.060525590  0.001351023
##                                                          PC17
## num_casos.x                                       0.240990076
## num_casos_prueba_pcr                             -0.268631818
## num_casos_prueba_test_ac                         -0.021750653
## num_casos_prueba_ag                              -0.011200484
## num_casos_prueba_elisa                           -0.011645113
## num_casos_prueba_desconocida                     -0.023795278
## num_casos.y                                      -0.004070413
## num_hosp                                         -0.023157112
## num_uci                                          -0.031579126
## num_def                                          -0.188994438
## retail_and_recreation_percent_change_from_baseline -0.477435985
## grocery_and_pharmacy_percent_change_from_baseline   0.258994881
## parks_percent_change_from_baseline               -0.204134909
## transit_stations_percent_change_from_baseline     0.023188610
## workplaces_percent_change_from_baseline          -0.420560743
## residential_percent_change_from_baseline         -0.563055806
## Total                                            -0.007482262
```

```r
if(!require(FactoMineR)){
    install.packages('FactoMineR', repos='http://cran.us.r-project.org')
    library(FactoMineR)}
if(!require(factoextra)){
```

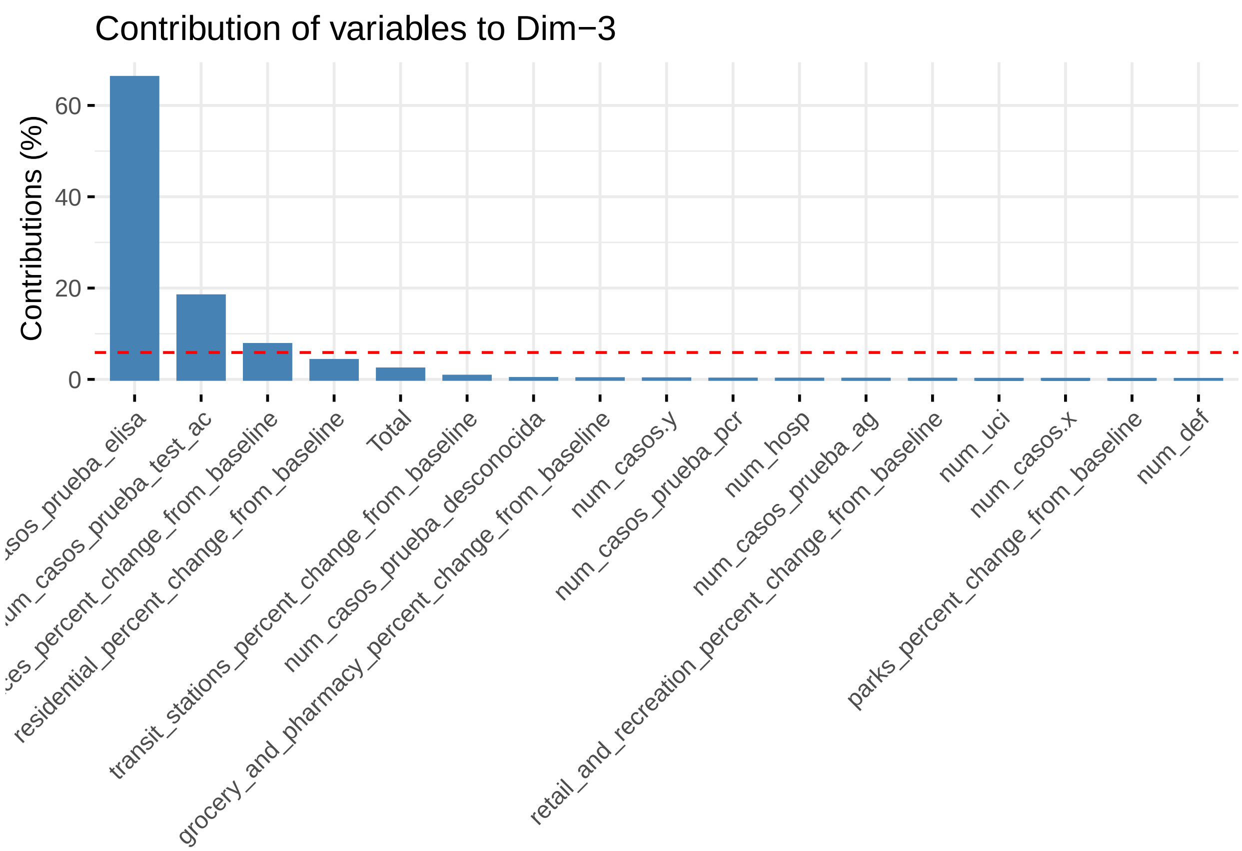
```r
    install.packages('factoextra', repos='http://cran.us.r-project.org')
    library(factoextra)}

# Var contribution for PC1-PC5
fviz_contrib(pca, choice = "var", axes = 1)
```



