PEC 3: Desing and Implementation

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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.).

```
# At section - Data types and modifications
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(data.table)){
    install.packages('data.table', repos='http://cran.us.r-project.org')
    library(data.table)}
```

```
## Loading required package: data.table
```

```
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 dplyr::between()   masks data.table::between()
## x dplyr::filter()    masks stats::filter()
## x dplyr::first()     masks data.table::first()
## x dplyr::lag()       masks stats::lag()
## x dplyr::last()      masks data.table::last()
## x purrr::transpose() masks data.table::transpose()
```

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

```
## Loading required package: VIM
```

```
## Loading required package: colorspace
```

```
## Loading required package: grid
```

```
## VIM is ready to use.
##  Since version 4.0.0 the GUI is in its own package VIMGUI.
##
##           Please use the package to use the new (and old) GUI.
```

```
## Suggestions and bug-reports can be submitted at: https://github.com/alexkowa/VIM/issues
```

```
##
## Attaching package: 'VIM'
```

```
## The following object is masked from 'package:datasets':
##
##     sleep
```

```r
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
```

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

```
## Loading required package: xts
```

```
## Loading required package: zoo
```

```
##
## Attaching package: 'zoo'
```

```
## The following object is masked from 'package:imputeTS':
##
##     na.locf
```

```
## The following objects are masked from 'package:base':
##
##     as.Date, as.Date.numeric
```

```
##
## Attaching package: 'xts'
```

```
## The following objects are masked from 'package:dplyr':
##
##     first, last
```

```
## The following objects are masked from 'package:data.table':
##
```

```
##     first, last
```

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

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

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

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

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

```
## v lubridate   1.7.8     v feasts      0.2.1
## v tsibble     1.0.0     v fable       0.3.0
## v tsibbledata 0.3.0
```

```
## -- Conflicts ------------------------------------------------------------------------------------
## x dplyr::between()     masks data.table::between()
## x lubridate::date()    masks base::date()
## x dplyr::filter()      masks stats::filter()
## x xts::first()         masks dplyr::first(), data.table::first()
## x lubridate::hour()    masks data.table::hour()
## x tsibble::index()     masks zoo::index()
## x tsibble::intersect() masks base::intersect()
## x tsibble::interval()  masks lubridate::interval()
## x lubridate::isoweek() masks data.table::isoweek()
## x tsibble::key()       masks data.table::key()
## x dplyr::lag()         masks stats::lag()
## x xts::last()          masks dplyr::last(), data.table::last()
## x lubridate::mday()    masks data.table::mday()
## x lubridate::minute()  masks data.table::minute()
## x lubridate::month()   masks data.table::month()
## x lubridate::quarter() masks data.table::quarter()
## x lubridate::second()  masks data.table::second()
## x tsibble::setdiff()   masks base::setdiff()
## x purrr::transpose()   masks data.table::transpose()
## x tsibble::union()     masks base::union()
## x lubridate::wday()    masks data.table::wday()
## x lubridate::week()    masks data.table::week()
## x lubridate::yday()    masks data.table::yday()
## x lubridate::year()    masks data.table::year()
```

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

```
## Loading required package: corrplot
```

```
## corrplot 0.84 loaded
```

```
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:fabletools':
##
##     MAE, MAPE, MSE, RMSE
## The following object is masked from 'package:data.table':
##
##     %like%
```

```
# At sections - ARIMA
#if(!require(forecast)){
#    install.packages('forecast', repos='http://cran.us.r-project.org')
#    library(forecast)}
#if(!require(tseries)){
#    install.packages('tseries', repos='http://cran.us.r-project.org')
#    library(tseries)}
#if(!require(astsa)){
#    install.packages('astsa', repos='http://cran.us.r-project.org')
#    library(astsa)}

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

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

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 (na and impute)

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
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
```

```
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
```

```
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 and dates missing generation

Due to the nature of this dataset we have to transpose it in order to analyse the missing values by province and impute them. There are some dates that are not provided by EM3 study.

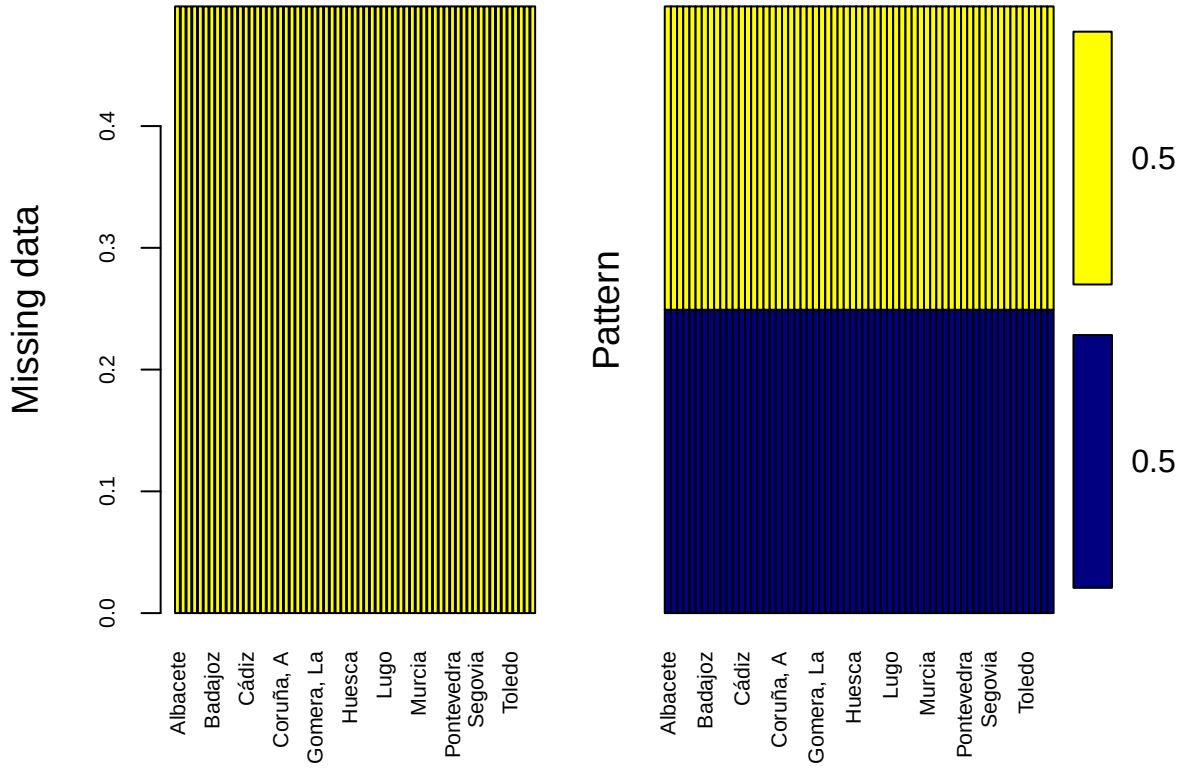
```
#library(data.table)
# Transpose dataframe
EM3_t<-dcast(EM3, Periodo~Zonas.de.movilidad)#, fill=NA)

#library(tidyverse)
# Create dates missing (for time series).
# Note: Acccording INE some "dates" are not provided.
EM3_t<-EM3_t %>%
  complete(Periodo = seq.Date(min(Periodo), max(Periodo), by="day"))

# Filter the interest period according INE EM3 study
# "2019-11-18" is the reference date EM3 study (for us it is excluded)
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).

```
#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"))
```

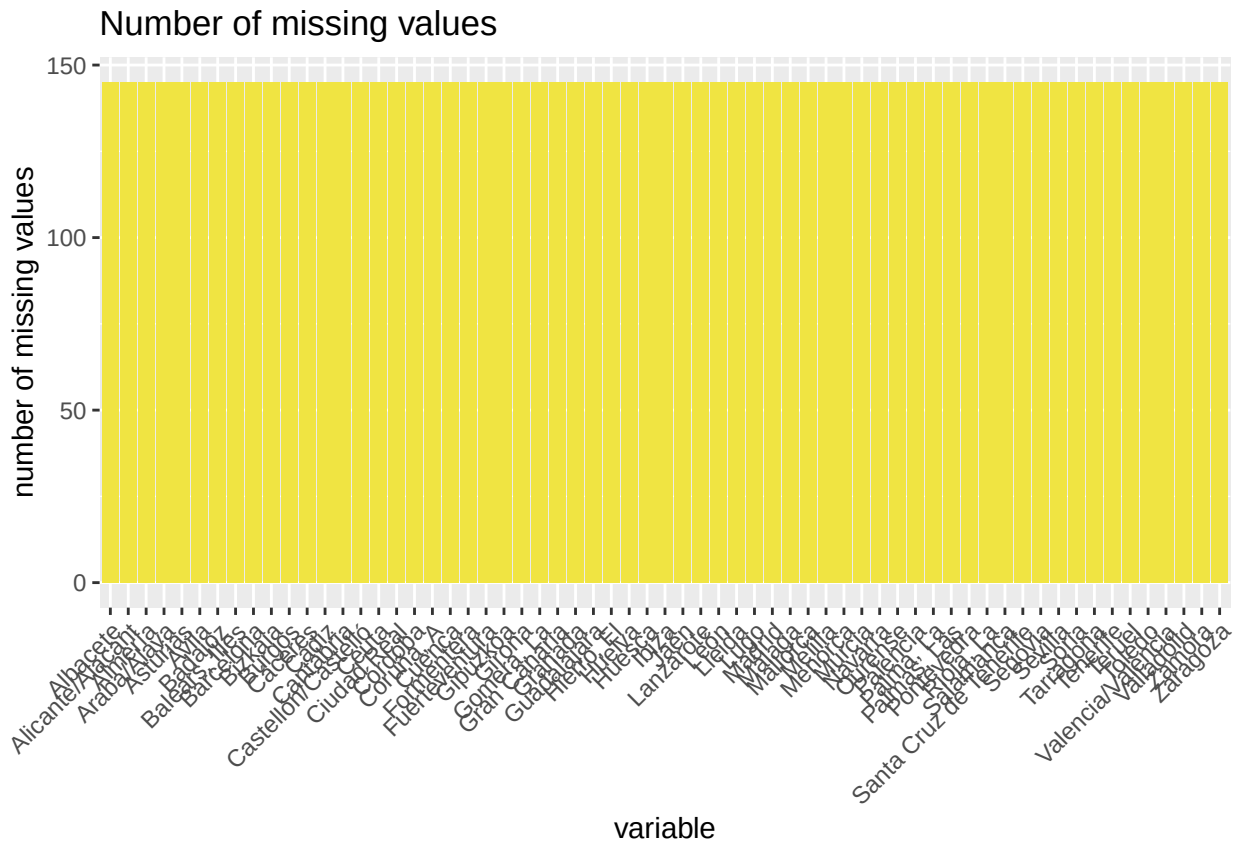



```
##
##  Variables sorted by number of missings:
##                Variable     Count
##                Albacete 0.4982818
##       Alicante/Alacant 0.4982818
##                Almería 0.4982818
##            Araba/Álava 0.4982818
##                Asturias 0.4982818
##                   Ávila 0.4982818
##                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) %>%
```

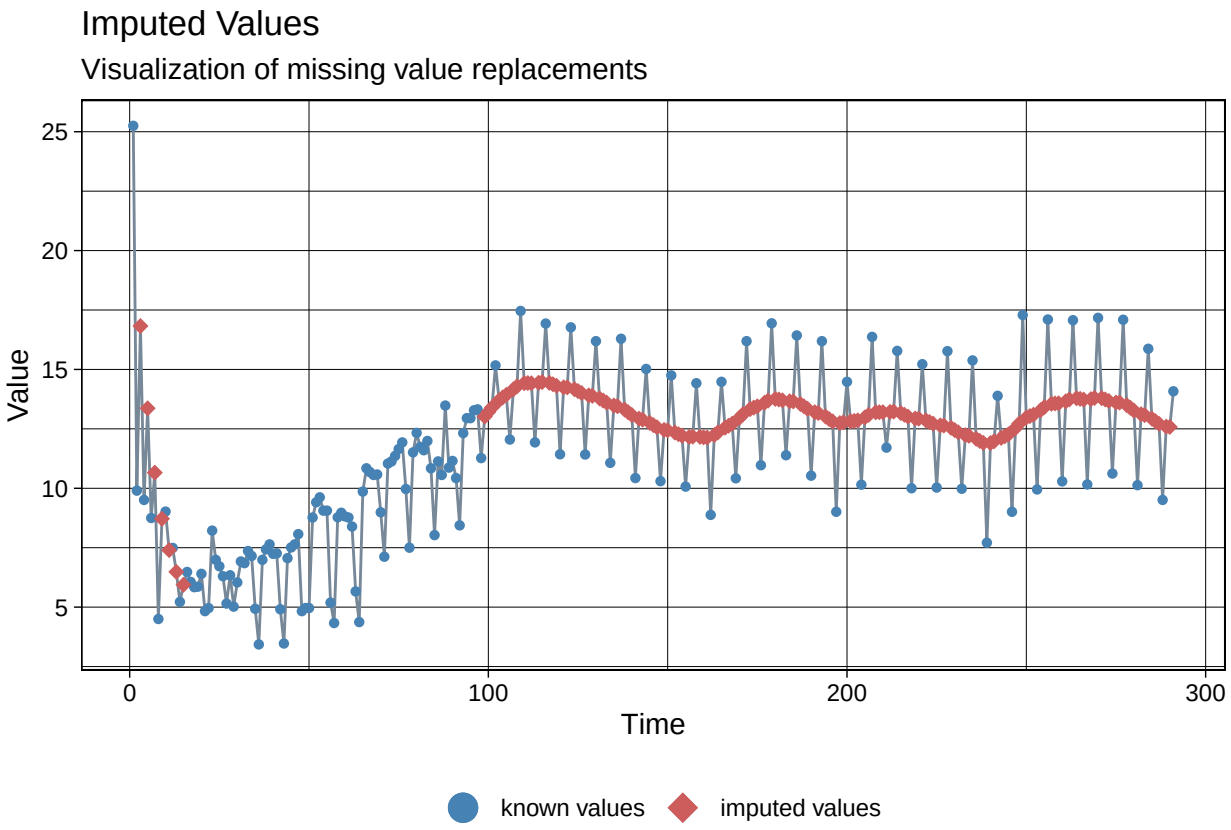
```
    summarise(num.missing = n()) %>%
    filter(is.missing==T) %>%
    select(-is.missing) %>%
    arrange(desc(num.missing)) %>%
    ggplot() +
    geom_bar(aes(x=key, y=num.missing), stat = 'identity',fill="#F0E442") +
    labs(x='variable', y="number of missing values",
         title='Number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



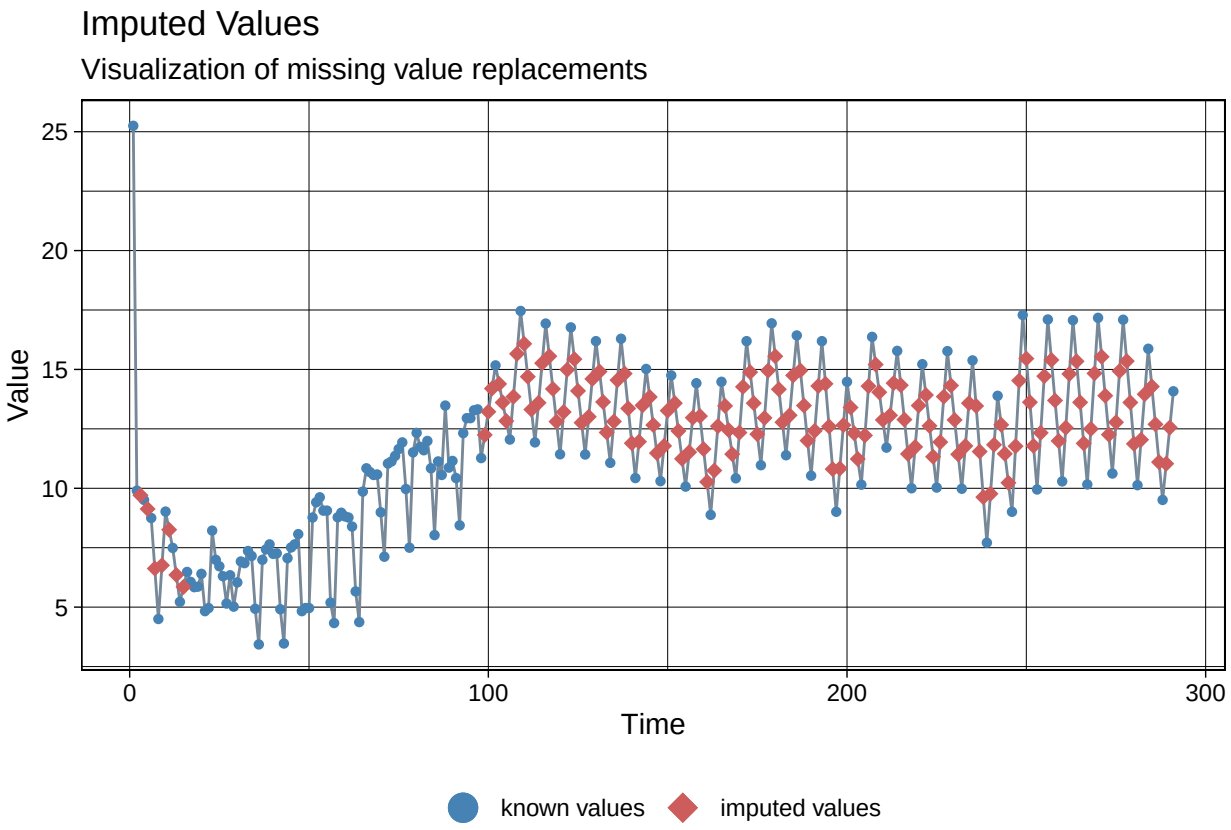
We impute the missing values following the principales stated for imputeTS. Thanks to this approach we almost double the amount of data for analysis by province (It was selected "na_seadec" due to it covers seasonality aspects -weekdays/weekends in our case-).

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

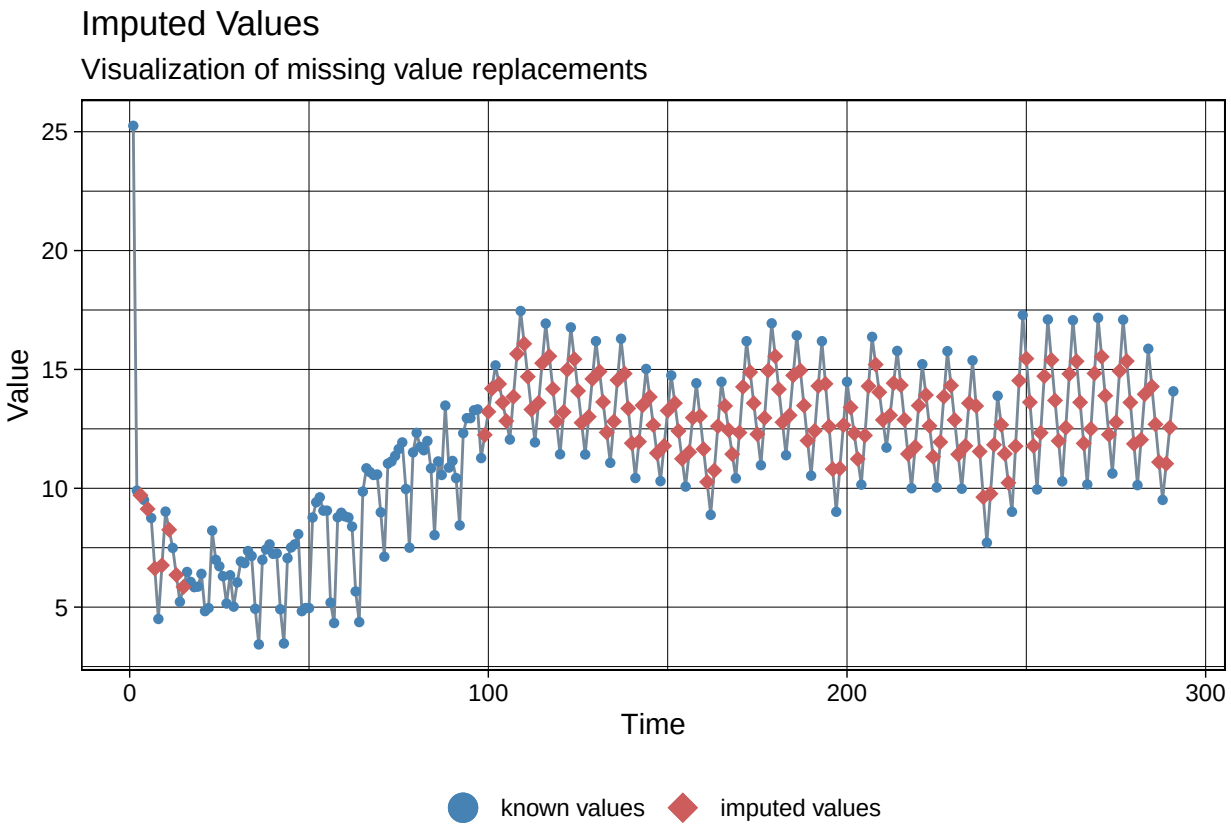
```
# Used to convert dataframe to ts object
#library(xts)
EM3_t_ts<-xts(EM3_t[-1],EM3_t$Periodo)

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



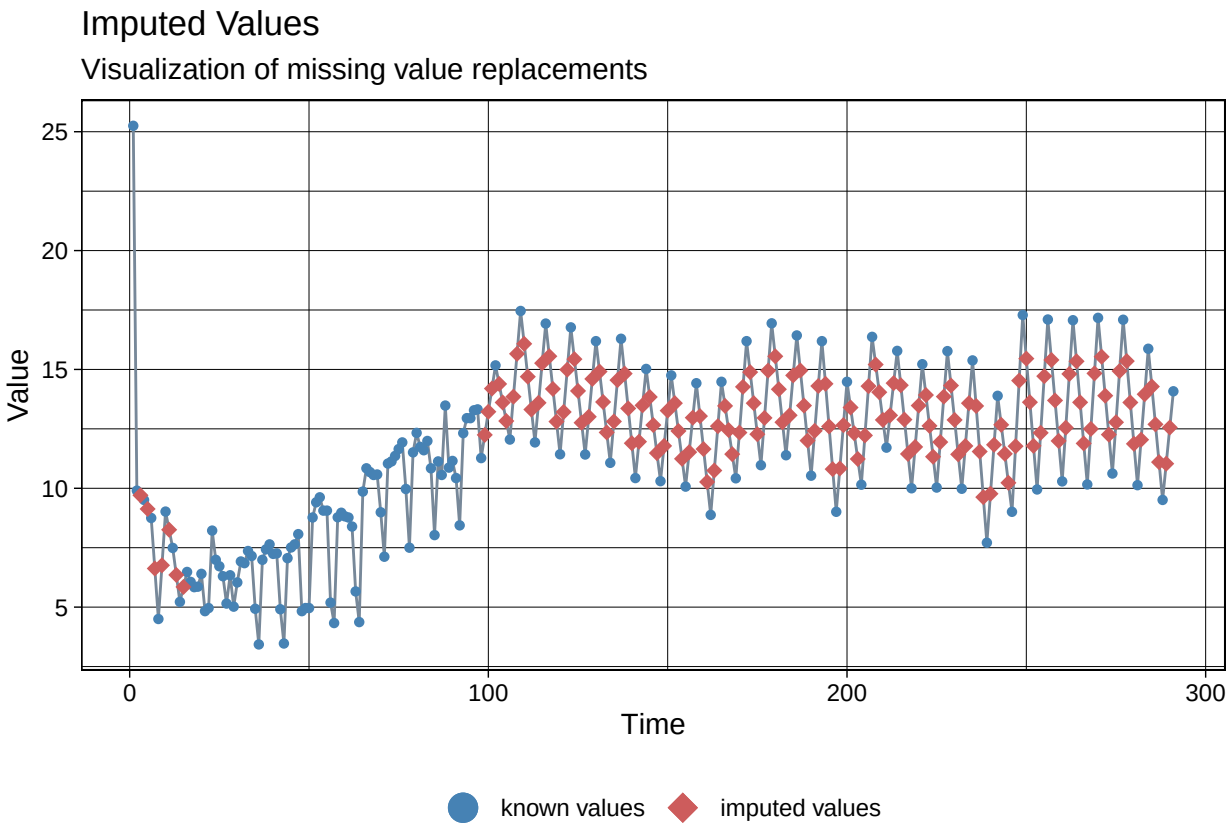

```
imp2 <- na_seadec(EM3_t_ts[,1])
ggplot_na_imputations(EM3_t_ts[,1], imp2)
```



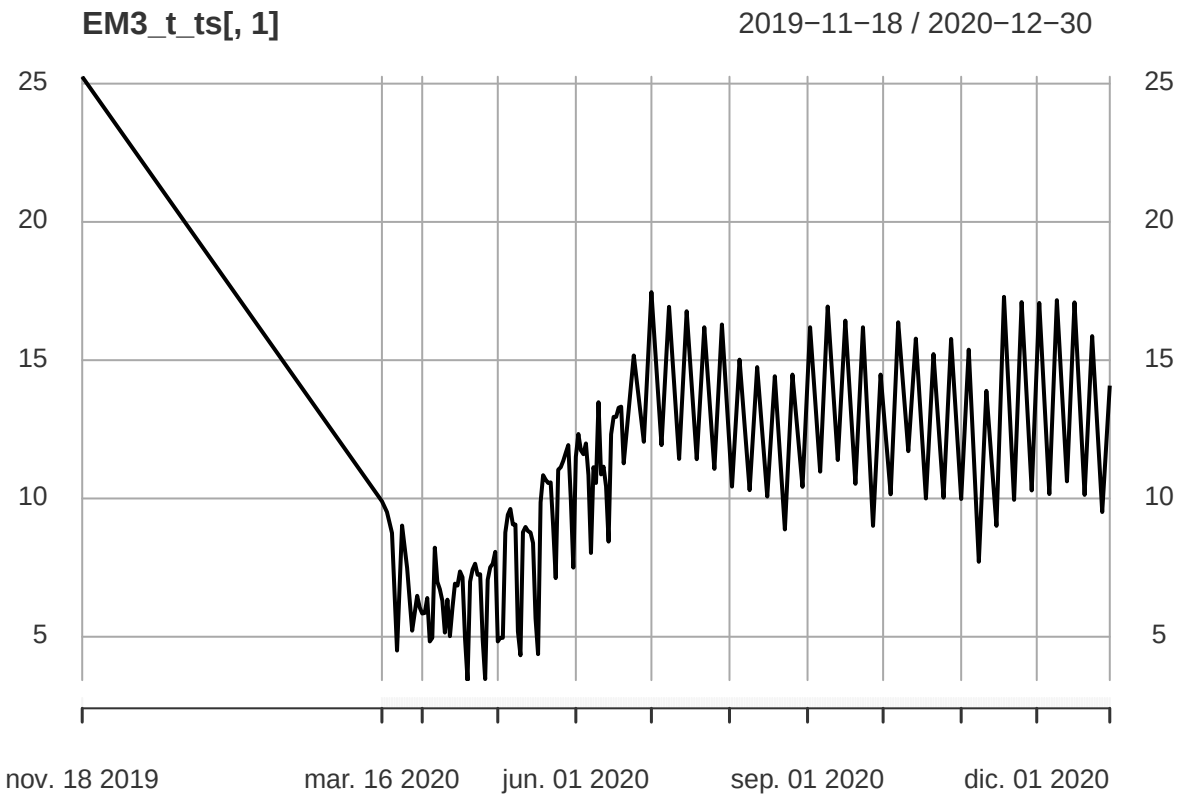

```
imp3 <- na_seasplit(EM3_t_ts[,1])
ggplot_na_imputations(EM3_t_ts[,1], imp3)
```



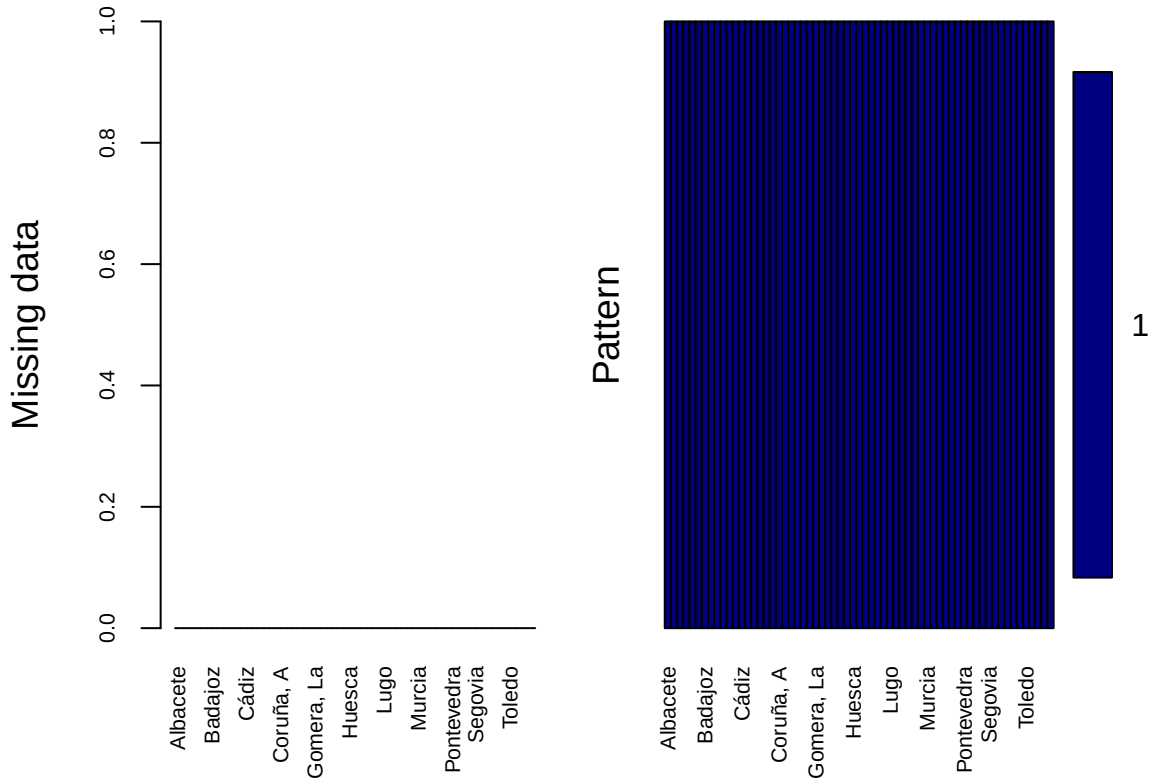

```
imp4 <- na_interpolation(EM3_t_ts[,1])
ggplot_na_imputations(EM3_t_ts[,1], imp4)
```




```
# 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
#library(tsbox)
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))
```


```
head(str(EM3_t,vec.len=2))
```

```
## 'data.frame':    291 obs. of  64 variables:
##  $ Periodo               : Date, format: "2019-11-18" "2020-03-16" ...
##  $ Albacete              : num  25.2 9.9 ...
##  $ Alicante/Alacant      : num  28.1 14.4 ...
##  $ Almería               : num  24.4 11 ...
##  $ Araba/Álava           : num  31.9 15.9 ...
##  $ Asturias              : num  29.9 13.1 ...
##  $ Ávila                 : num  26.62 9.44 ...
##  $ Badajoz               : num  19.5 10.7 ...
##  $ Balears, Illes        : num  25.9 12.3 ...
##  $ Barcelona             : num  34.9 14.6 ...
##  $ Bizkaia               : num  33.9 17.9 ...
##  $ Burgos                : num  24.9 11.3 ...
##  $ Cáceres               : num  21.37 9.08 ...
##  $ Cádiz                 : num  24.5 10.7 ...
##  $ Cantabria             : num  31.5 14.5 ...
##  $ Castellón/Castelló    : num  26.9 11.7 ...
##  $ Ceuta                 : num  31.9 12.3 ...
##  $ Ciudad Real           : num  17.07 8.29 ...
##  $ Córdoba               : num  22.4 11.9 ...
##  $ Coruña, A             : num  26.8 15.8 ...
##  $ Cuenca                : num  20.27 8.54 ...
##  $ Formentera            : num  12.98 3.08 ...
##  $ Fuerteventura         : num  11.9 5.76 5.31 4.86 4.62 ...
```

```
##  $ Gipuzkoa              : num  31.3 14.1 ...
##  $ Girona                : num  25.6 10.9 ...
##  $ Gomera, La            : num  11.43 4.26 ...
##  $ Gran Canaria          : num  31.4 16 ...
##  $ Granada               : num  24.2 11.4 ...
##  $ Guadalajara           : num  31.3 12.8 ...
##  $ Hierro, El            : num  14.82 5.75 ...
##  $ Huelva                : num  21.8 11.4 ...
##  $ Huesca                : num  25.5 10.3 ...
##  $ Ibiza                 : num  20.3 10.1 ...
##  $ Jaén                  : num  18.71 8.81 ...
##  $ Lanzarote             : num  25.1 13.6 ...
##  $ León                  : num  29.8 13.2 ...
##  $ Lleida                : num  28.4 11.9 ...
##  $ Lugo                  : num  23.6 12.4 ...
##  $ Madrid                : num  36.7 13.9 ...
##  $ Málaga                : num  23.7 11.4 ...
##  $ Mallorca              : num  28.1 13.3 ...
##  $ Melilla               : num  35 12.5 ...
##  $ Menorca               : num  16.26 7.21 ...
##  $ Murcia                : num  24.6 12.4 ...
##  $ Navarra               : num  30.6 13.7 ...
##  $ Ourense               : num  27.5 15.6 ...
##  $ Palencia              : num  31.1 12.9 ...
##  $ Palma, La             : num  24.6 13.1 ...
##  $ Palmas, Las           : num  28.5 14.6 ...
##  $ Pontevedra            : num  26.2 17.1 ...
##  $ Rioja, La             : num  28 12.1 ...
##  $ Salamanca             : num  28.1 12.9 ...
##  $ Santa Cruz de Tenerife: num  28 13.7 ...
##  $ Segovia               : num  29 12.6 ...
##  $ Sevilla               : num  25.9 12.3 ...
##  $ Soria                 : num  17.67 7.85 ...
##  $ Tarragona             : num  28.4 11.4 ...
##  $ Tenerife              : num  28.9 14.1 ...
##  $ Teruel                : num  16.35 6.77 ...
##  $ Toledo                : num  25.7 12.3 ...
##  $ Valencia/València     : num  31 15.3 ...
##  $ Valladolid            : num  29 14.3 ...
##  $ Zamora                : num  26 11.5 ...
##  $ Zaragoza              : num  32.3 14.8 ...
```

```
## NULL
```

```
summary(EM3_t)
```

```
##     Periodo              Albacete      Alicante/Alacant    Almería
##  Min.   :2019-11-18   Min.   : 3.430   Min.   : 5.72    Min.   : 4.10
##  1st Qu.:2020-05-26   1st Qu.: 9.738   1st Qu.:14.42    1st Qu.:11.31
##  Median :2020-08-07   Median :11.960   Median :17.19    Median :13.84
##  Mean   :2020-08-06   Mean   :11.592   Mean   :16.16    Mean   :13.19
##  3rd Qu.:2020-10-18   3rd Qu.:13.873   3rd Qu.:18.70    3rd Qu.:15.56
##  Max.   :2020-12-30   Max.   :25.250   Max.   :28.12    Max.   :24.35
##   Araba/Álava       Asturias         Ávila          Badajoz
##  Min.   : 6.30   Min.   : 5.24   Min.   : 4.51   Min.   : 4.90
```

```
##  1st Qu.:14.48   1st Qu.:11.93   1st Qu.:10.10   1st Qu.:11.29
##  Median :18.09   Median :16.28   Median :12.71   Median :13.10
##  Mean   :17.52   Mean   :15.65   Mean   :11.93   Mean   :12.74
##  3rd Qu.:21.11   3rd Qu.:19.41   3rd Qu.:14.26   3rd Qu.:14.79
##  Max.   :31.92   Max.   :29.94   Max.   :26.62   Max.   :19.46
##  Balears, Illes    Barcelona        Bizkaia          Burgos
##  Min.   : 3.92   Min.   : 6.42   Min.   : 7.53   Min.   : 3.97
##  1st Qu.:13.09   1st Qu.:13.95   1st Qu.:15.41   1st Qu.:10.74
##  Median :16.14   Median :17.51   Median :19.70   Median :13.06
##  Mean   :15.29   Mean   :17.05   Mean   :19.21   Mean   :12.68
##  3rd Qu.:18.46   3rd Qu.:20.25   3rd Qu.:23.06   3rd Qu.:15.26
##  Max.   :25.95   Max.   :34.90   Max.   :33.93   Max.   :24.88
##     Cáceres          Cádiz         Cantabria     Castellón/Castelló
##  Min.   : 4.02   Min.   : 5.42   Min.   : 5.84   Min.   : 4.95
##  1st Qu.:10.34   1st Qu.:12.59   1st Qu.:13.40   1st Qu.:12.59
##  Median :12.39   Median :15.98   Median :17.57   Median :15.00
##  Mean   :11.81   Mean   :14.92   Mean   :16.93   Mean   :14.43
##  3rd Qu.:13.84   3rd Qu.:17.82   3rd Qu.:20.63   3rd Qu.:16.76
##  Max.   :21.37   Max.   :24.46   Max.   :31.50   Max.   :26.93
##      Ceuta        Ciudad Real        Córdoba        Coruña, A
##  Min.   : 4.87   Min.   : 3.080   Min.   : 5.68   Min.   : 6.02
##  1st Qu.:11.90   1st Qu.: 8.291   1st Qu.:11.49   1st Qu.:12.73
##  Median :13.93   Median :10.050   Median :13.69   Median :15.84
##  Mean   :13.34   Mean   : 9.597   Mean   :13.41   Mean   :15.63
##  3rd Qu.:15.34   3rd Qu.:11.453   3rd Qu.:15.67   3rd Qu.:18.96
##  Max.   :31.88   Max.   :17.070   Max.   :22.38   Max.   :26.84
##      Cuenca         Formentera     Fuerteventura       Gipuzkoa
##  Min.   : 3.010   Min.   : 0.830   Min.   : 1.140   Min.   : 4.71
##  1st Qu.: 9.298   1st Qu.: 2.520   1st Qu.: 5.745   1st Qu.:11.95
##  Median :11.620   Median : 3.562   Median : 7.490   Median :15.49
##  Mean   :10.843   Mean   : 4.559   Mean   : 6.954   Mean   :14.94
##  3rd Qu.:12.892   3rd Qu.: 7.320   3rd Qu.: 8.503   3rd Qu.:18.27
##  Max.   :20.270   Max.   :12.980   Max.   :11.900   Max.   :31.31
##      Girona        Gomera, La      Gran Canaria      Granada
##  Min.   : 4.16   Min.   : 1.340   Min.   : 5.70   Min.   : 5.71
##  1st Qu.:10.24   1st Qu.: 4.860   1st Qu.:15.07   1st Qu.:11.38
##  Median :14.60   Median : 6.635   Median :18.21   Median :14.72
##  Mean   :13.45   Mean   : 6.111   Mean   :17.54   Mean   :14.07
##  3rd Qu.:16.65   3rd Qu.: 7.416   3rd Qu.:20.93   3rd Qu.:16.66
##  Max.   :25.56   Max.   :11.430   Max.   :31.44   Max.   :24.25
##   Guadalajara      Hierro, El        Huelva          Huesca
##  Min.   : 4.89   Min.   : 1.560   Min.   : 5.51   Min.   : 4.24
##  1st Qu.:12.19   1st Qu.: 6.645   1st Qu.:10.94   1st Qu.:11.12
##  Median :14.93   Median : 8.470   Median :13.65   Median :13.77
##  Mean   :14.52   Mean   : 7.933   Mean   :13.23   Mean   :12.96
##  3rd Qu.:17.29   3rd Qu.: 9.710   3rd Qu.:15.62   3rd Qu.:15.14
##  Max.   :31.33   Max.   :14.820   Max.   :21.79   Max.   :25.48
##      Ibiza             Jaén         Lanzarote          León
##  Min.   : 2.960   Min.   : 4.17   Min.   : 4.73   Min.   : 5.56
##  1st Qu.: 9.411   1st Qu.: 9.43   1st Qu.:12.87   1st Qu.:12.58
##  Median :11.550   Median :11.77   Median :14.89   Median :15.65
##  Mean   :12.017   Mean   :11.24   Mean   :14.22   Mean   :14.92
##  3rd Qu.:15.325   3rd Qu.:13.22   3rd Qu.:16.58   3rd Qu.:17.50
##  Max.   :20.650   Max.   :18.71   Max.   :25.07   Max.   :29.80
```

```
##      Lleida           Lugo           Madrid          Málaga
##  Min.   : 5.16   Min.   : 4.88   Min.   : 6.03   Min.   : 4.56
##  1st Qu.:11.73   1st Qu.:10.94   1st Qu.:13.21   1st Qu.:12.25
##  Median :14.89   Median :13.64   Median :16.58   Median :15.41
##  Mean   :14.25   Mean   :13.11   Mean   :16.19   Mean   :14.51
##  3rd Qu.:16.81   3rd Qu.:15.65   3rd Qu.:19.51   3rd Qu.:17.51
##  Max.   :28.38   Max.   :23.60   Max.   :36.70   Max.   :23.71
##     Mallorca        Melilla         Menorca          Murcia
##  Min.   : 4.36   Min.   : 6.48   Min.   : 1.590   Min.   : 5.13
##  1st Qu.:14.31   1st Qu.:13.60   1st Qu.: 8.134   1st Qu.:11.81
##  Median :17.52   Median :15.85   Median :10.110   Median :14.19
##  Mean   :16.44   Mean   :15.37   Mean   :10.846   Mean   :13.97
##  3rd Qu.:19.72   3rd Qu.:17.39   3rd Qu.:15.880   3rd Qu.:16.45
##  Max.   :28.06   Max.   :35.05   Max.   :19.490   Max.   :24.65
##     Navarra         Ourense         Palencia       Palma, La
##  Min.   : 5.33   Min.   : 6.43   Min.   : 5.05   Min.   : 5.28
##  1st Qu.:13.45   1st Qu.:12.87   1st Qu.:12.18   1st Qu.:12.96
##  Median :16.51   Median :15.62   Median :14.78   Median :15.39
##  Mean   :15.89   Mean   :15.35   Mean   :14.40   Mean   :14.79
##  3rd Qu.:18.87   3rd Qu.:18.06   3rd Qu.:16.94   3rd Qu.:17.03
##  Max.   :30.61   Max.   :27.48   Max.   :31.07   Max.   :24.63
##   Palmas, Las      Pontevedra      Rioja, La       Salamanca
##  Min.   : 5.11   Min.   : 6.15   Min.   : 4.74   Min.   : 6.02
##  1st Qu.:13.98   1st Qu.:13.41   1st Qu.:12.51   1st Qu.:12.61
##  Median :16.65   Median :17.23   Median :15.78   Median :15.07
##  Mean   :15.98   Mean   :16.63   Mean   :15.01   Mean   :14.54
##  3rd Qu.:18.99   3rd Qu.:20.39   3rd Qu.:17.73   3rd Qu.:17.00
##  Max.   :28.53   Max.   :26.22   Max.   :28.00   Max.   :28.12
##  Santa Cruz de Tenerife    Segovia         Sevilla          Soria
##  Min.   : 5.20          Min.   : 4.96   Min.   : 5.44   Min.   : 3.03
##  1st Qu.:13.71          1st Qu.:11.83   1st Qu.:12.13   1st Qu.: 8.78
##  Median :16.54          Median :14.48   Median :14.96   Median :10.95
##  Mean   :15.99          Mean   :13.80   Mean   :14.73   Mean   :10.19
##  3rd Qu.:18.98          3rd Qu.:16.27   3rd Qu.:17.70   3rd Qu.:12.20
##  Max.   :28.02          Max.   :29.04   Max.   :25.95   Max.   :17.67
##    Tarragona        Tenerife         Teruel           Toledo
##  Min.   : 4.93   Min.   : 5.32   Min.   : 1.950   Min.   : 4.15
##  1st Qu.:10.64   1st Qu.:14.13   1st Qu.: 6.582   1st Qu.:11.00
##  Median :14.95   Median :17.02   Median : 8.680   Median :13.52
##  Mean   :13.90   Mean   :16.42   Mean   : 8.210   Mean   :13.01
##  3rd Qu.:16.90   3rd Qu.:19.58   3rd Qu.: 9.999   3rd Qu.:15.57
##  Max.   :28.38   Max.   :28.87   Max.   :16.350   Max.   :25.70
##  Valencia/València   Valladolid        Zamora         Zaragoza
##  Min.   : 6.17     Min.   : 5.55   Min.   : 4.82   Min.   : 5.80
##  1st Qu.:15.39     1st Qu.:12.60   1st Qu.:10.79   1st Qu.:13.44
##  Median :18.16     Median :15.95   Median :13.09   Median :16.45
##  Mean   :17.53     Mean   :15.71   Mean   :12.79   Mean   :16.37
##  3rd Qu.:20.38     3rd Qu.:19.10   3rd Qu.:14.95   3rd Qu.:19.37
##  Max.   :30.97     Max.   :28.99   Max.   :25.99   Max.   :32.26
```

```
#library(DataExplorer)
#plot_histogram(EM3_t)
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 mobility from autonomus-communities and provinces.

```
#Source Google
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
```

```
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
```

```
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
```

```
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.

```
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
```

```
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.