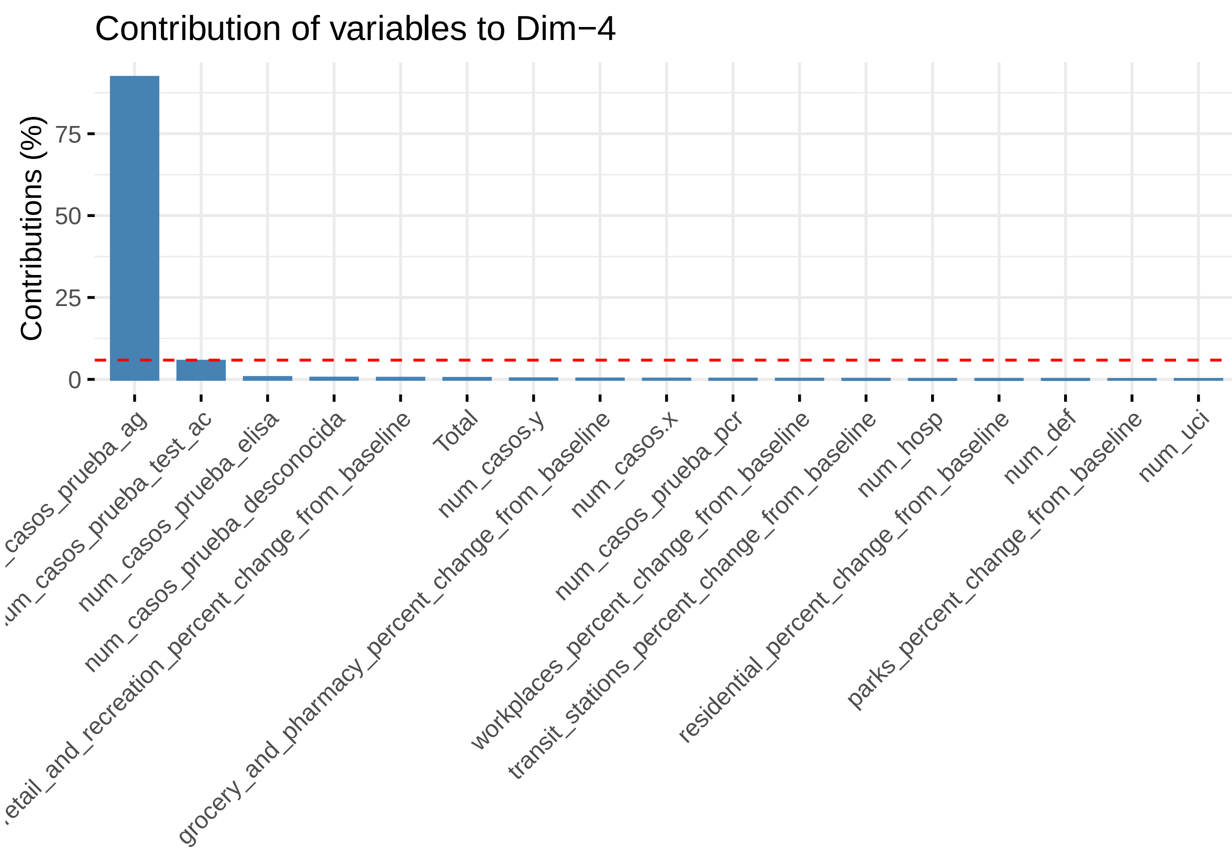

```r
fviz_contrib(pca, choice = "var", axes = 2)
```



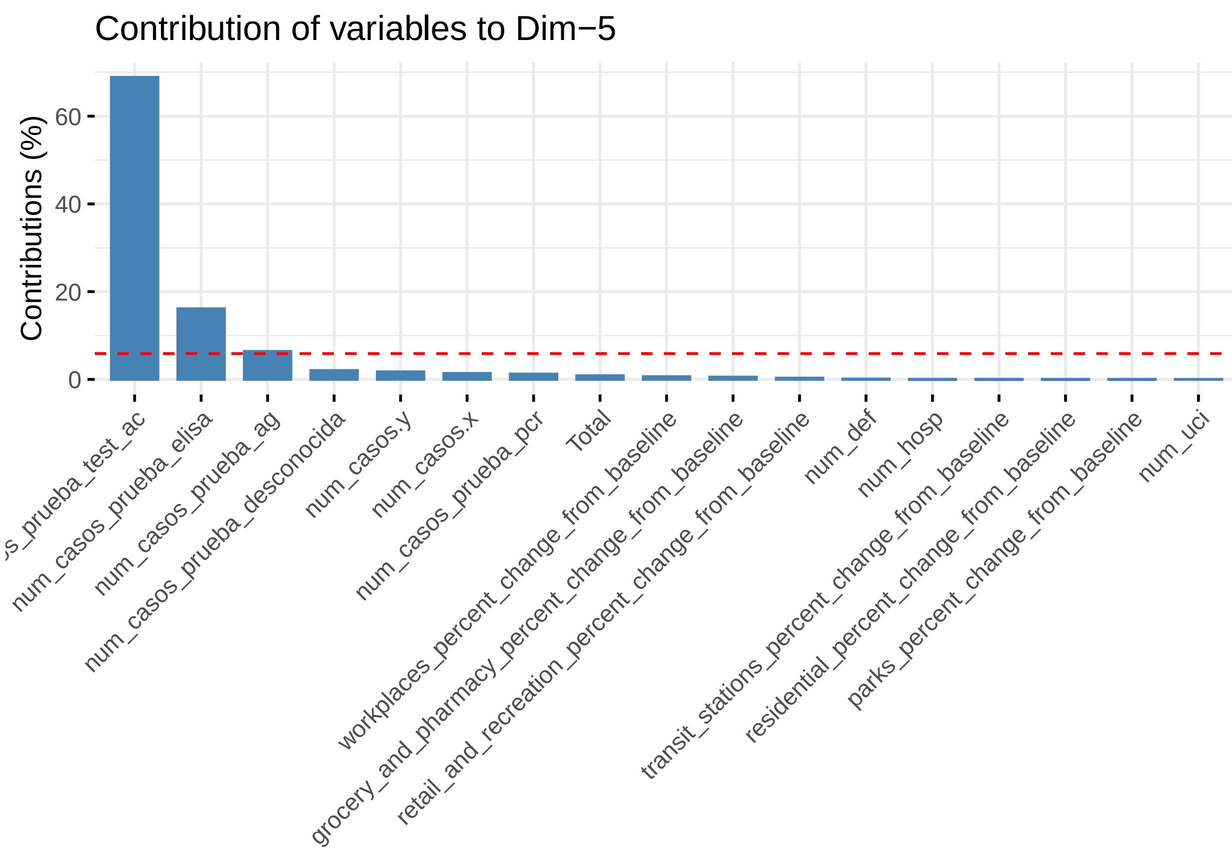

```r
fviz_contrib(pca, choice = "var", axes = 3)
```




```r
fviz_contrib(pca, choice = "var", axes = 4)
```




```
fviz_contrib(pca, choice = "var", axes = 5)
```



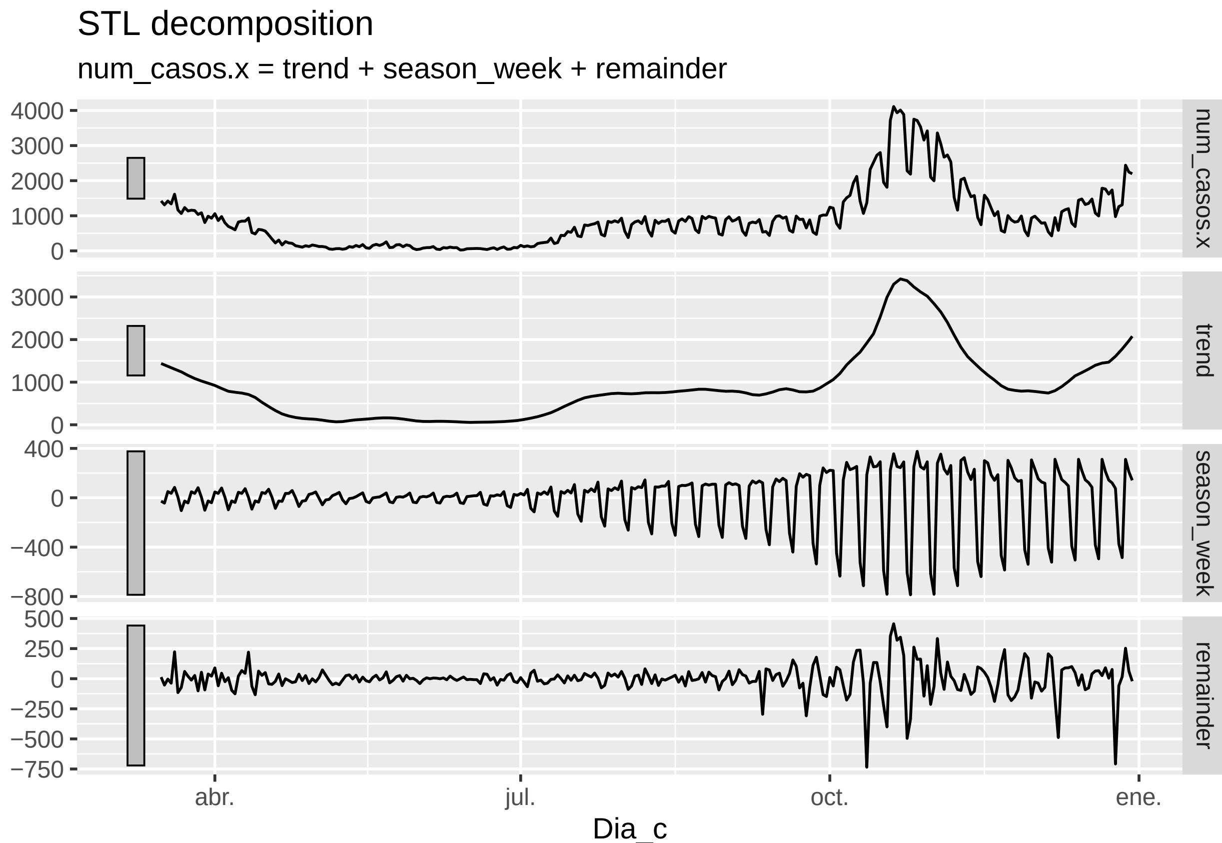
3 Seasonal and trend decomposition

3.1 STL (Seasonal and Trend decomposition using Loess)

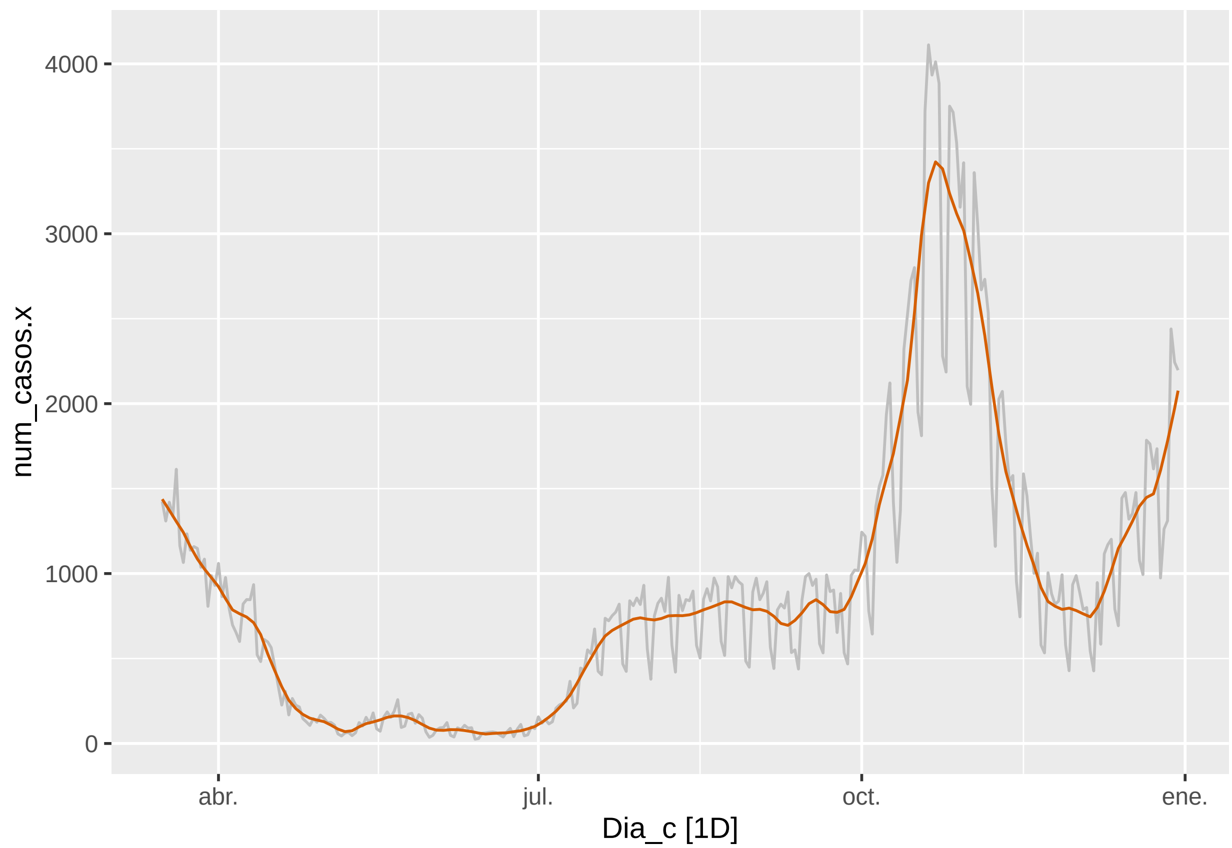