```
# Modification 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"

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"

# Modification 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=="Alicante"]<-"Alicante/Alacant"
Google$sub_region_2[Google$sub_region_2=="Biscay"]<-"Bizkaia"
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=="CastellÃ³n"]<-"Castellón/Castelló"
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=="MÃ¡laga"]<-"Málaga"
Google$sub_region_2[Google$sub_region_2=="Province of Ourense"]<-"Ourense"
Google$sub_region_2[Google$sub_region_2=="Seville"]<-"Sevilla"
Google$sub_region_2[Google$sub_region_2=="Valencia"]<-"Valencia/València"
Google$sub_region_2 <- with(Google, ifelse(grepl("^Almer", sub_region_2),
                                           "Almería", sub_region_2))
# Table check
table(Google$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
```

```
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.
- E - We changed from integer to numeric, integer columns.

```
# 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)

# We pass from integer to numeric
Google$retail_and_recreation_percent_change_from_baseline <-
  as.numeric(Google$retail_and_recreation_percent_change_from_baseline)
Google$grocery_and_pharmacy_percent_change_from_baseline <-as.numeric(Google$grocery_and_pharmacy_percen
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_change
Google$workplaces_percent_change_from_baseline <-as.numeric(Google$workplaces_percent_change_from_baseli
Google$residential_percent_change_from_baseline <-as.numeric(Google$residential_percent_change_from_base

# Check table
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
```

```
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
```

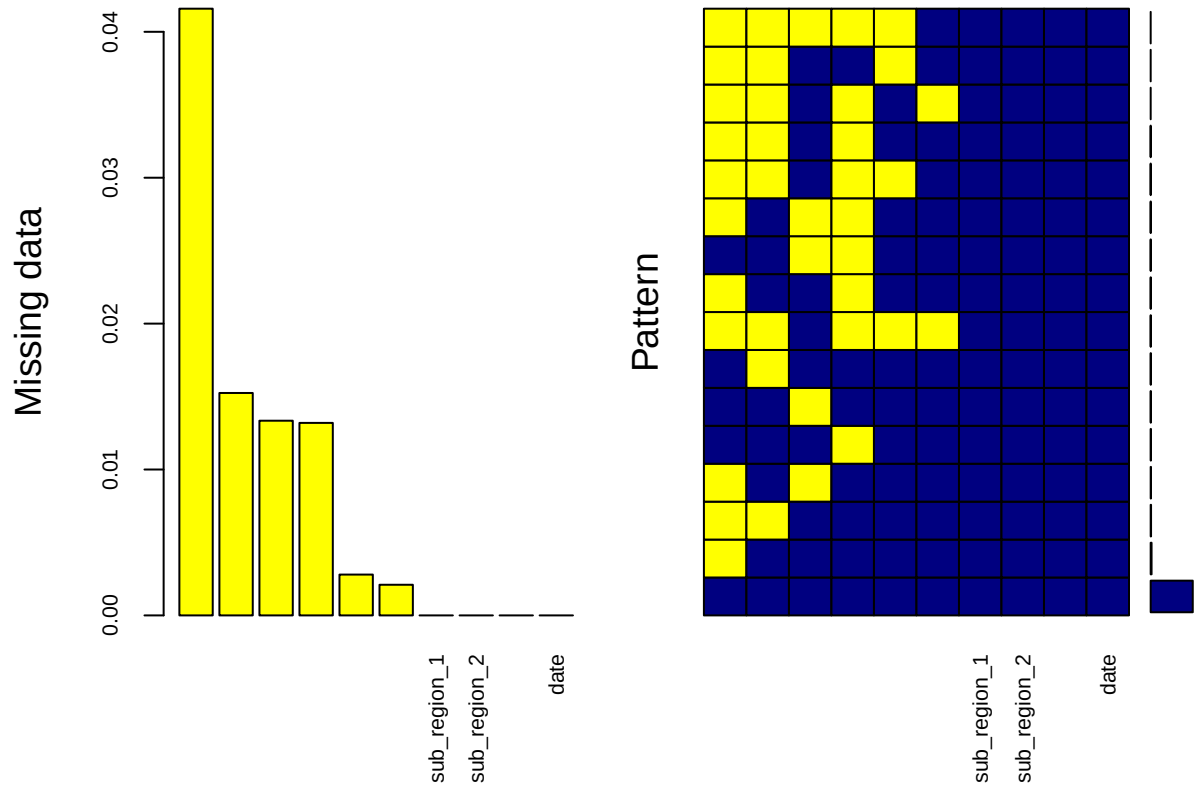
```
## 385 385 385 385 385 385 385 385 385 385 385 385
```

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

2.1.8 Google review missing values & impute

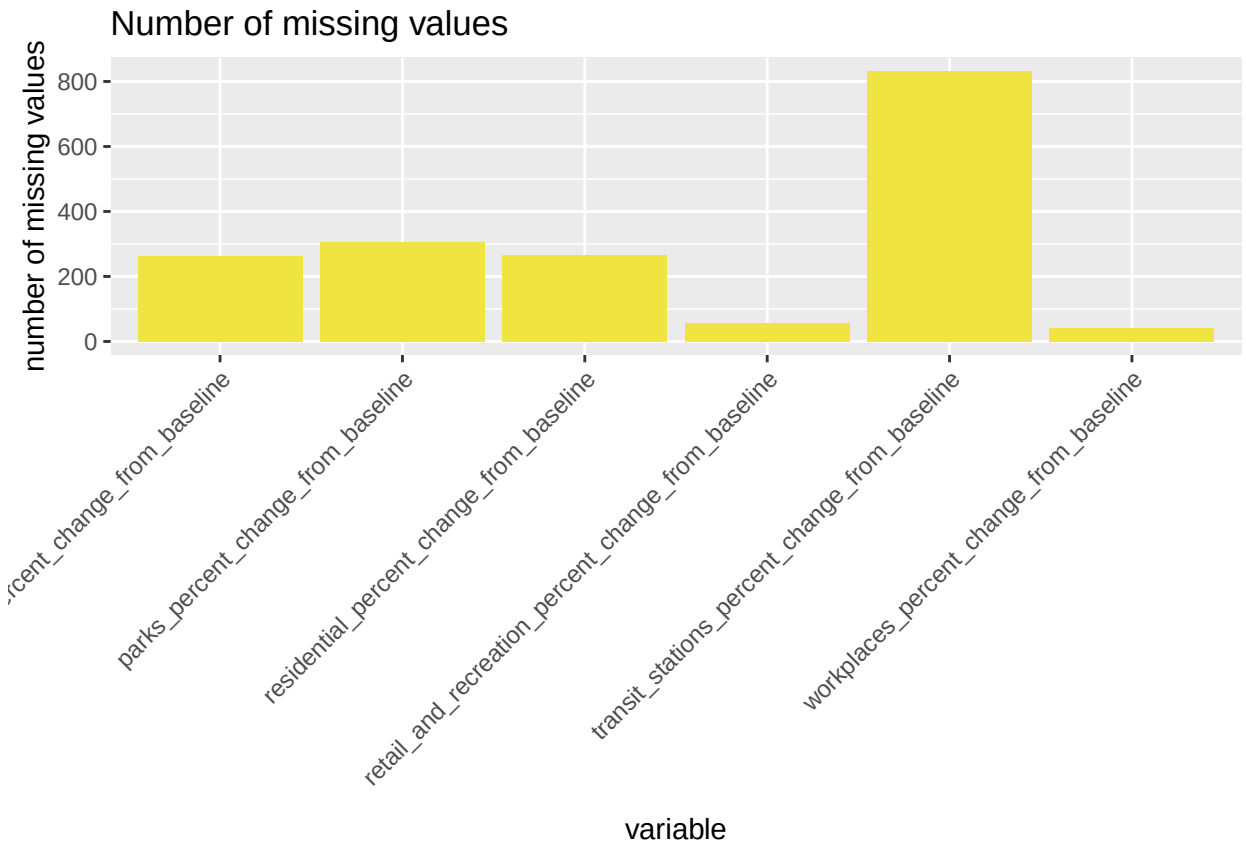
We check missing values.

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



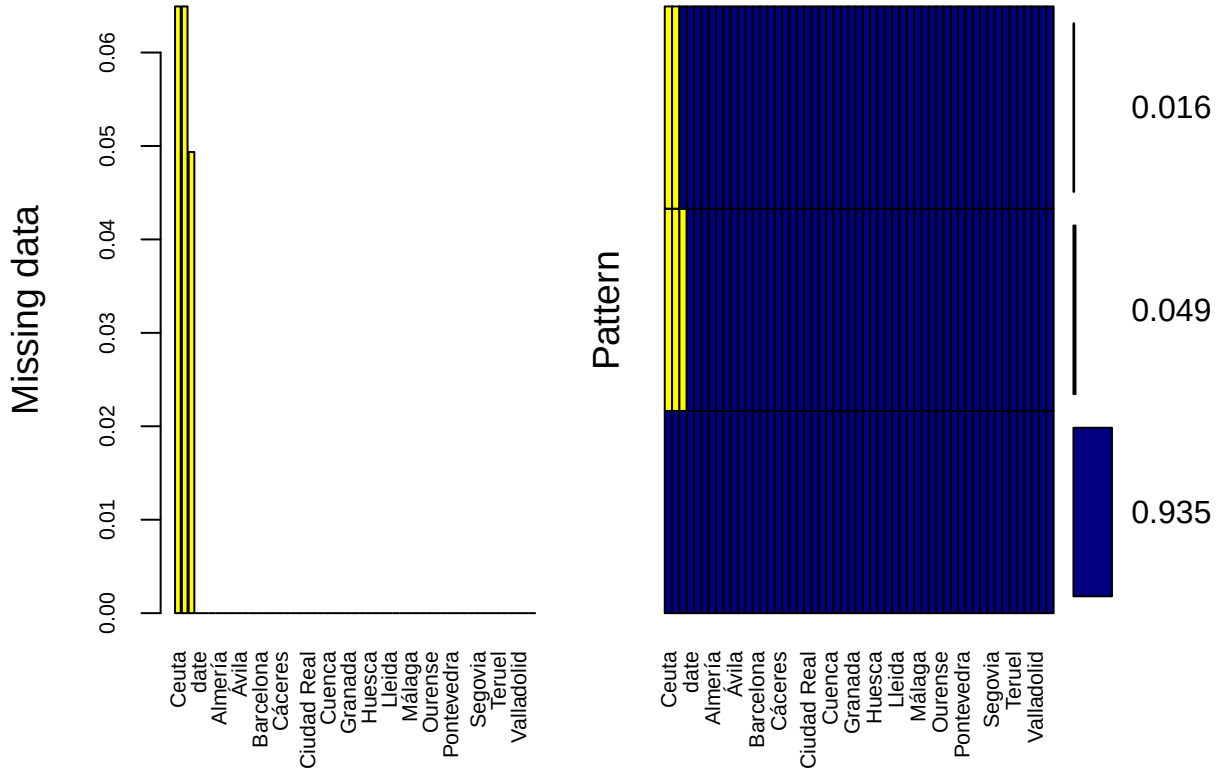

```
##
##  Variables sorted by number of missings:
##                                          Variable       Count
##       transit_stations_percent_change_from_baseline 0.041585445
##                   parks_percent_change_from_baseline 0.015244664
##             residential_percent_change_from_baseline 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
```

```
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 by province using the approach stated at "imputeTS" library (and also used at EM3).

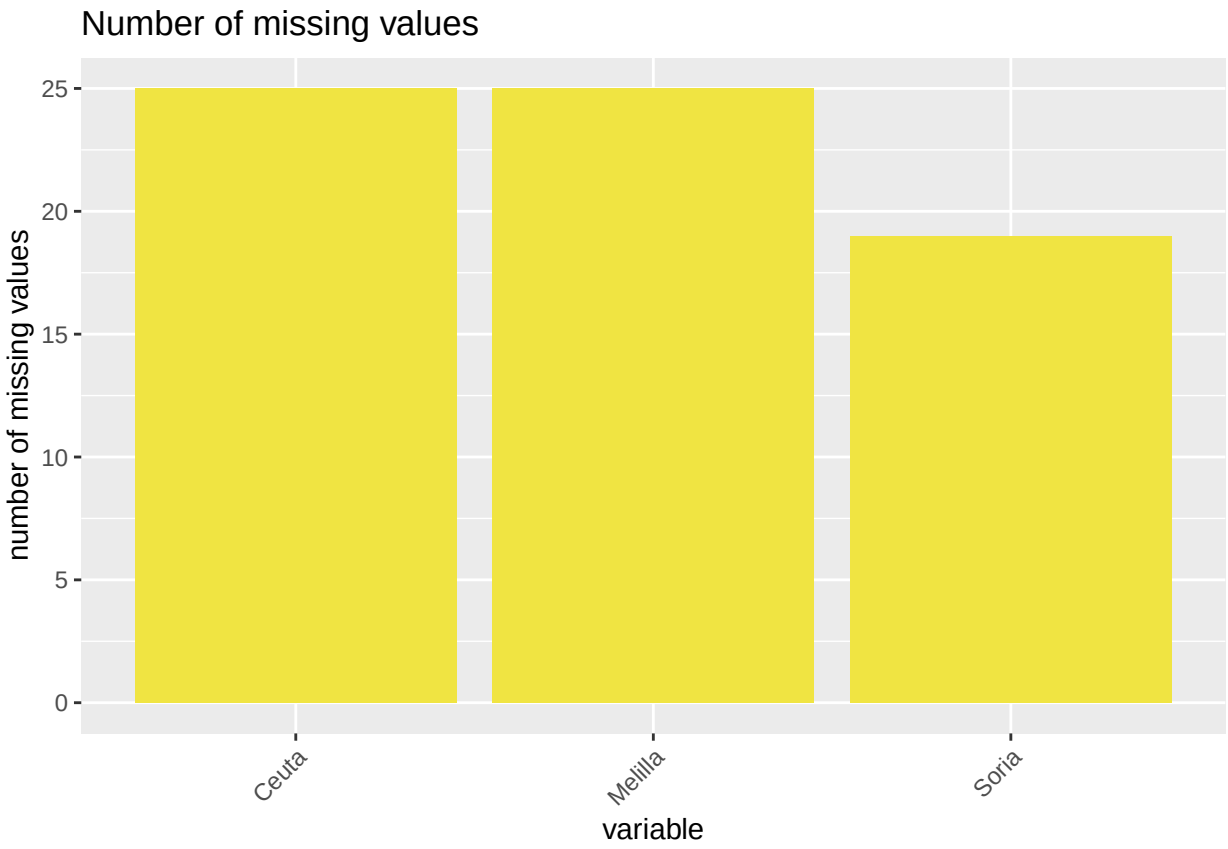
```
# Transpose dataframe
Google_retail<-Google[c(2,4,5)]
Google_t_retail<-dcast(Google_retail, date~sub_region_2, fill=NA)

# 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"))
```



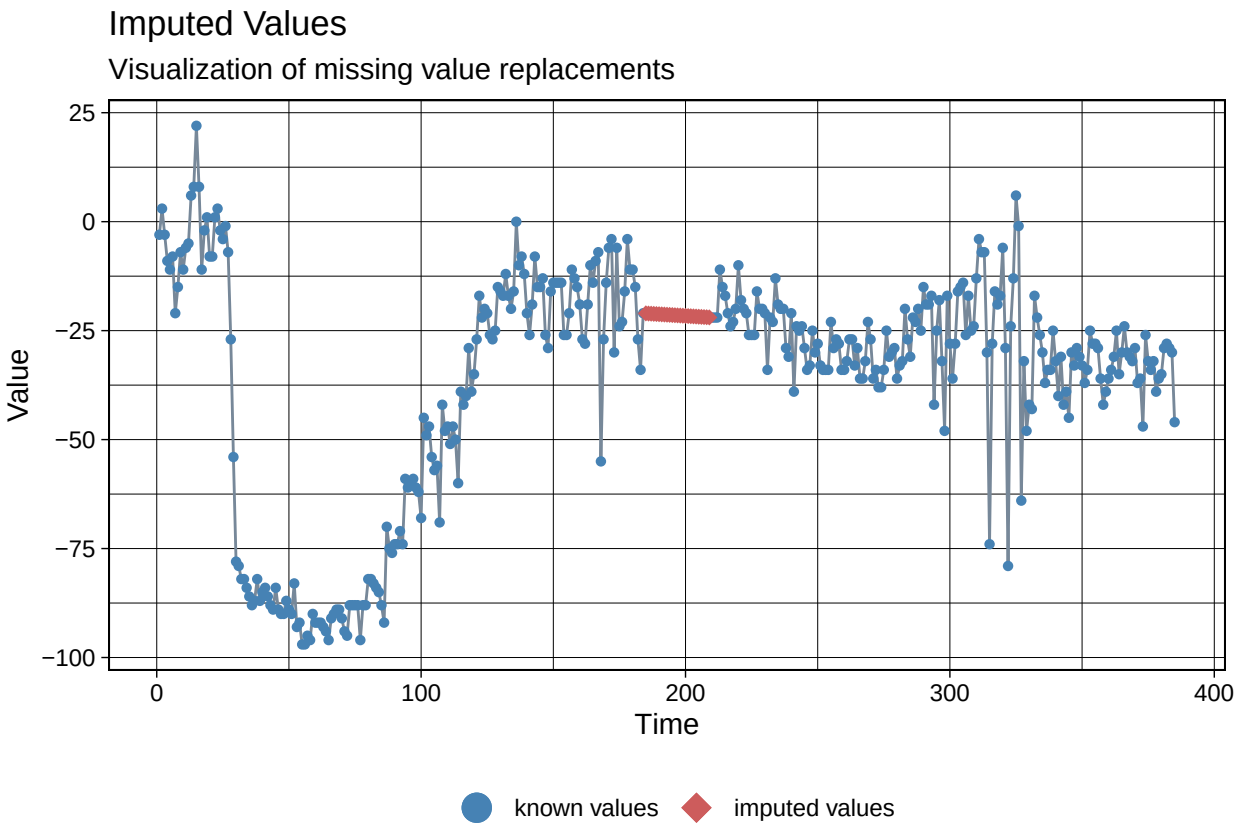

```
##
##  Variables sorted by number of missings:
##                 Variable      Count
##                    Ceuta 0.06493506
##                  Melilla 0.06493506
##                    Soria 0.04935065
##                     date 0.00000000
##                 Albacete 0.00000000
##        Alicante/Alacant 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
```

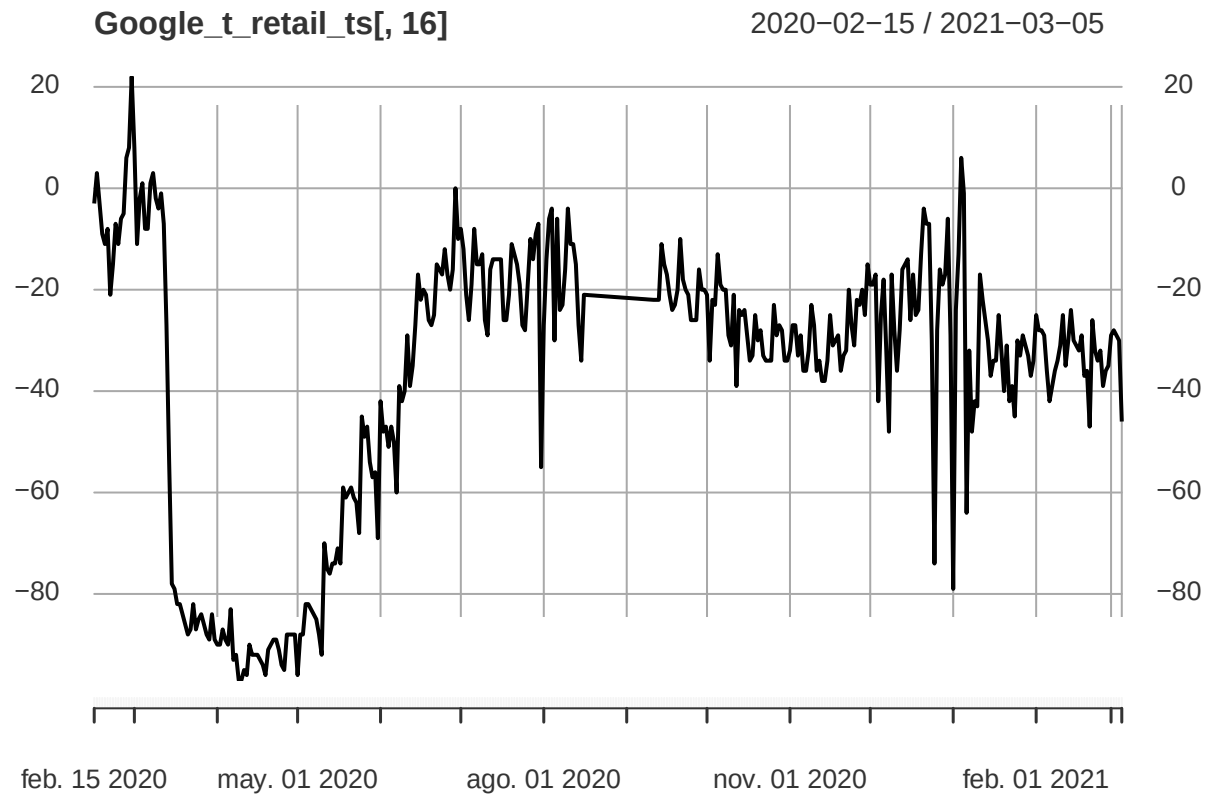
```
Google_t_retail %>%
    gather(key = "key", value = "val") %>%
    mutate(is.missing = is.na(val)) %>%
    group_by(key, is.missing) %>%
    summarise(num.missing = n()) %>%
    filter(is.missing==T) %>%
    select(-is.missing) %>%
    arrange(desc(num.missing)) %>%
    ggplot() +
    geom_bar(aes(x=key, 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))
```



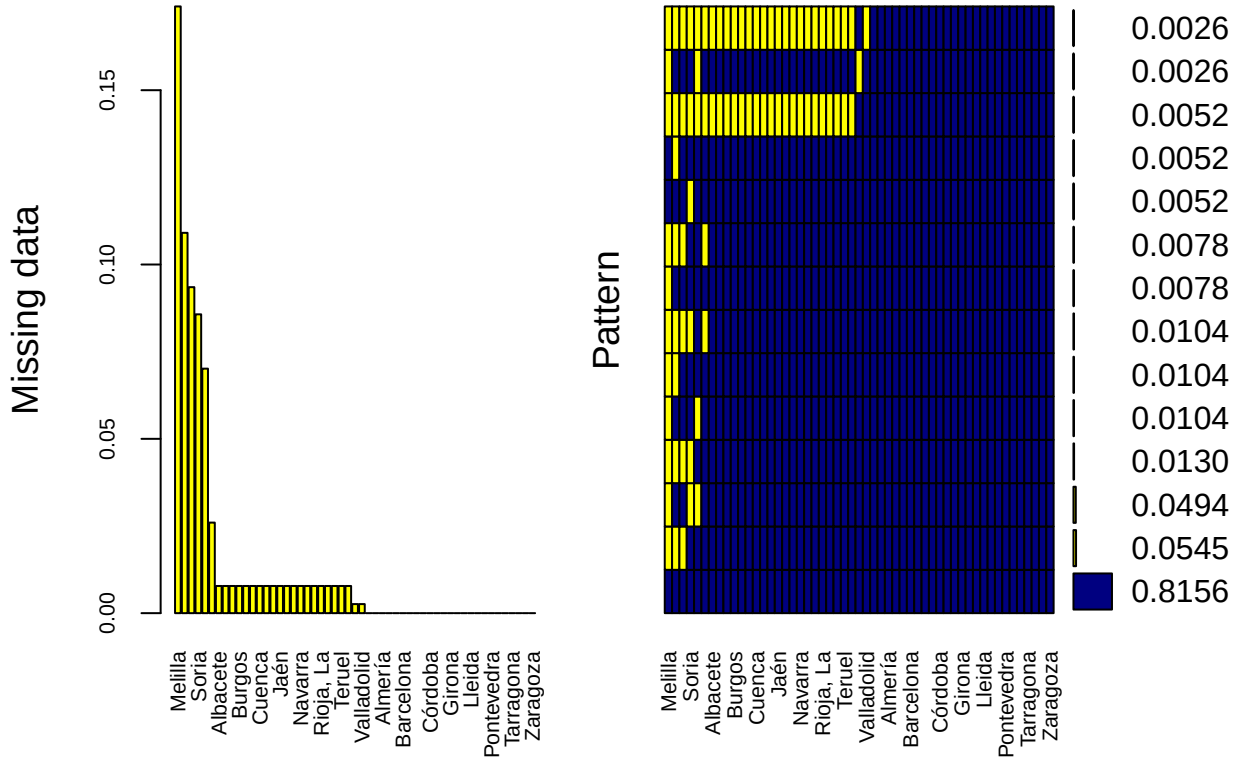

```
# Convert dataframe to ts object
Google_t_retail_ts<-xts(Google_t_retail[-1],Google_t_retail$date)

# 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)
```




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



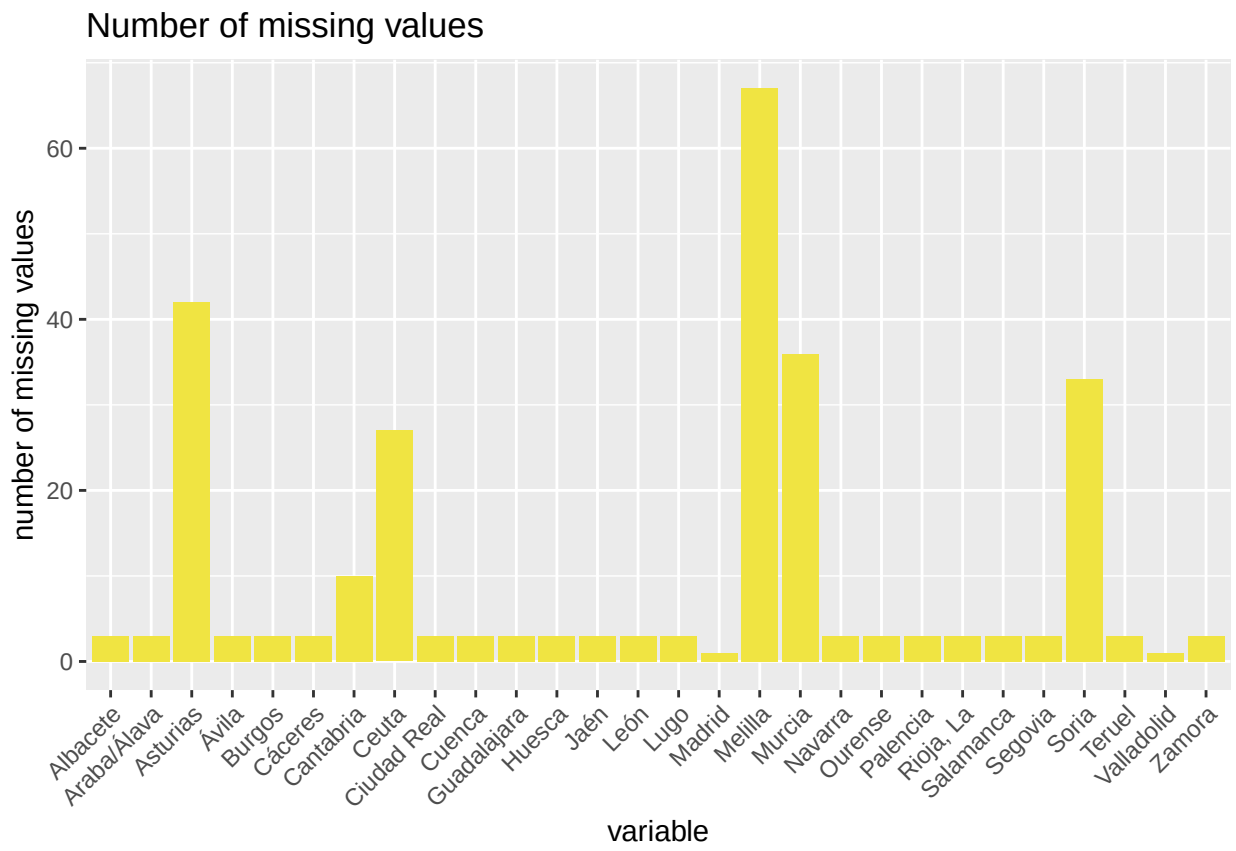

```
# We convert the time series object to a dataframe
Google_retail <- ts_df(Google_t_retail_ts)

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_baseline"

#####################################################################
# 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"))
```



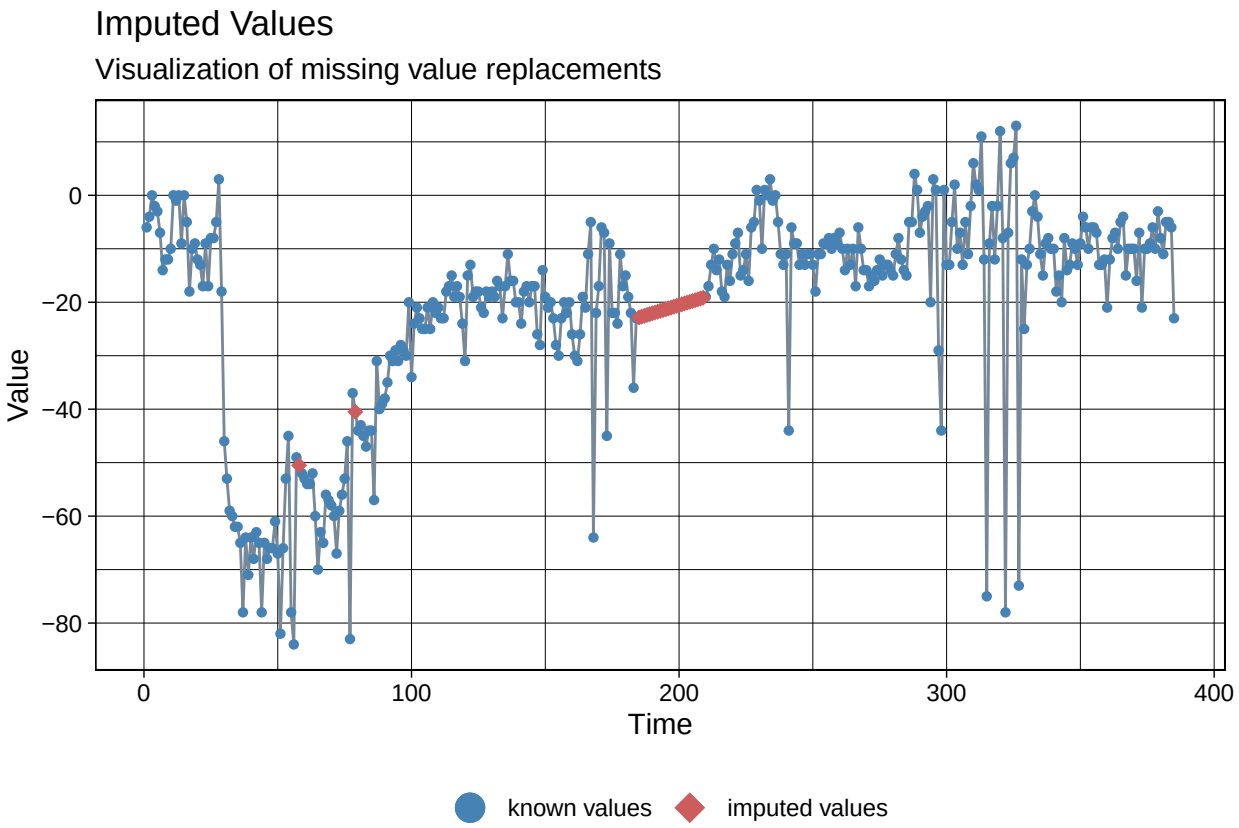

```
##
##  Variables sorted by number of missings:
##                 Variable       Count
##                  Melilla 0.174025974
##                 Asturias 0.109090909
##                   Murcia 0.093506494
##                    Soria 0.085714286
##                    Ceuta 0.070129870
##                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
```

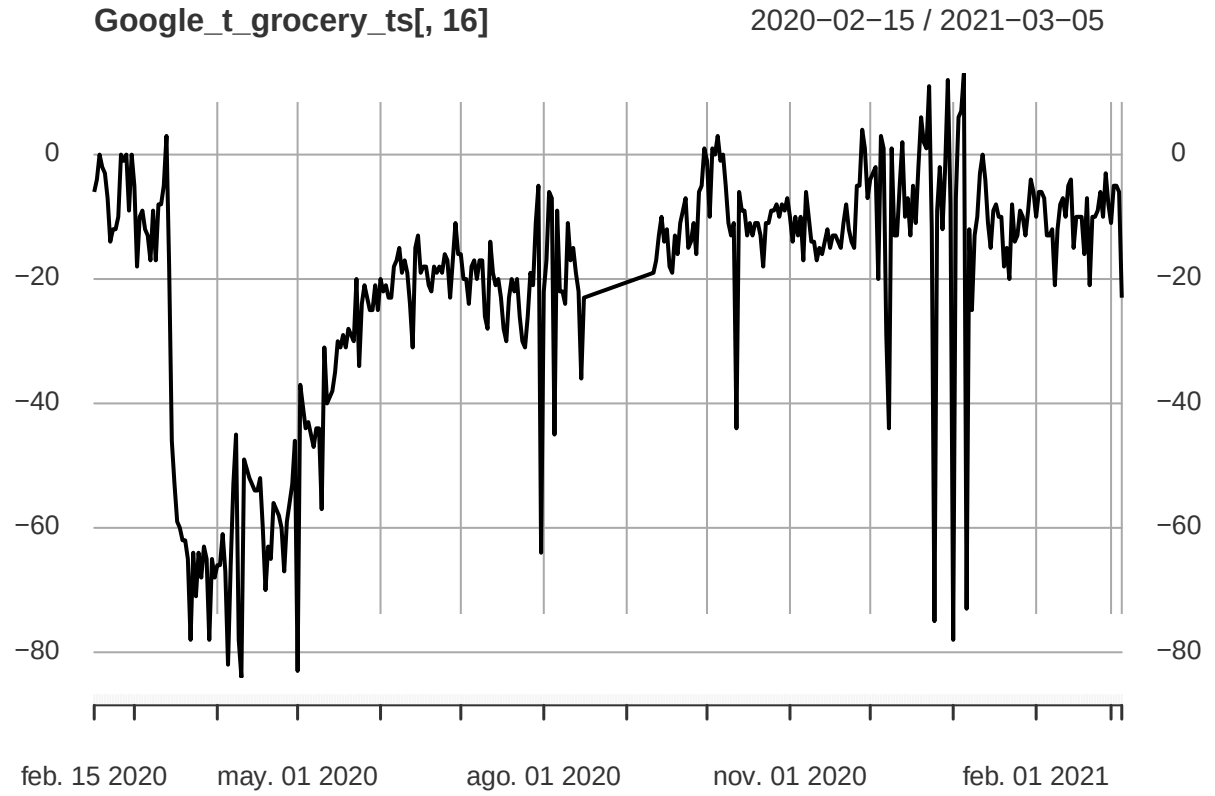
```
Google_t_grocery %>%
    gather(key = "key", value = "val") %>%
    mutate(is.missing = is.na(val)) %>%
    group_by(key, is.missing) %>%
    summarise(num.missing = n()) %>%
    filter(is.missing==T) %>%
    select(-is.missing) %>%
    arrange(desc(num.missing)) %>%
    ggplot() +
    geom_bar(aes(x=key, 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))
```



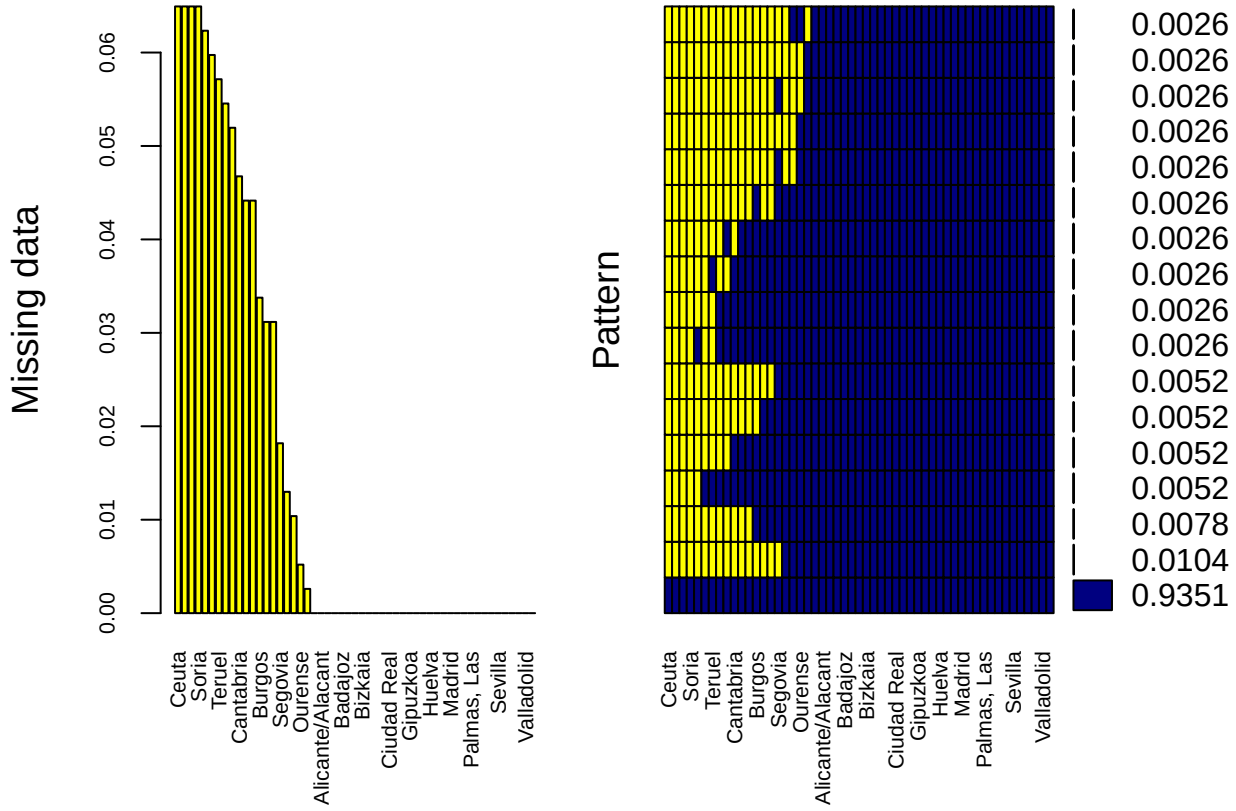

```
# Convert dataframe to ts object
Google_t_grocery_ts<-xts(Google_t_grocery[-1],Google_t_grocery$date)

# 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)
```




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



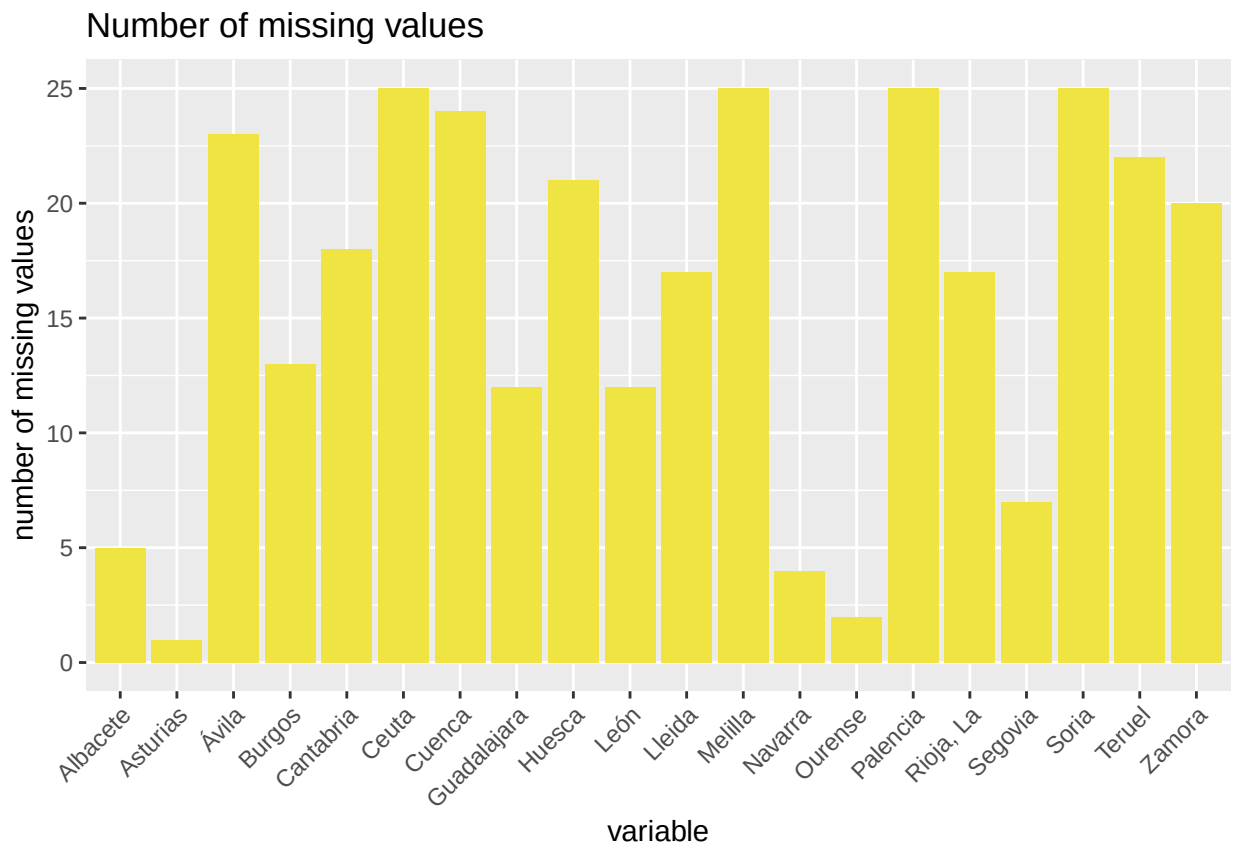

```
# We convert the time series object to a dataframe
Google_grocery <- ts_df(Google_t_grocery_ts)

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_baseline"

#####################################################################
# 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"))
```



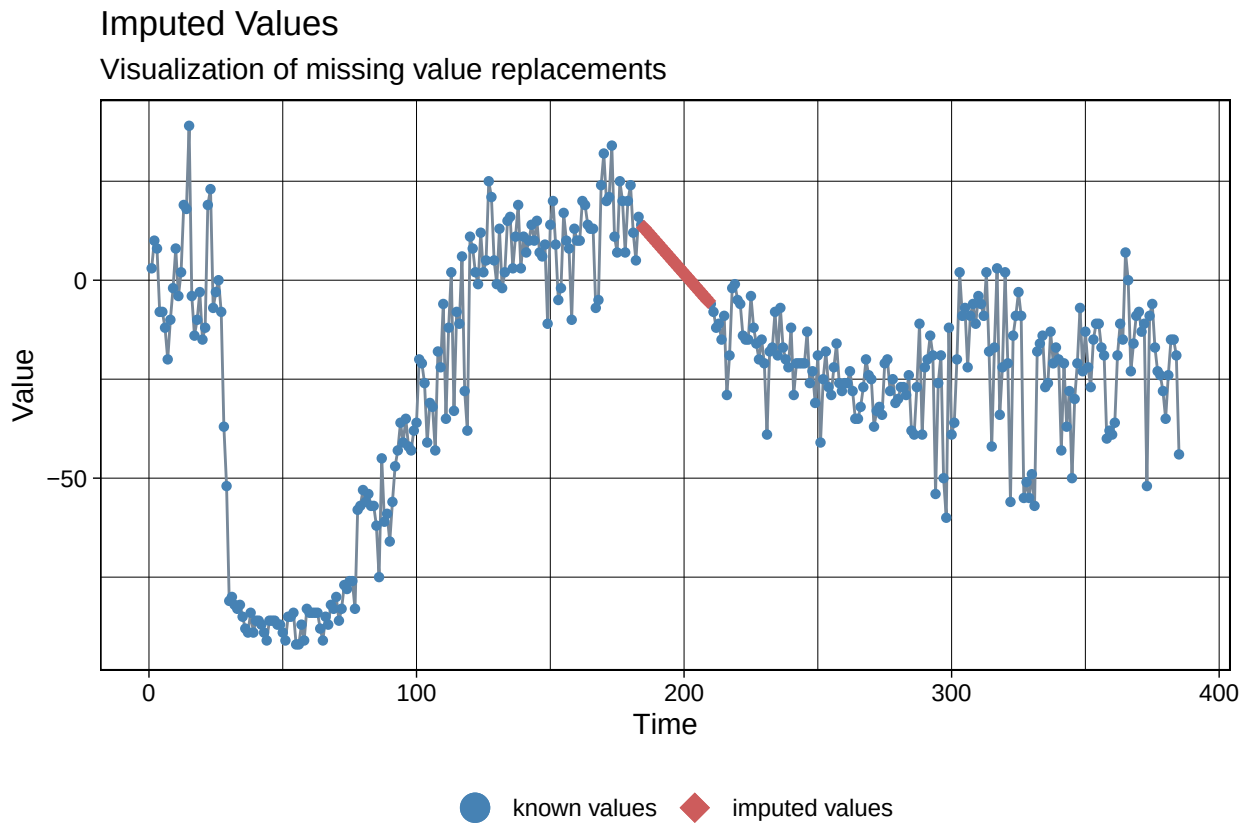

```
##
##  Variables sorted by number of missings:
##                 Variable       Count
##                    Ceuta 0.064935065
##                  Melilla 0.064935065
##                 Palencia 0.064935065
##                    Soria 0.064935065
##                   Cuenca 0.062337662
##                    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
```

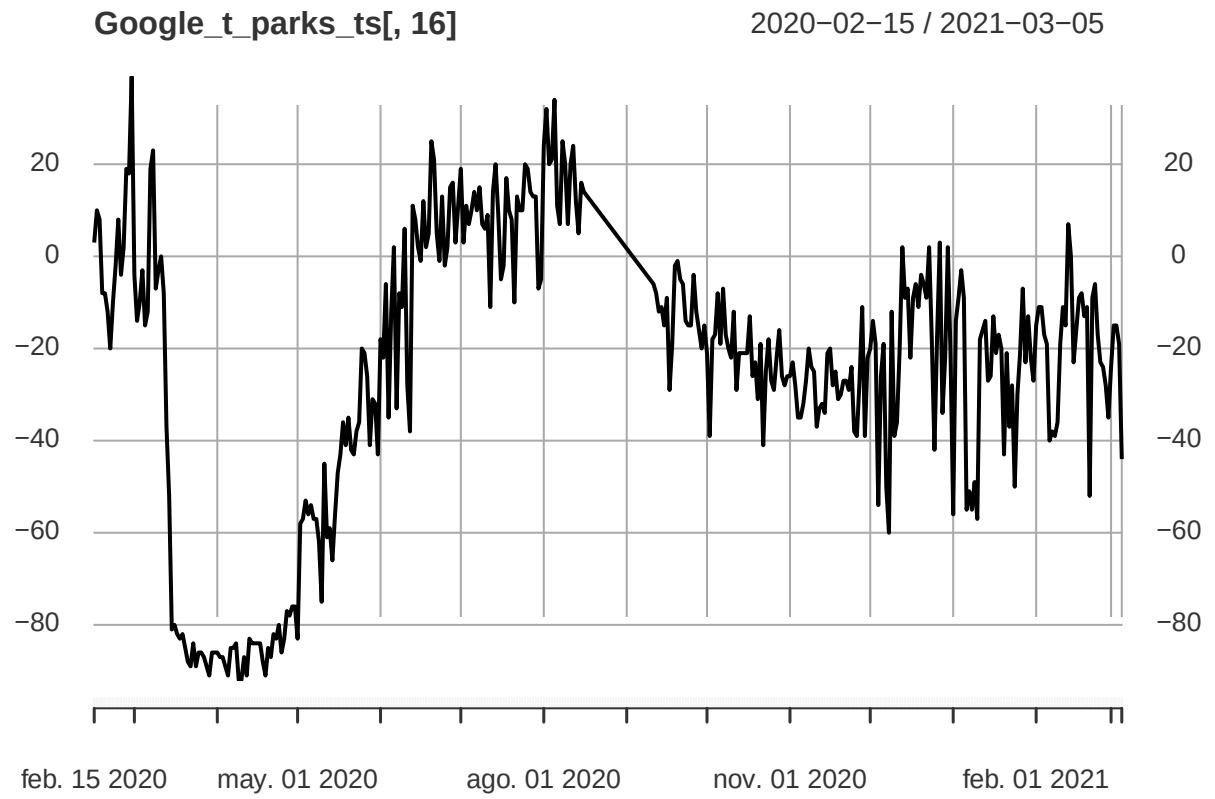
```
Google_t_parks %>%
    gather(key = "key", value = "val") %>%
    mutate(is.missing = is.na(val)) %>%
    group_by(key, is.missing) %>%
    summarise(num.missing = n()) %>%
    filter(is.missing==T) %>%
    select(-is.missing) %>%
    arrange(desc(num.missing)) %>%
    ggplot() +
    geom_bar(aes(x=key, 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))
```



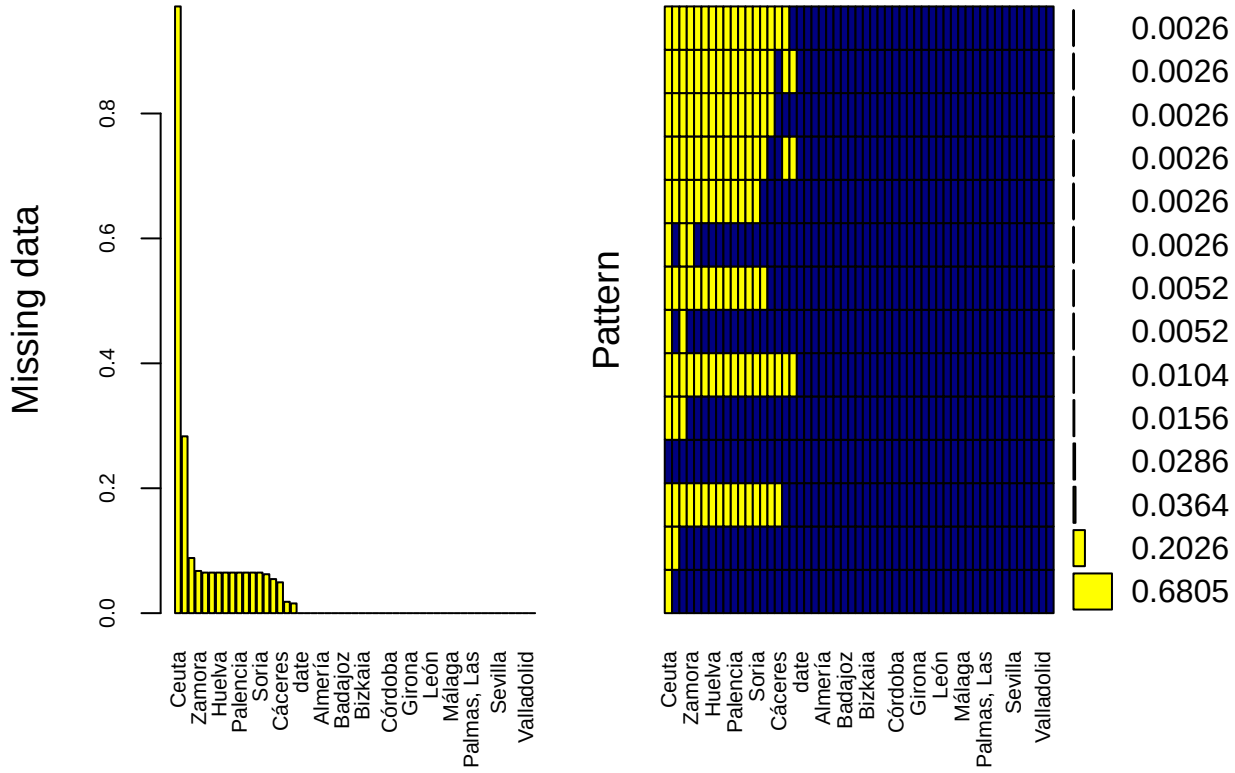