As stated by (Hyndman and Athanasopoulos 2021)… ”STL has several advantages over classical decomposition, and the SEATS and X-11 methods:

- Unlike SEATS and X-11, STL will handle any type of seasonality, not only monthly and quarterly data.
- The seasonal component is allowed to change over time, and the rate of change can be controlled by the user.
- The smoothness of the trend-cycle can also be controlled by the user.
- It can be robust to outliers (i.e., the user can specify a robust decomposition), so that occasional unusual observations will not affect the estimates of the trend-cycle and seasonal components. They will, however, affect the remainder component”…

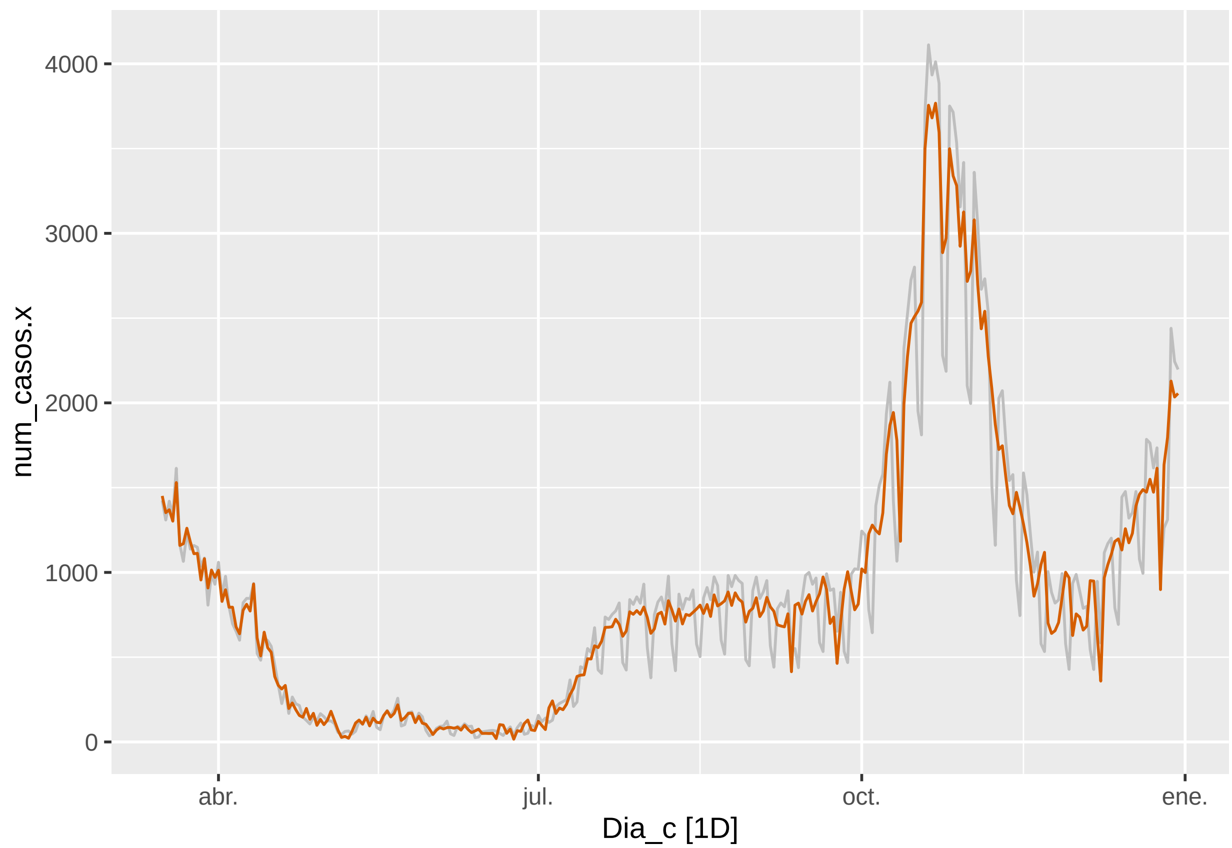
```
dcmp <- Total_ts %>%
  filter(sub_region_2 == "Barcelona") %>%
  model(STL(num_casos.x))

components(dcmp) %>% autoplot()
```



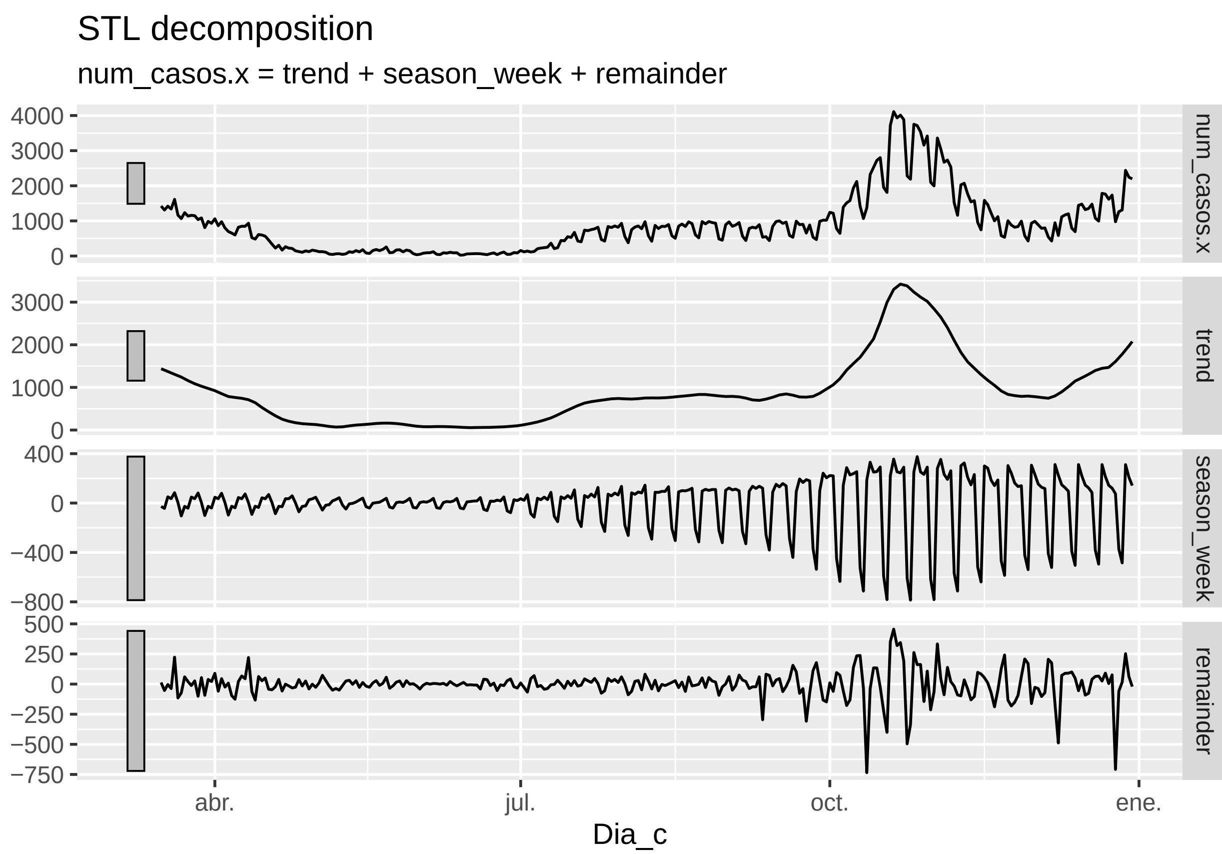

```r
components(dcmp) %>%
  as_tsibble() %>%
  autoplot(num_casos.x, color="gray") +
  geom_line(aes(y=trend), color = "#D55E00")
```



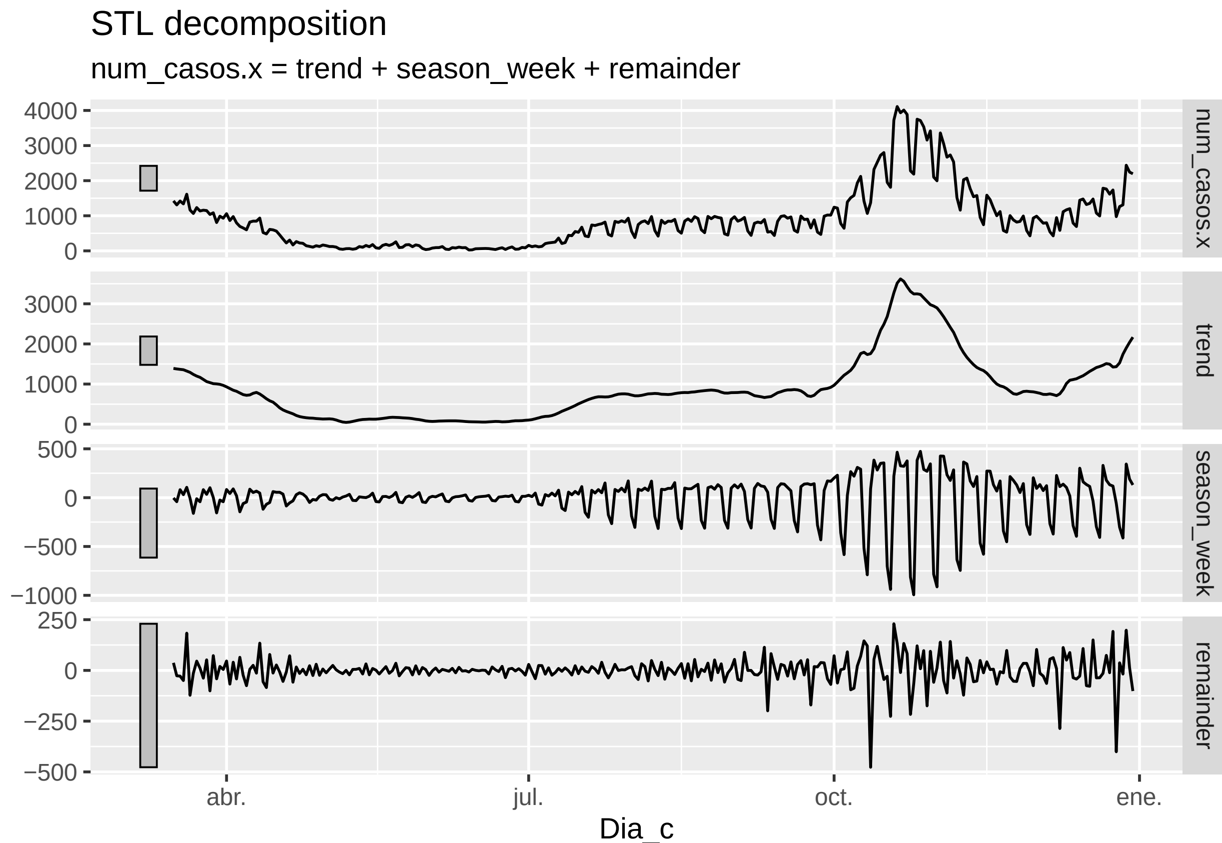

```
components(dcmp) %>%
  as_tsibble() %>%
  autoplot(num_casos.x, color="gray") +
  geom_line(aes(y=season_adjust), color = "#D55E00")
```




```r
############################
Total_ts %>%
  filter(sub_region_2 == "Barcelona") %>%
  model(STL(num_casos.x)) %>%
  components() %>%
  autoplot()
```




```r
Total_ts %>%
  filter(sub_region_2 == "Barcelona") %>%
  model(STL(num_casos.x ~ season(window = 7) +
              trend(window = 7))) %>%
  components() %>%
  autoplot()
```



3.2 Till here 06-Apr-2021

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