```
# Convert dataframe to ts object
Google_t_parks_ts<-xts(Google_t_parks[-1],Google_t_parks$date)

# 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)
```




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



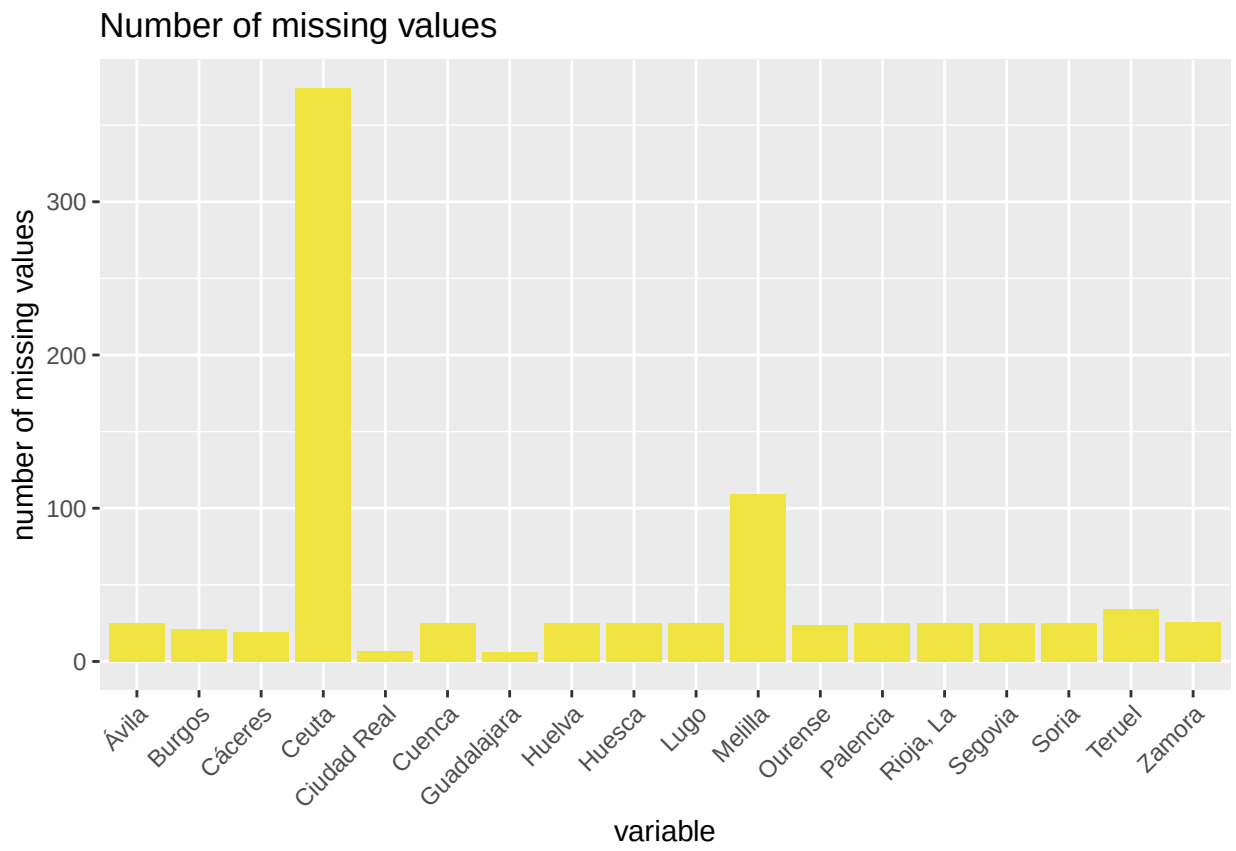

```
# We convert the time series object to a dataframe
Google_parks <- ts_df(Google_t_parks_ts)

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"))
```



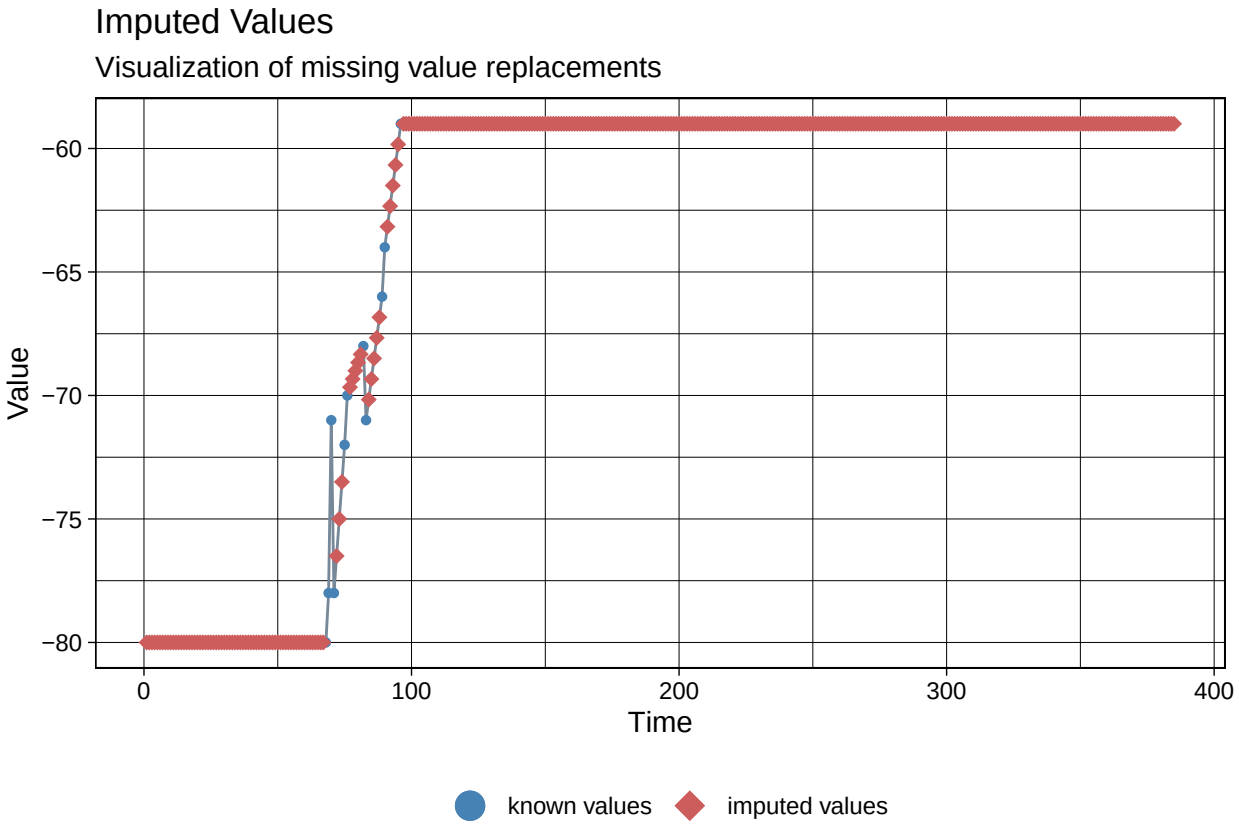

```
##
##  Variables sorted by number of missings:
##                 Variable      Count
##                    Ceuta 0.97142857
##                  Melilla 0.28311688
##                   Teruel 0.08831169
##                   Zamora 0.06753247
##                    Ávila 0.06493506
##                   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
```

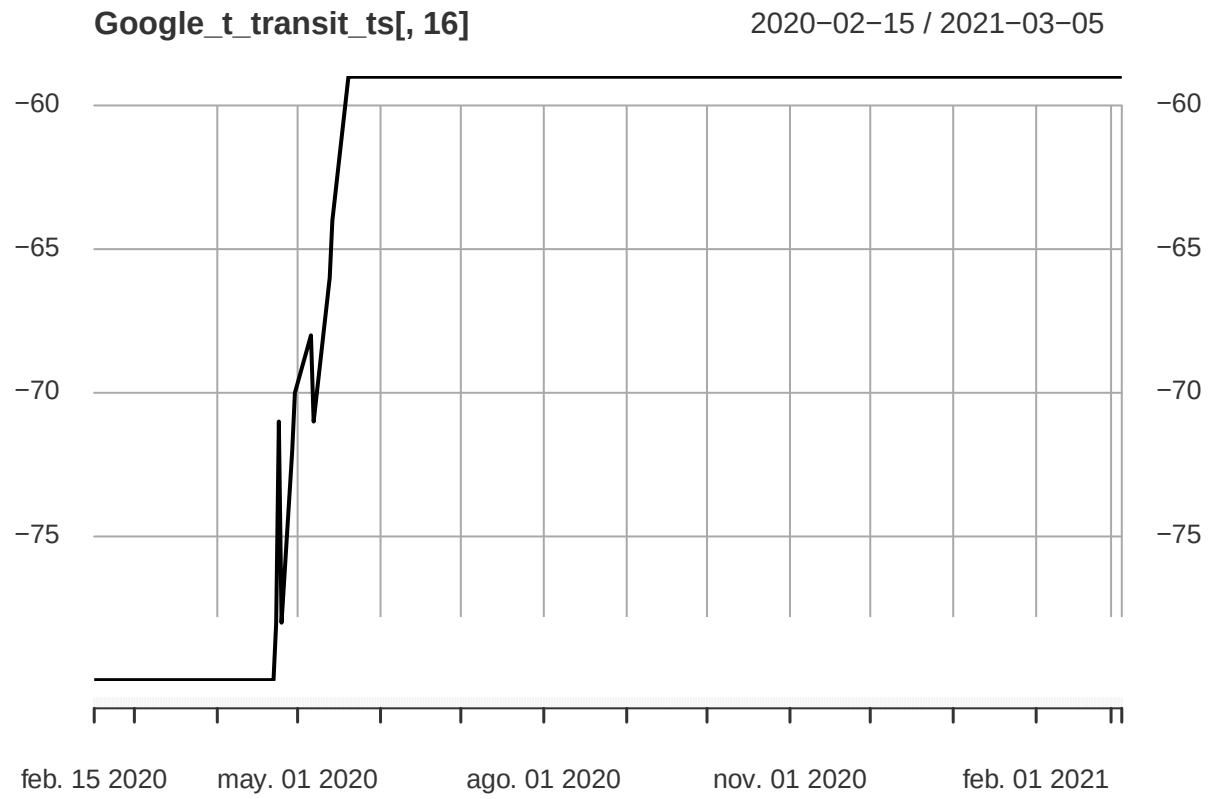
```
Google_t_transit %>%
    gather(key = "key", value = "val") %>%
    mutate(is.missing = is.na(val)) %>%
    group_by(key, is.missing) %>%
    summarise(num.missing = n()) %>%
    filter(is.missing==T) %>%
    select(-is.missing) %>%
    arrange(desc(num.missing)) %>%
    ggplot() +
    geom_bar(aes(x=key, 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))
```



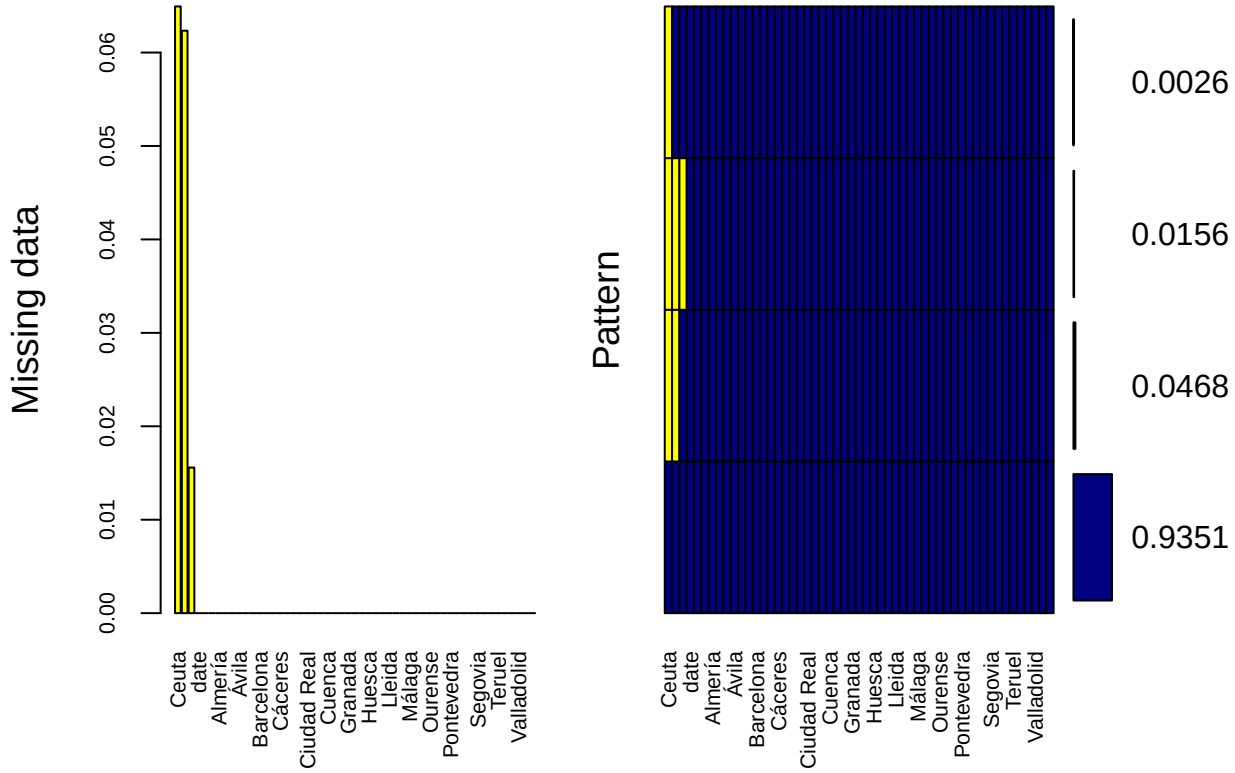

```
# Convert dataframe to ts object
Google_t_transit_ts<-xts(Google_t_transit[-1],Google_t_transit$date)

# 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)
```




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



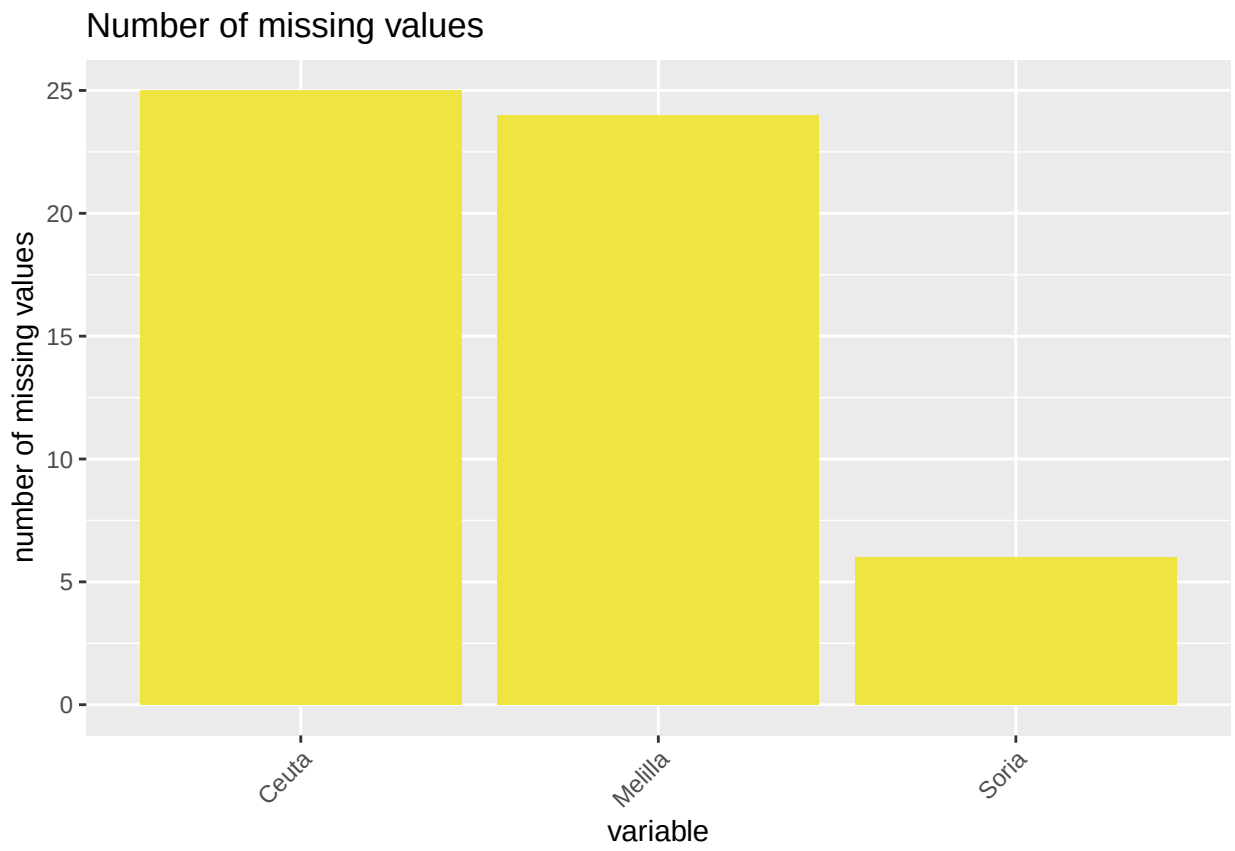

```
# We convert the time series object to a dataframe
Google_transit <- ts_df(Google_t_transit_ts)

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_baseline"

#####################################################################
# 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"))
```



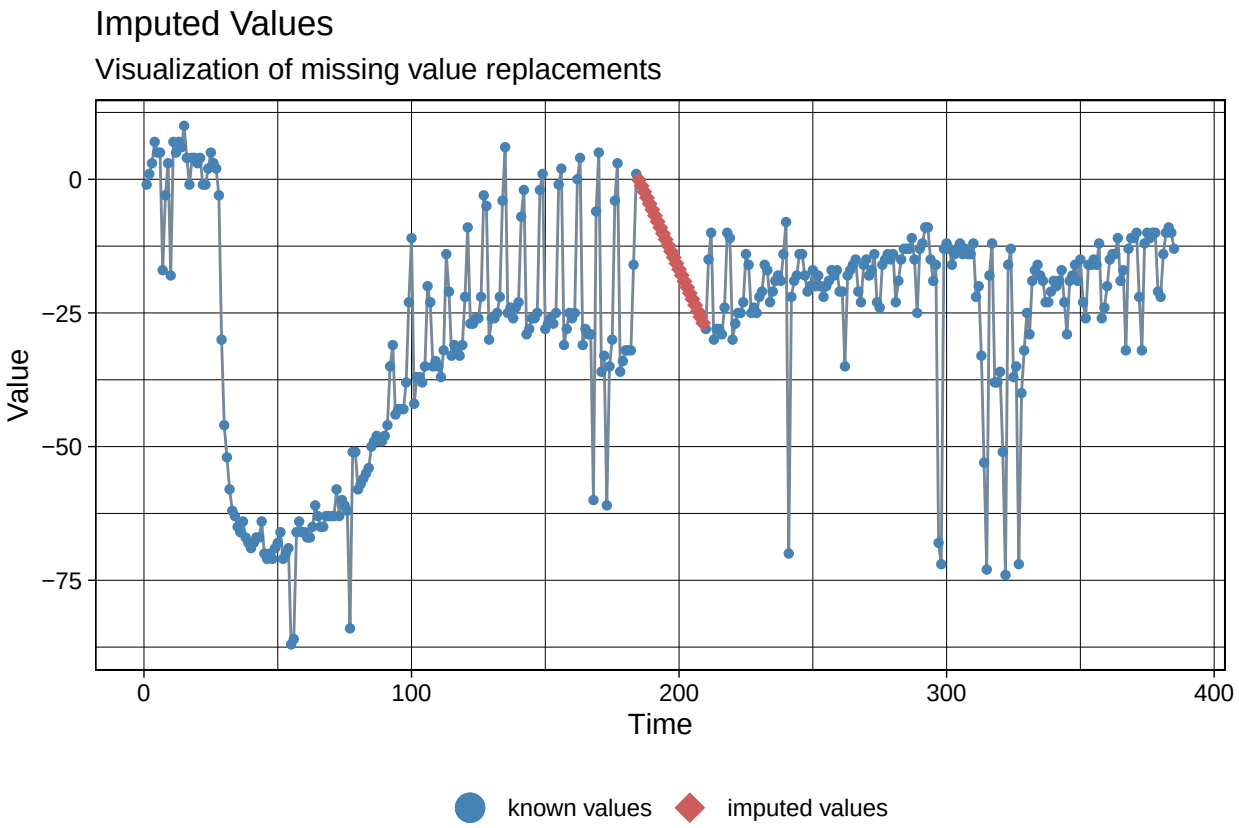

```
##
##  Variables sorted by number of missings:
##                 Variable      Count
##                    Ceuta 0.06493506
##                  Melilla 0.06233766
##                    Soria 0.01558442
##                     date 0.00000000
##                 Albacete 0.00000000
##        Alicante/Alacant 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
```

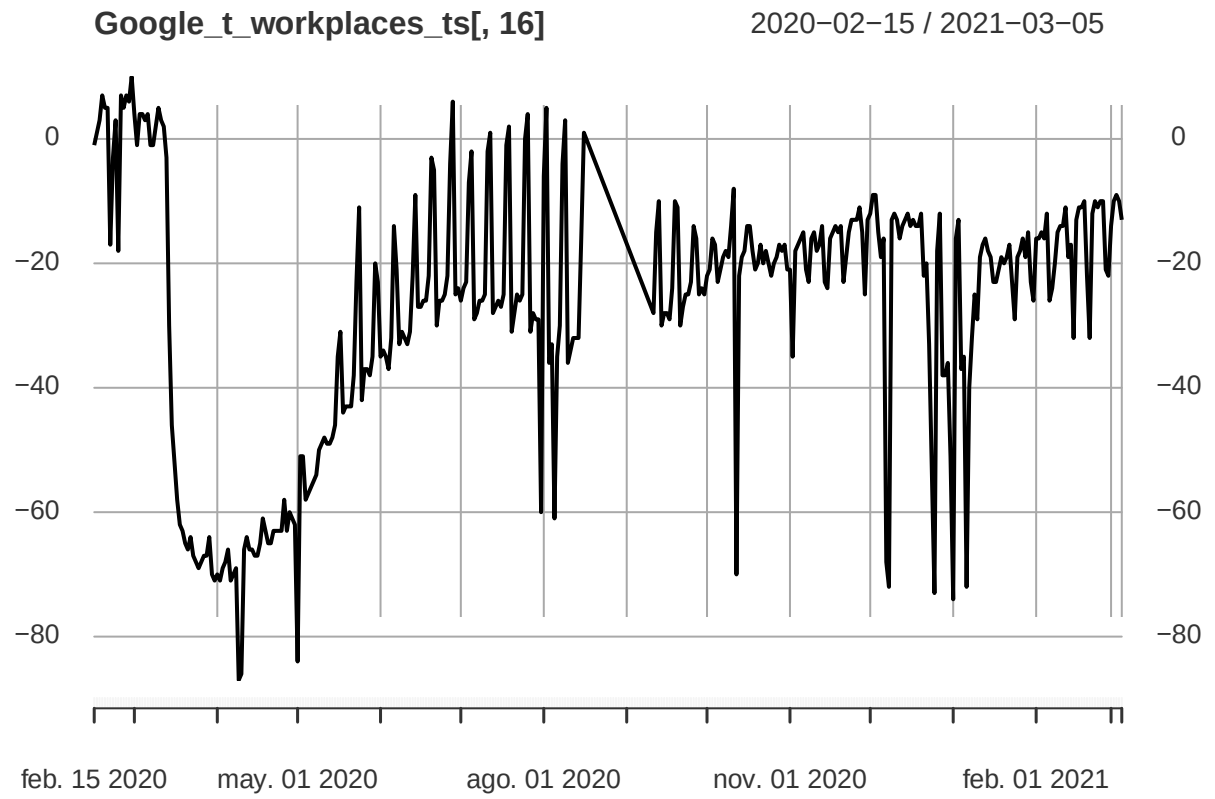
```
Google_t_workplaces %>%
    gather(key = "key", value = "val") %>%
    mutate(is.missing = is.na(val)) %>%
    group_by(key, is.missing) %>%
    summarise(num.missing = n()) %>%
    filter(is.missing==T) %>%
    select(-is.missing) %>%
    arrange(desc(num.missing)) %>%
    ggplot() +
    geom_bar(aes(x=key, 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))
```



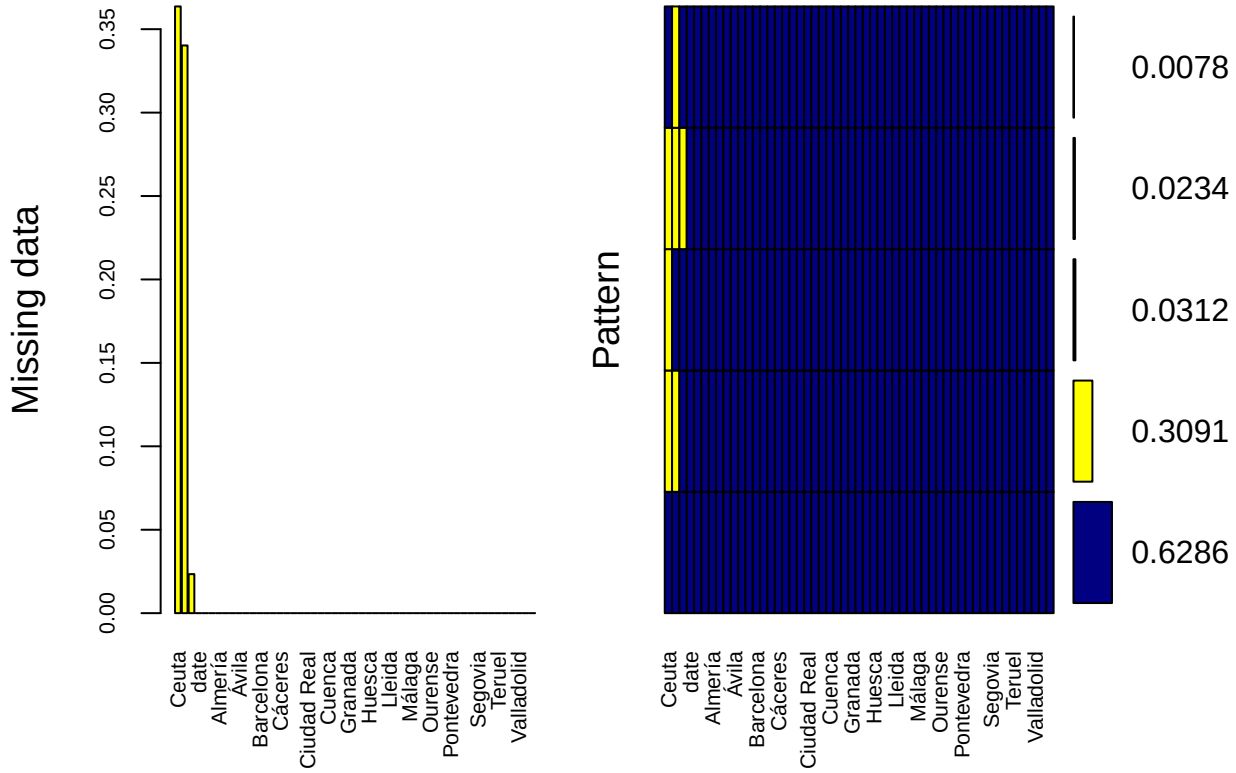

```
# Convert dataframe to ts object
Google_t_workplaces_ts<-xts(Google_t_workplaces[-1],Google_t_workplaces$date)

# 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])
```



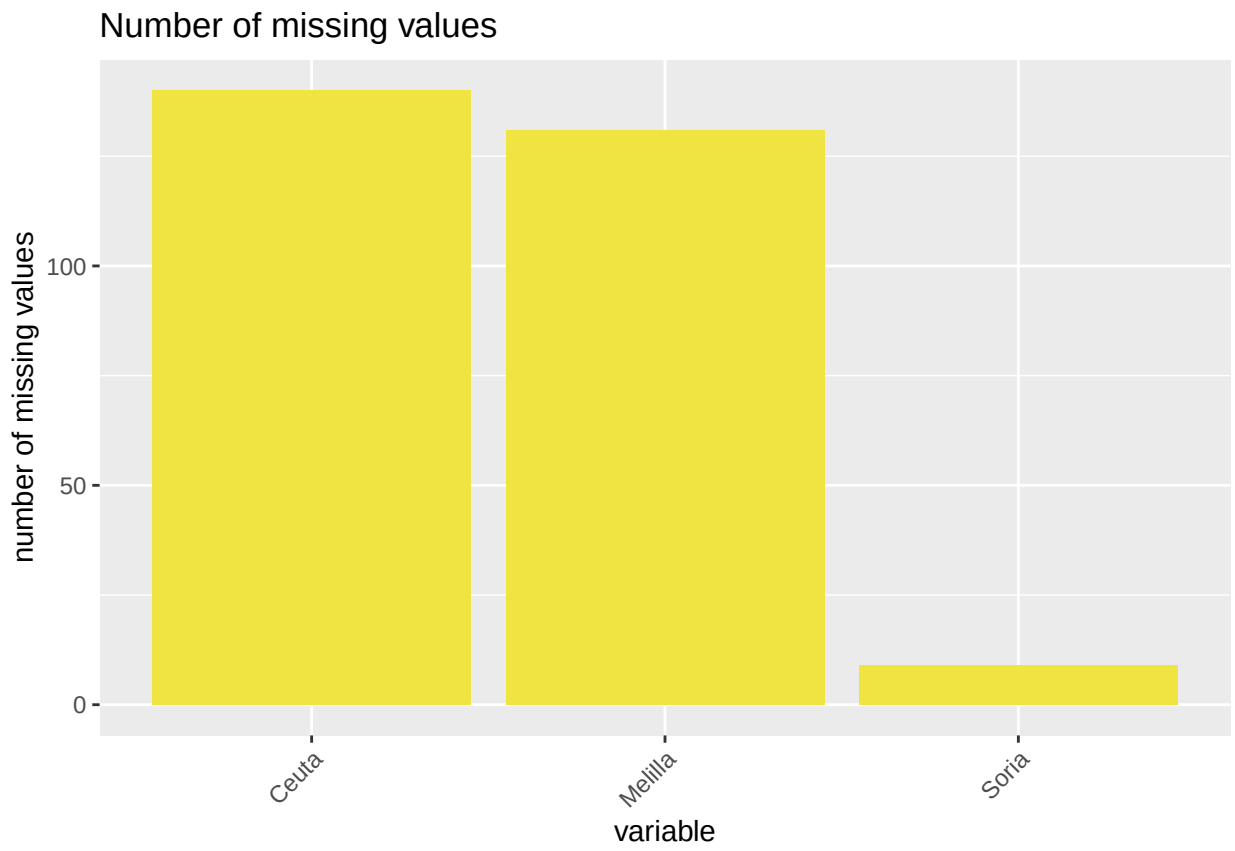

```
# We convert the time series object to a dataframe
Google_workplaces <- ts_df(Google_t_workplaces_ts)

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_baseline"

#####################################################################
# 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"))
```



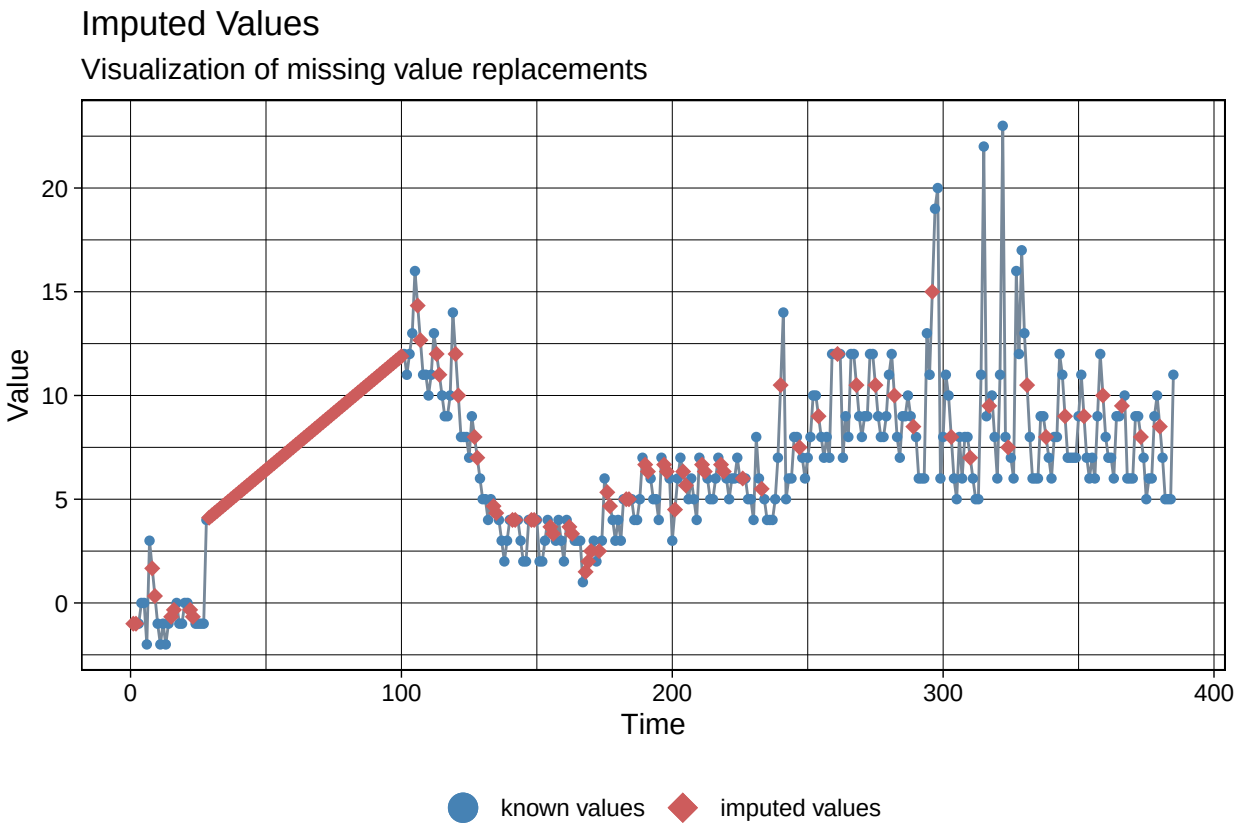

```
##
##  Variables sorted by number of missings:
##                 Variable      Count
##                    Ceuta 0.36363636
##                  Melilla 0.34025974
##                    Soria 0.02337662
##                     date 0.00000000
##                 Albacete 0.00000000
##         Alicante/Alacant 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
```

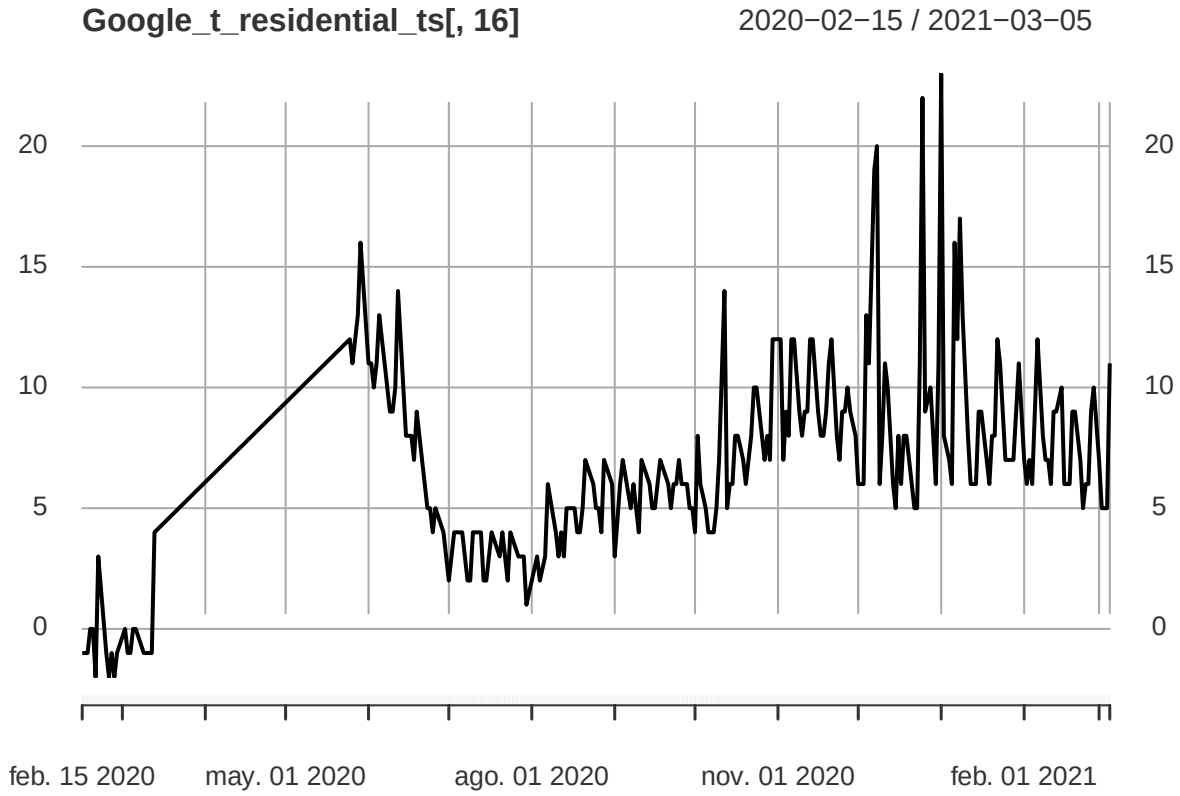
```
Google_t_residential %>%
    gather(key = "key", value = "val") %>%
    mutate(is.missing = is.na(val)) %>%
    group_by(key, is.missing) %>%
    summarise(num.missing = n()) %>%
    filter(is.missing==T) %>%
    select(-is.missing) %>%
    arrange(desc(num.missing)) %>%
    ggplot() +
    geom_bar(aes(x=key, 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])
```




```
# 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_baseline"
```

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

```
# New dataframe Google_b
# This approach assumes that the column names are the same and that there's the same number of rows (ou
# Any duplicated columns are automatically eliminated used in the merging process.
Google_b <- merge(Google_retail, Google_grocery) %>%
              merge(Google_parks) %>%
              merge(Google_transit) %>%
              merge(Google_workplaces) %>%
              merge(Google_residential)

# We add the iso code for the province
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")
```

```r
# Check table
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
```

```r
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
```

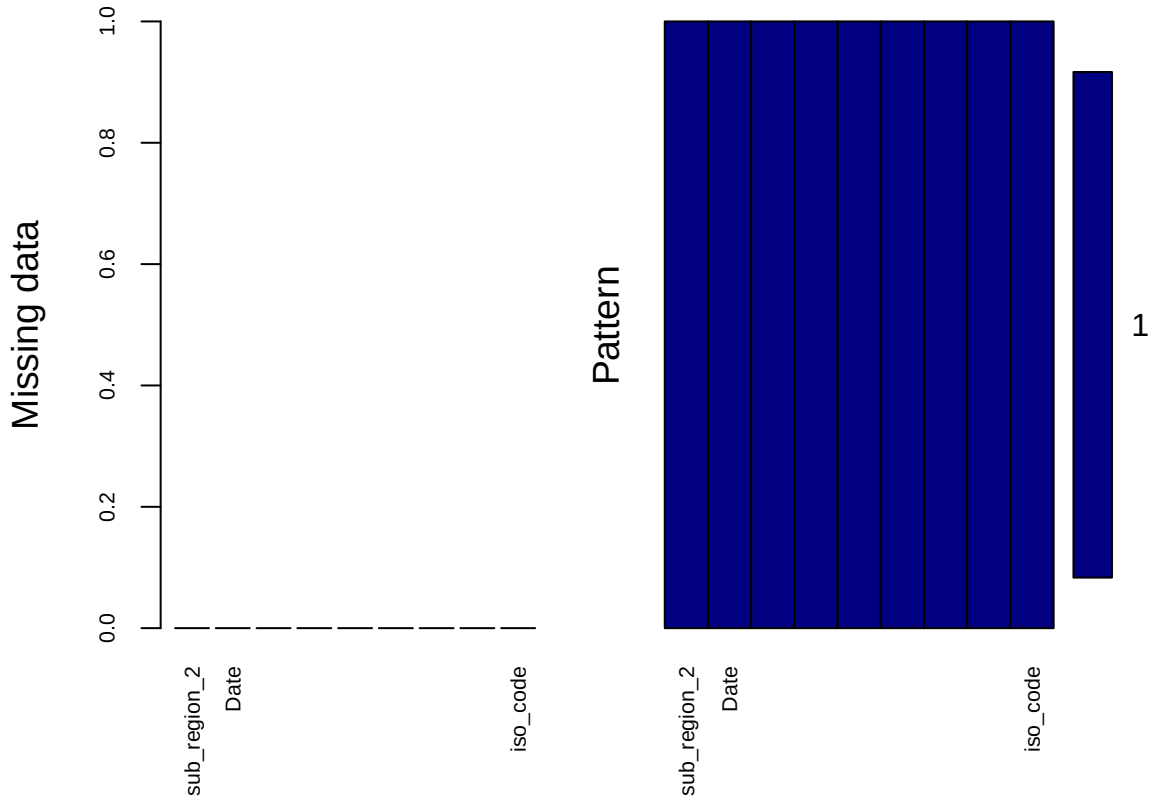
```
##                 385                 385                 385
##          Coruña, A              Cuenca            Gipuzkoa
##                 385                 385                 385
##             Girona             Granada         Guadalajara
##                 385                 385                 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
```

```
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.

```
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.

```
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
```

```
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
```

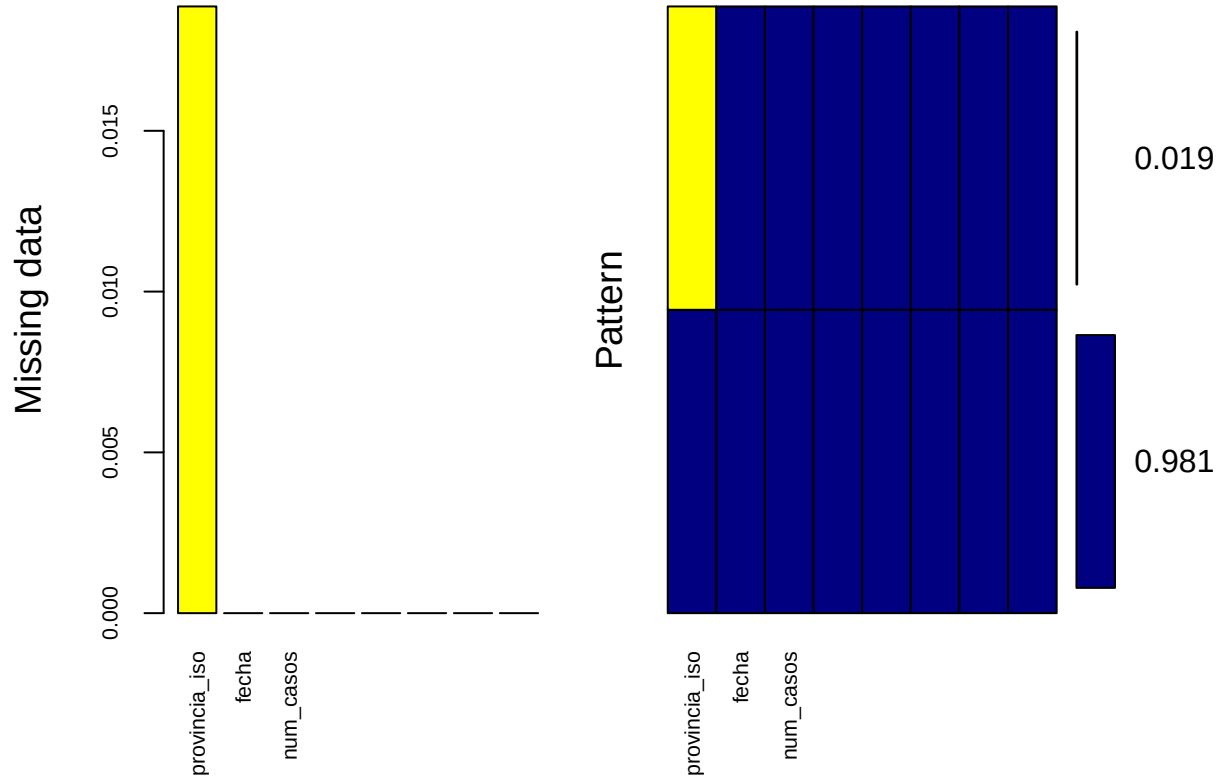
```
table(CNE_tecnica$provincia_iso)
```

```
##
##   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
```

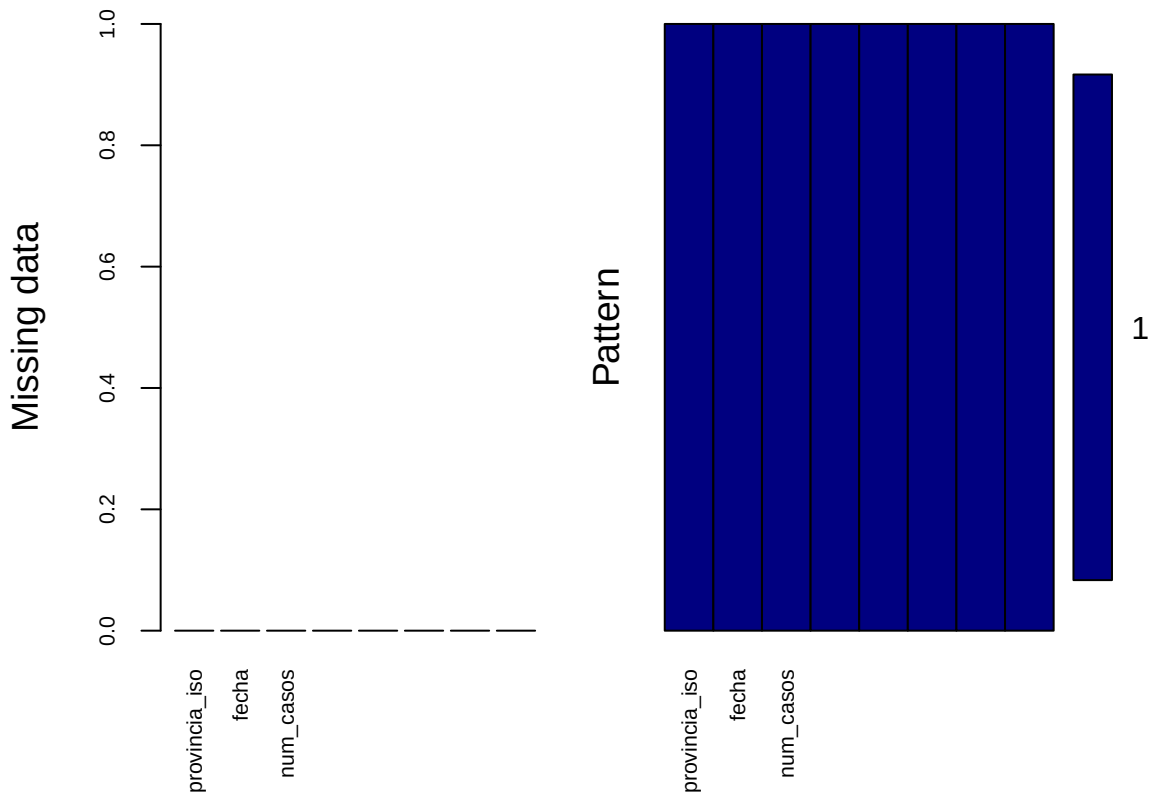
```r
CNE_tecnica %>%
    gather(key = "key", value = "val") %>%
    mutate(is.missing = is.na(val)) %>%
    group_by(key, is.missing) %>%
    summarise(num.missing = n()) %>%
    filter(is.missing==T) %>%
    select(-is.missing) %>%
    arrange(desc(num.missing)) %>%
    ggplot() +
    geom_bar(aes(x=key, 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))
```


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

```
## List of 1
##  $ axis.text.x:List of 11
##   ..$ family       : NULL
##   ..$ face         : NULL
##   ..$ colour       : NULL
##   ..$ size         : NULL
##   ..$ hjust        : num 1
##   ..$ vjust        : NULL
##   ..$ angle        : num 45
##   ..$ lineheight   : NULL
##   ..$ margin       : NULL
##   ..$ debug        : NULL
##   ..$ inherit.blank: logi FALSE
##   ..- attr(*, "class")= chr [1:2] "element_text" "element"
##  - attr(*, "class")= chr [1:2] "theme" "gg"
##  - attr(*, "complete")= logi FALSE
##  - attr(*, "validate")= logi TRUE
```

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

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

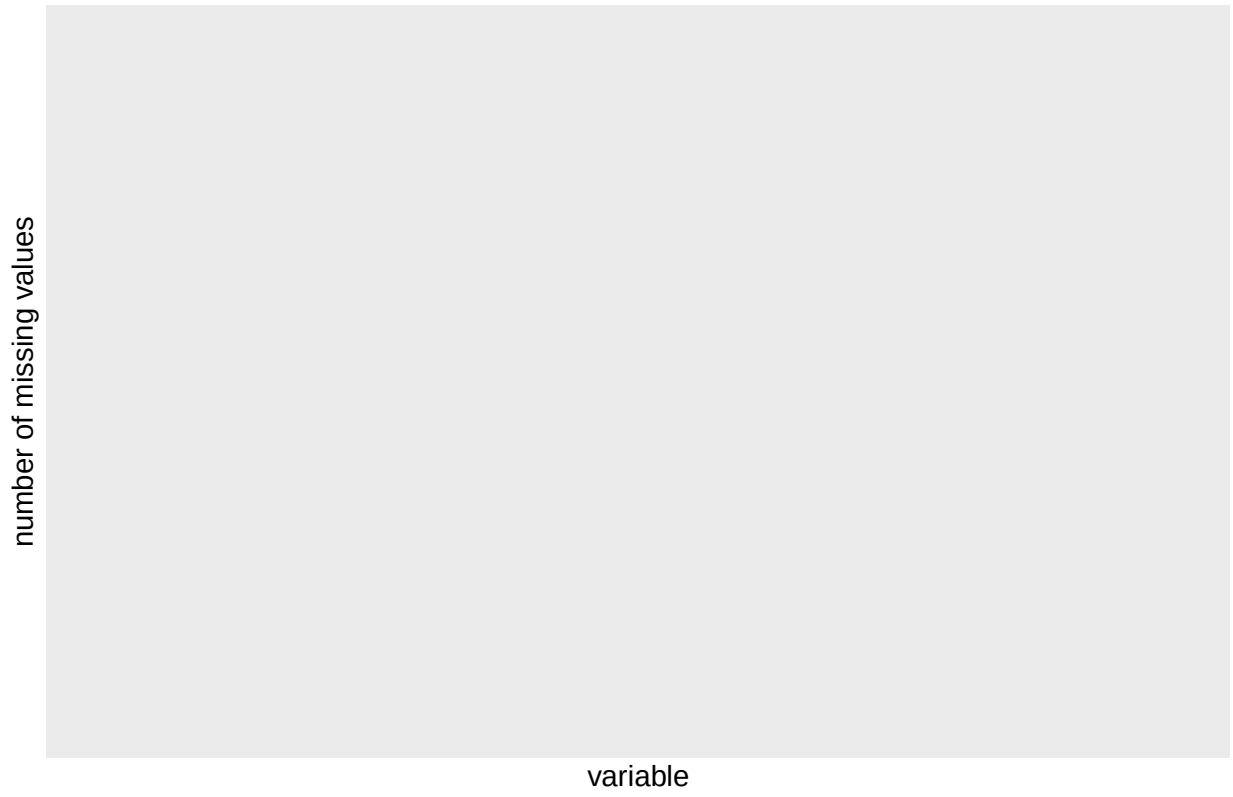
```
    gap=3, ylab=c("Missing data","Pattern"))
```




```
##
##  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))
```




```
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
```

```
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 ...
```

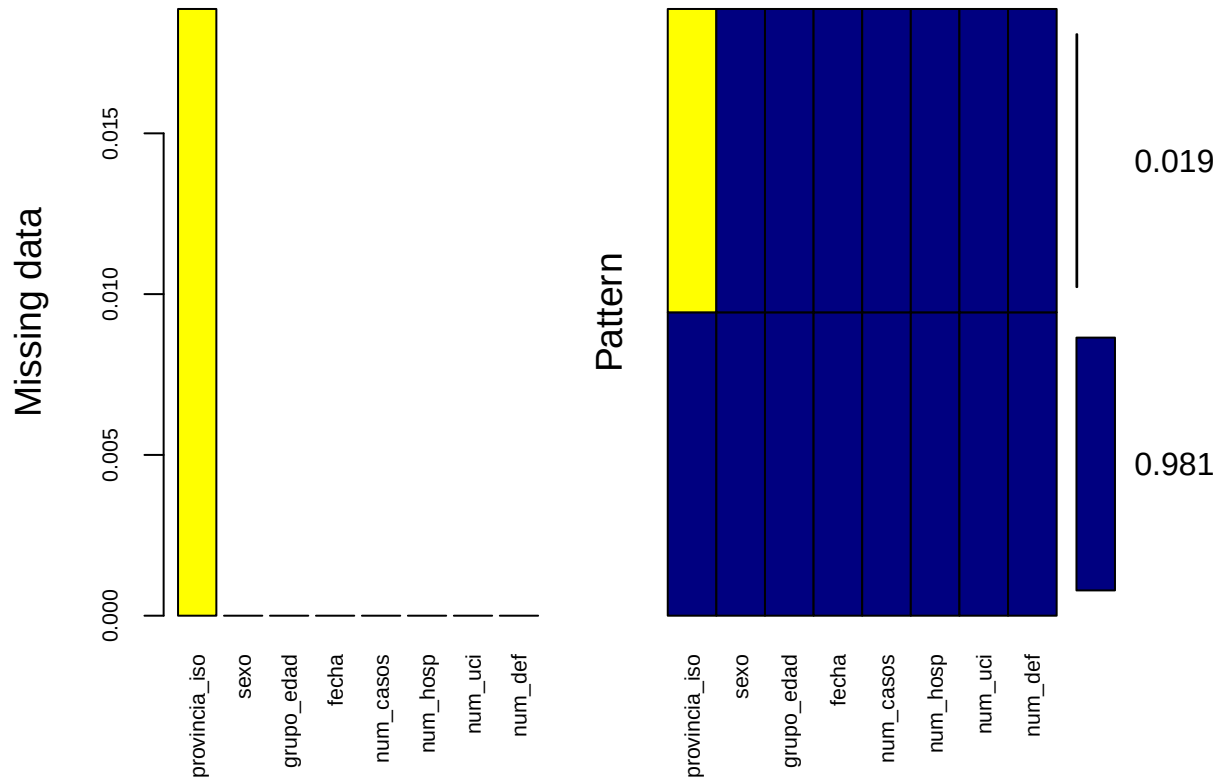
```
## NULL
```

```
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.

```
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"))
```



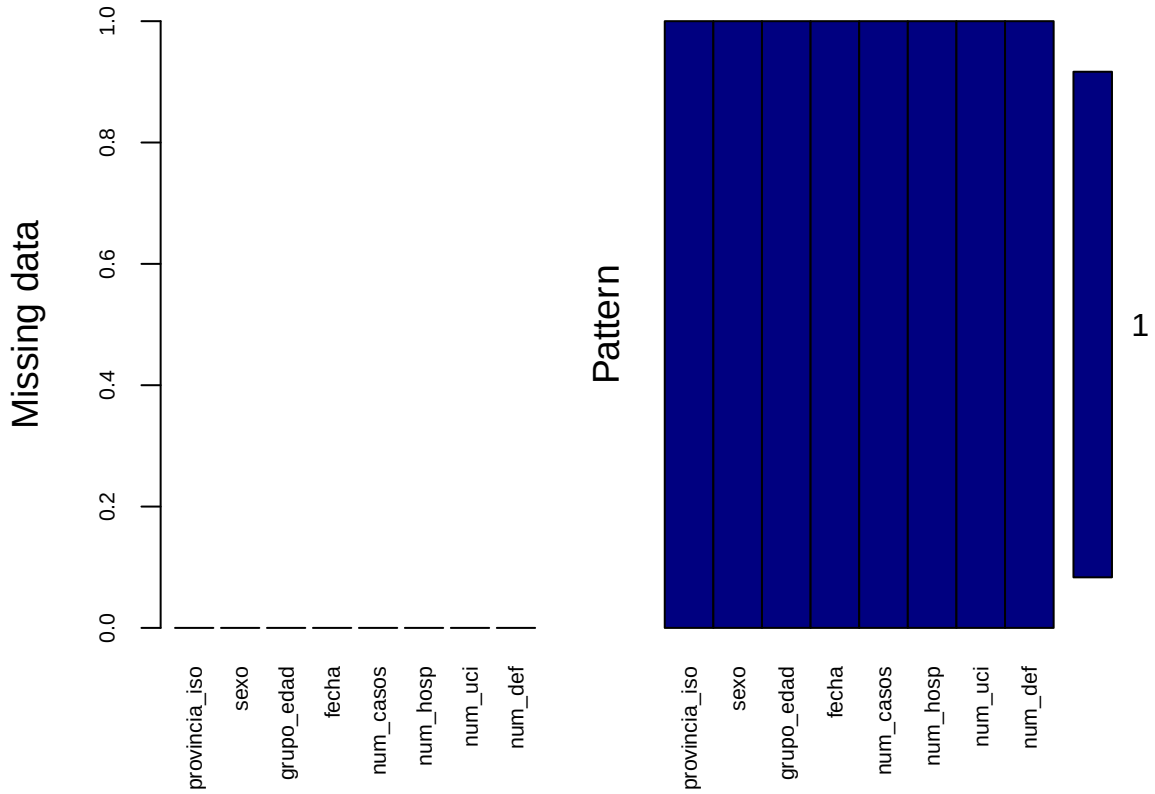

```
##
##  Variables sorted by number of missings:
##       Variable      Count
##  provincia_iso 0.01886792
```

```
##           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,
    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
```

```
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))
```

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.

```
# 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"

# Check table
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".

```
# 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
```

```
# 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
```

```
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
```

```
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
```

```
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
```

```
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.

```
# 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
```

```
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
```

```
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
```

```
Total$num_casos.x <- as.numeric(Total$num_casos.x)
Total$num_casos_prueba_pcr <- as.numeric(Total$num_casos_prueba_pcr)
Total$num_casos_prueba_test_ac <- as.numeric(Total$num_casos_prueba_test_ac)
Total$num_casos_prueba_ag <- as.numeric(Total$num_casos_prueba_ag)
Total$num_casos_prueba_elisa <- as.numeric(Total$num_casos_prueba_elisa)
Total$num_casos_prueba_desconocida   <- as.numeric(Total$num_casos_prueba_desconocida)
Total$num_casos.y <- as.numeric(Total$num_casos.y)
Total$num_hosp <- as.numeric(Total$num_hosp)
Total$num_uci <- as.numeric(Total$num_uci)
Total$num_def <- as.numeric(Total$num_def)

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
```

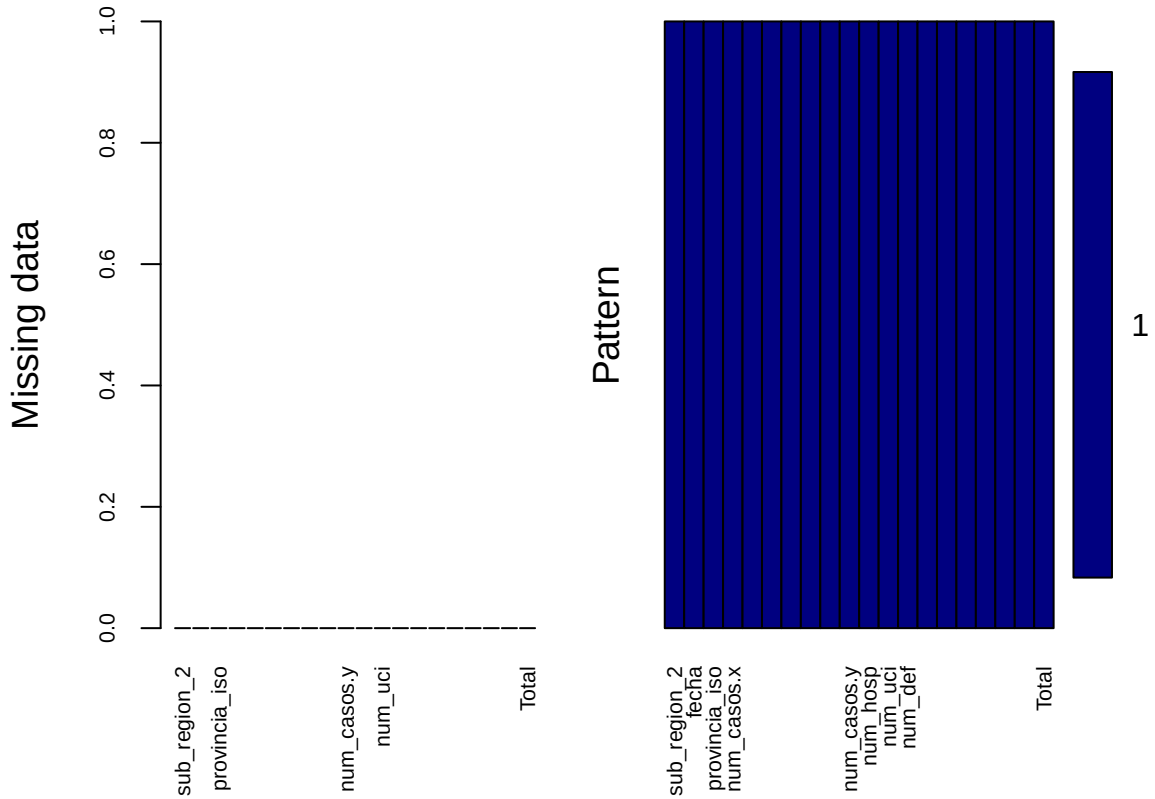
```
##                 Huelva                 Huesca                  Jaén
##                    290                    290                    290
##                  León                 Lleida                  Lugo
##                    290                    290                    290
##                 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
```

```
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

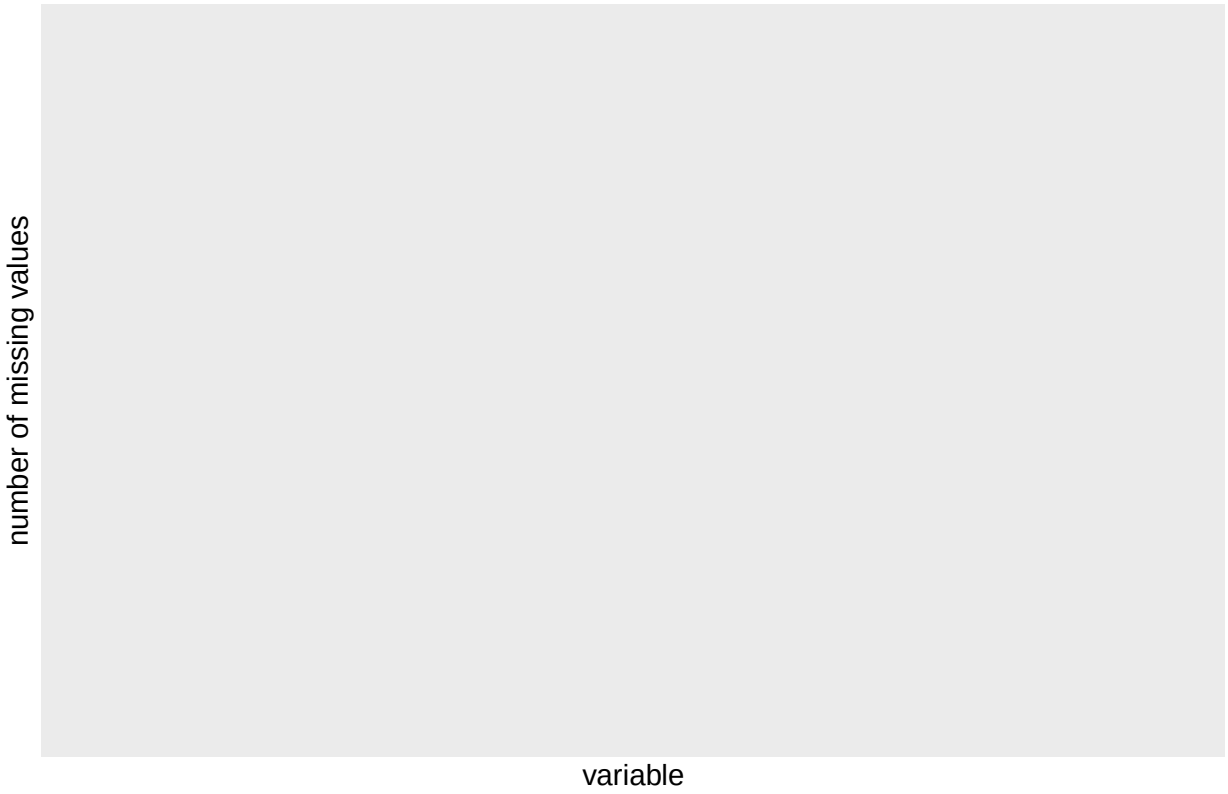
```
aggr(Total, col=c('navyblue','yellow'),
     numbers=TRUE, sortVars=TRUE,
     labels=names(Total), cex.axis=.7,
     gap=3, ylab=c("Missing data","Pattern"))
```




```
##
##  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))
```




```
# 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>               <dbl>       <dbl>
##  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
```

```
# 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
```

```
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                                        : num  137 128 ...
##  $ num_casos_prueba_pcr                               : num  132 123 ...
##  $ num_casos_prueba_test_ac                           : num  5 5 ...
##  $ num_casos_prueba_ag                                : num  0 0 ...
##  $ num_casos_prueba_elisa                             : num  0 0 ...
##  $ num_casos_prueba_desconocida                       : num  0 0 ...
##  $ num_casos.y                                        : num  65 29 ...
##  $ num_hosp                                           : num  43 40 ...
##  $ num_uci                                            : num  3 4 ...
##  $ num_def                                            : num  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
```

```
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
```

```
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
```

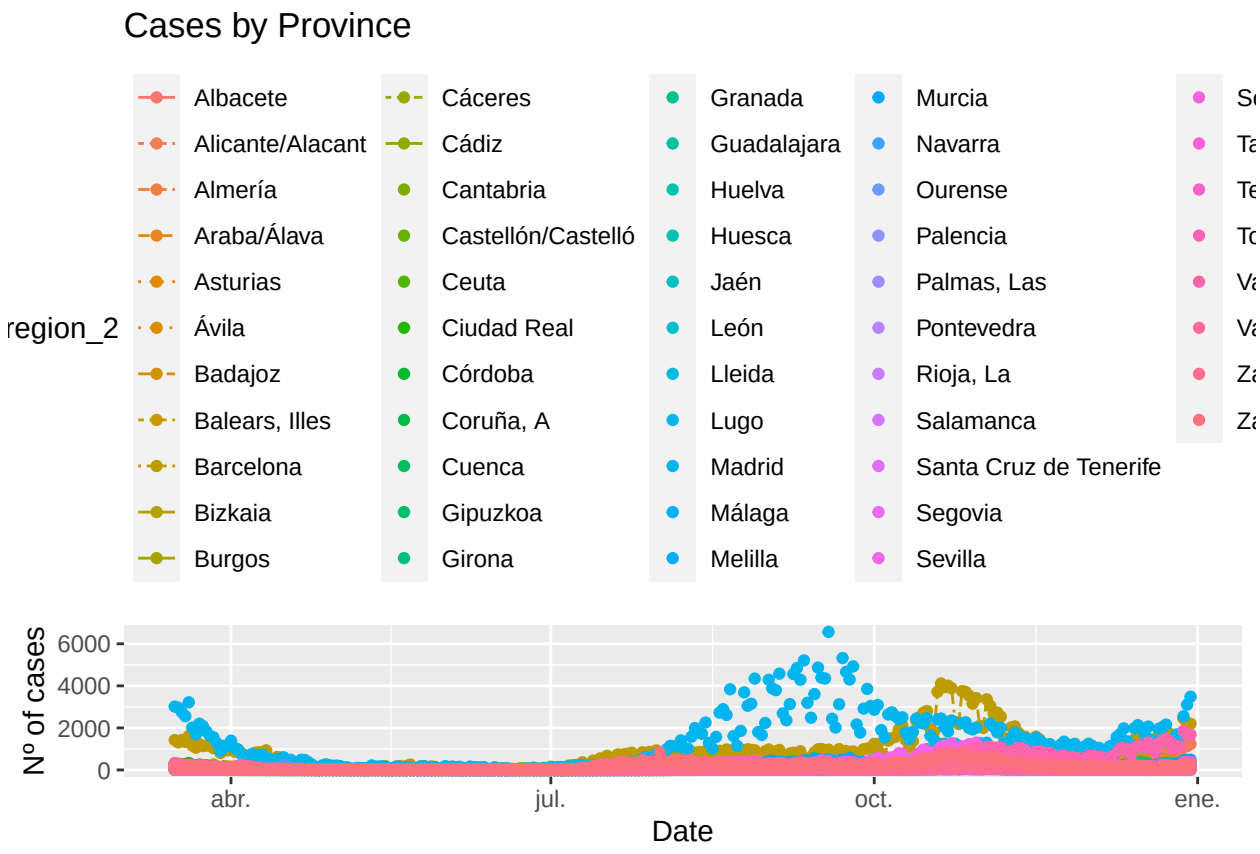
```
write.csv2(Total,"D:\\UOC Master Data Science\\_ M2.882 - TFM - Área 5\\UOC - Guia - PECS\\Pec3\\Total.
           row.names = FALSE)
```

2.3 Visual analysis

2.3.1 Dataframe plots (Málaga, Sevilla and Cádiz)

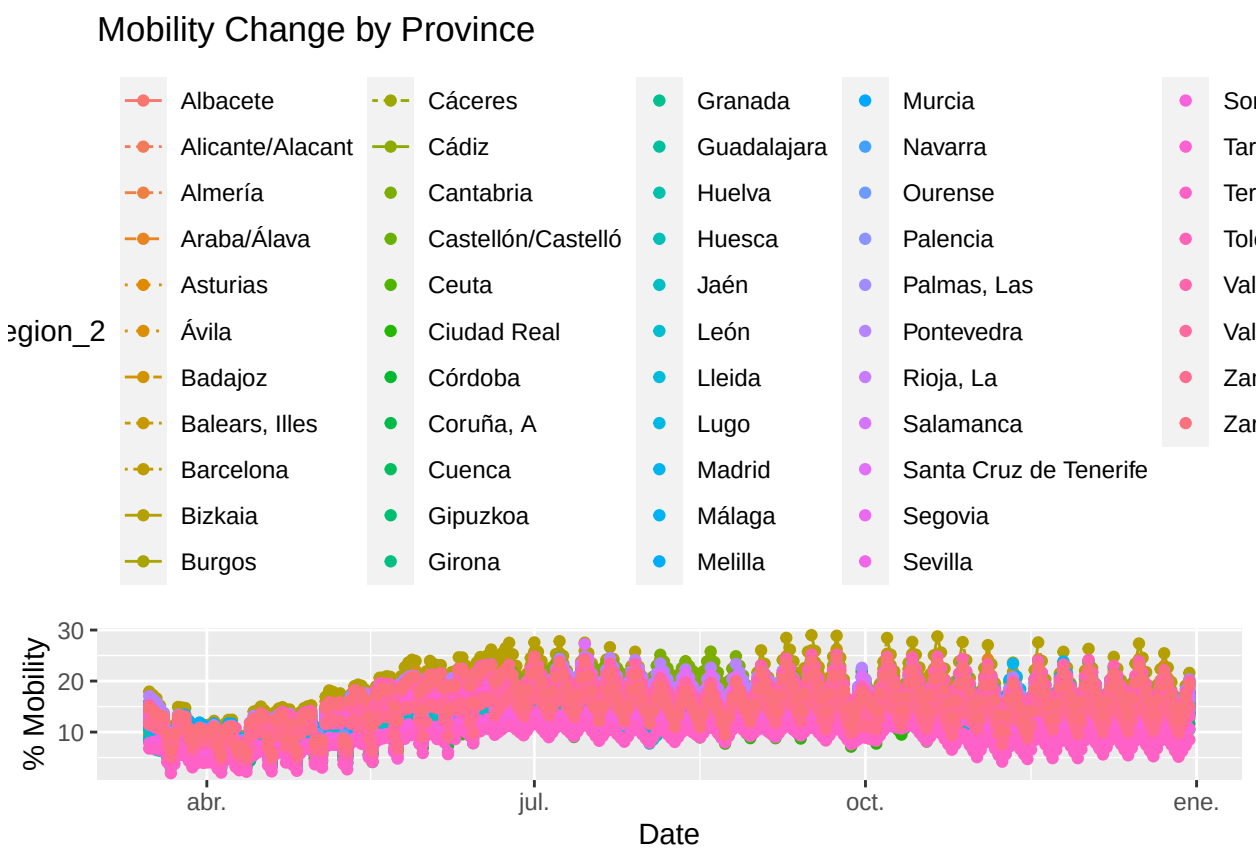
We have generated some plots from the **dataframe** object generated.

```
# 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")
```

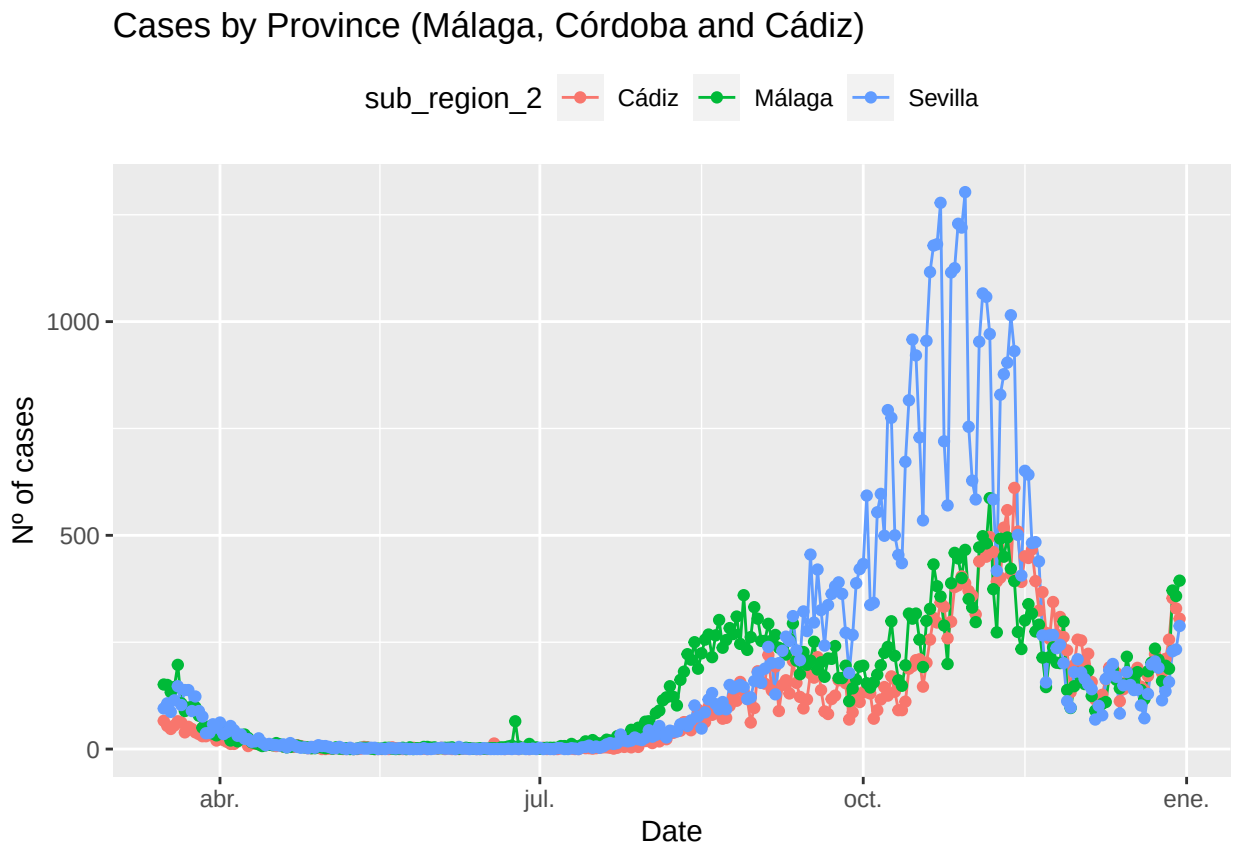



```
# All Total (mobility)
ggplot(Total, aes(x=fecha, y=Total, group=sub_region_2)) +
  geom_line(aes(linetype=sub_region_2, color=sub_region_2))+
```

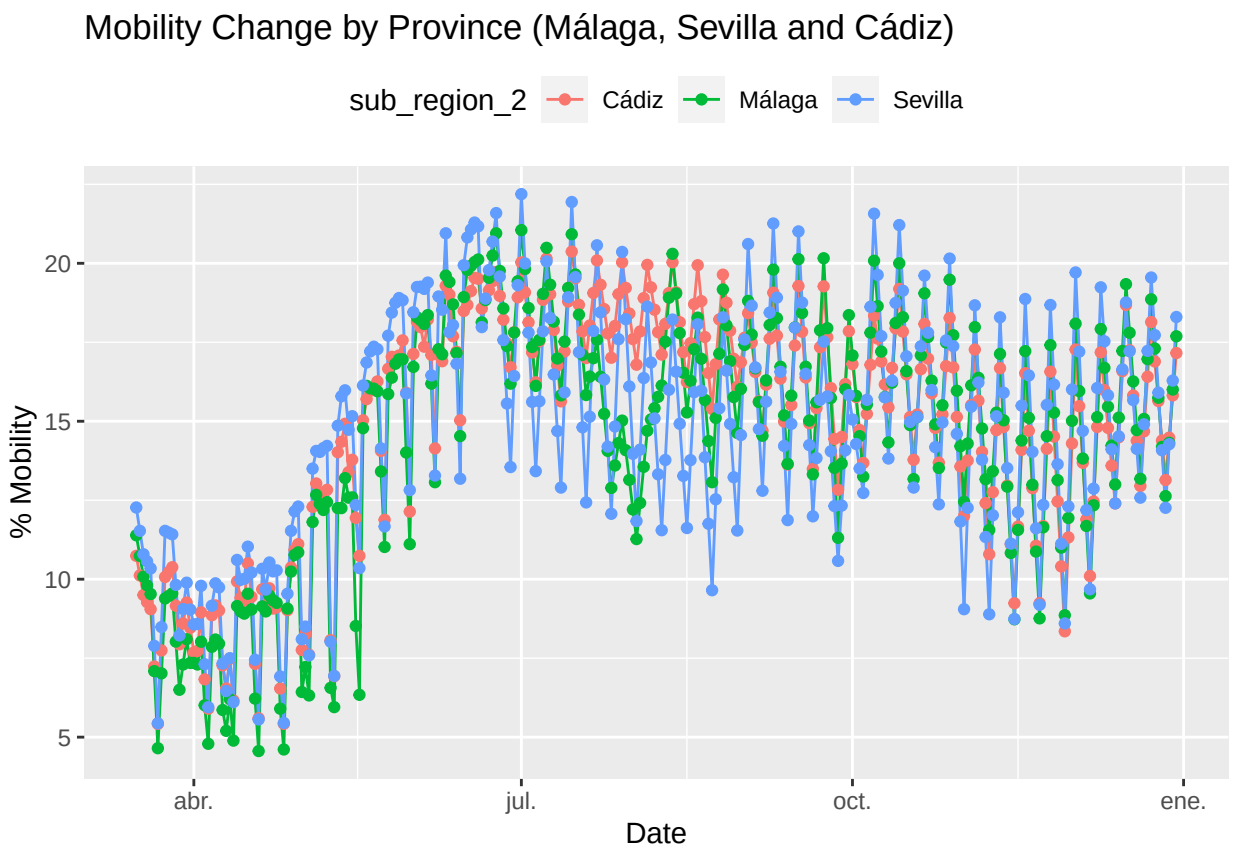
```
  geom_point(aes(color=sub_region_2))+
  theme(legend.position="top") +
  labs(title="Mobility Change by Province",
       x ="Date", y = "% Mobility")
```




```
# Mal, Sev and Cad - num_casos.x
Total %>%
  filter(sub_region_2 == "Málaga" | sub_region_2 == "Cádiz" |
         sub_region_2 == "Sevilla") %>%
  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, Sev and Cad - Total (mobility)
Total %>%
  filter(sub_region_2 == "Málaga" | sub_region_2 == "Cádiz" |
         sub_region_2 == "Sevilla") %>%
  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, Sevilla and Cádiz)",
       x ="Date", y = "% Mobility")
```



2.3.2 Time-series plots (Barcelona, Madrid, Málaga, Sevilla and Cádiz)

We have generated some plots from the **time-series** object generated. We use tsibble().

```
# Convert dataframe to ts object
#library(fpp3)
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 == "Cádiz") -> Total_ts_b

##############################################
Total_ts
```

```
## # A tsibble: 15,080 x 19 [1D]
## # Key:       sub_region_2 [52]
##    sub_region_2 num_casos.x num_casos_prueb~ num_casos_prueb~ num_casos_prueb~
##    <chr>              <dbl>            <dbl>            <dbl>            <dbl>
##  1 Albacete             137              132                5                0
##  2 Albacete             128              123                5                0
##  3 Albacete             114              107                7                0
```

```
##  4 Albacete             149              133               16                0
##  5 Albacete             131              121               10                0
##  6 Albacete             129              120                9                0
##  7 Albacete             125              112               13                0
##  8 Albacete             112              103                9                0
##  9 Albacete             107               91               16                0
## 10 Albacete              78               64               14                0
## # ... with 15,070 more rows, and 14 more variables:
## #   num_casos_prueba_elisa <dbl>, num_casos_prueba_desconocida <dbl>,
## #   num_casos.y <dbl>, num_hosp <dbl>, num_uci <dbl>, num_def <dbl>,
## #   retail_and_recreation_percent_change_from_baseline <dbl>,
## #   grocery_and_pharmacy_percent_change_from_baseline <dbl>,
## #   parks_percent_change_from_baseline <dbl>,
## #   transit_stations_percent_change_from_baseline <dbl>,
## #   workplaces_percent_change_from_baseline <dbl>,
## #   residential_percent_change_from_baseline <dbl>, Total <dbl>, Dia_c <date>
```

```
Total_ts_b
```

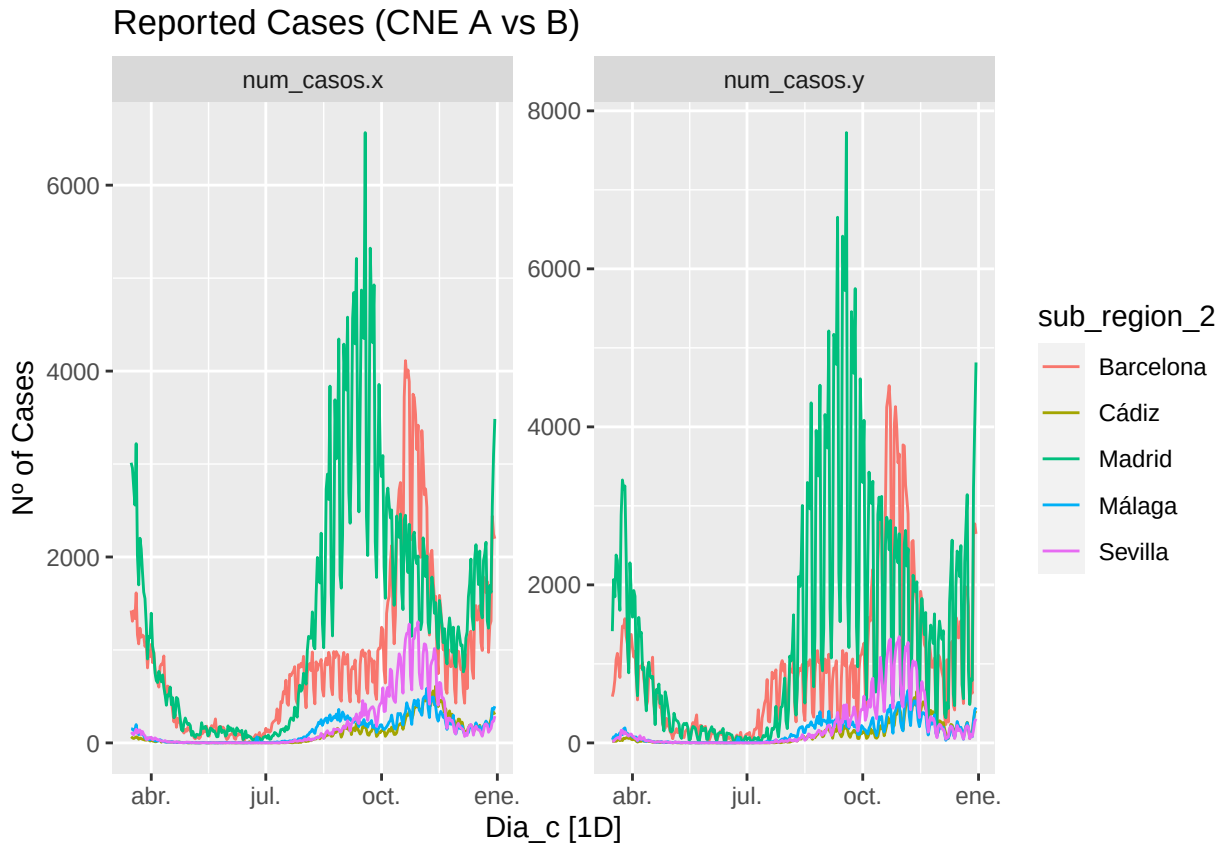
```
## # A tsibble: 1,450 x 19 [1D]
## # Key:       sub_region_2 [5]
##    sub_region_2 num_casos.x num_casos_prueb~ num_casos_prueb~ num_casos_prueb~
##    <chr>              <dbl>            <dbl>            <dbl>            <dbl>
##  1 Barcelona           1424             1351                0                0
##  2 Barcelona           1309             1273                0                0
##  3 Barcelona           1420             1379                0                0
##  4 Barcelona           1338             1289                0                0
##  5 Barcelona           1614             1557                0                0
##  6 Barcelona           1164             1136                0                0
##  7 Barcelona           1065             1032                0                0
##  8 Barcelona           1234             1187                0                0
##  9 Barcelona           1137             1095                0                0
## 10 Barcelona           1159             1131                0                0
## # ... with 1,440 more rows, and 14 more variables:
## #   num_casos_prueba_elisa <dbl>, num_casos_prueba_desconocida <dbl>,
## #   num_casos.y <dbl>, num_hosp <dbl>, num_uci <dbl>, num_def <dbl>,
## #   retail_and_recreation_percent_change_from_baseline <dbl>,
## #   grocery_and_pharmacy_percent_change_from_baseline <dbl>,
## #   parks_percent_change_from_baseline <dbl>,
## #   transit_stations_percent_change_from_baseline <dbl>,
## #   workplaces_percent_change_from_baseline <dbl>,
## #   residential_percent_change_from_baseline <dbl>, Total <dbl>, Dia_c <date>
```

```
Total_ts_b %>% distinct(sub_region_2)
```

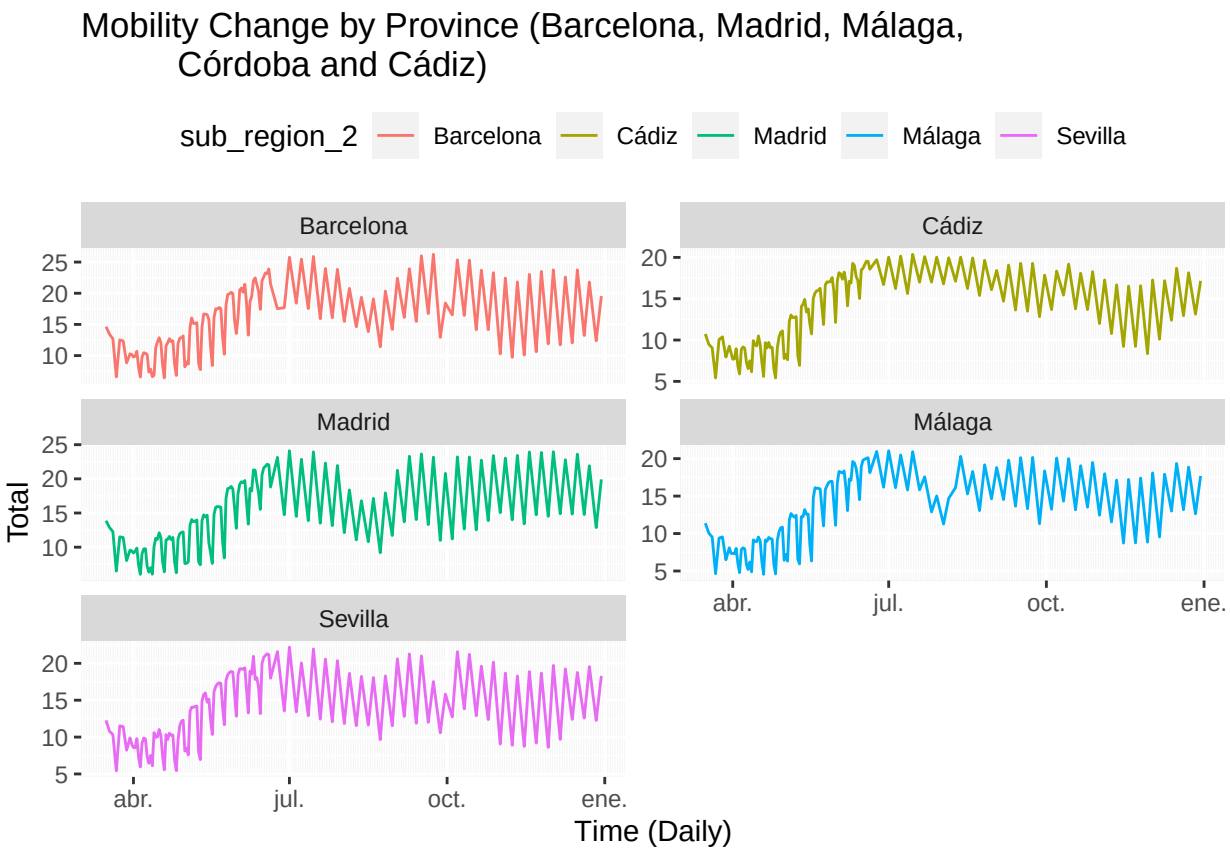
```
## # A tibble: 5 x 1
##   sub_region_2
##   <chr>
## 1 Barcelona
## 2 Cádiz
## 3 Madrid
## 4 Málaga
## 5 Sevilla
```

```
##########################################
```

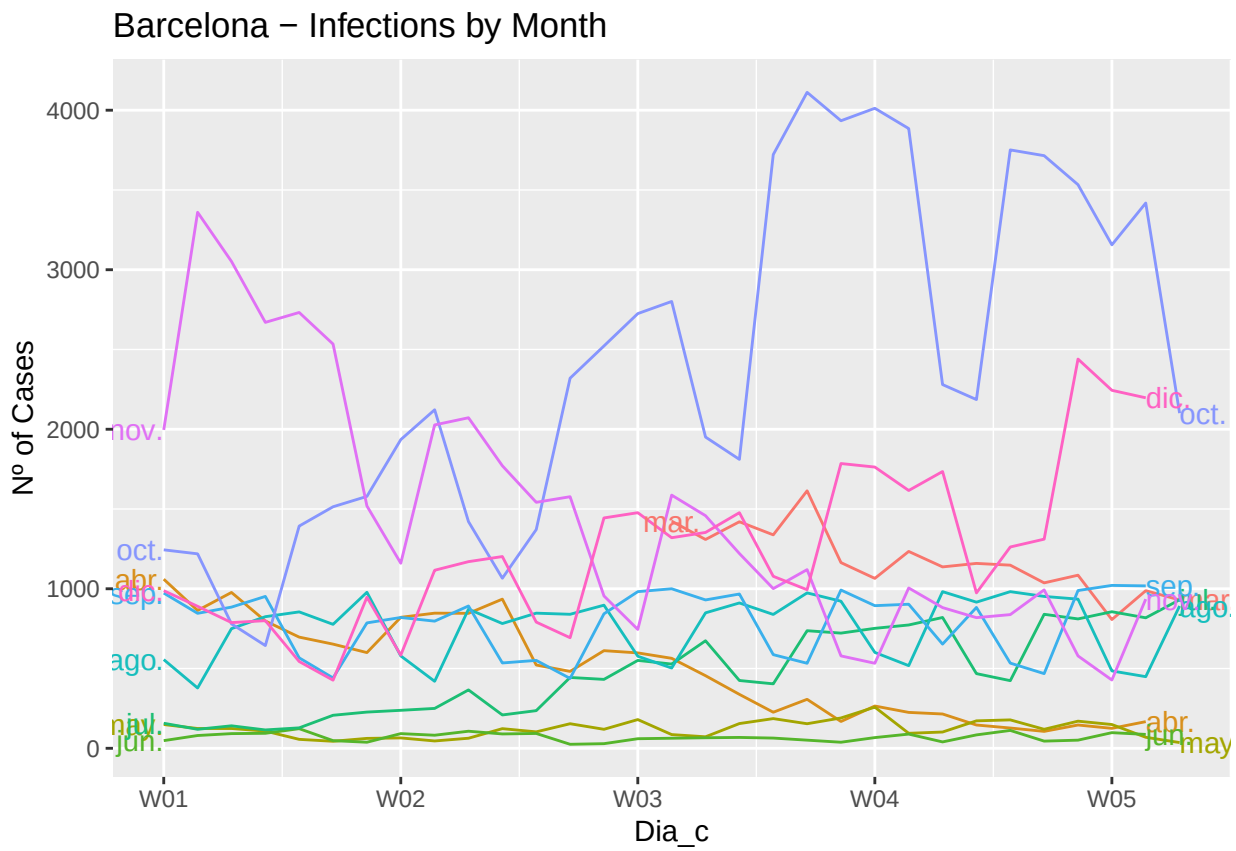
```r
# Plots
# A num_casos.x,num_casos.y
autoplot(Total_ts_b, vars(num_casos.x,num_casos.y)) +
  labs(y = "Nº of Cases",
       title = "Reported Cases (CNE A vs B)")
```




```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 (Barcelona, Madrid, Málaga,
          Córdoba and Cádiz)")
```

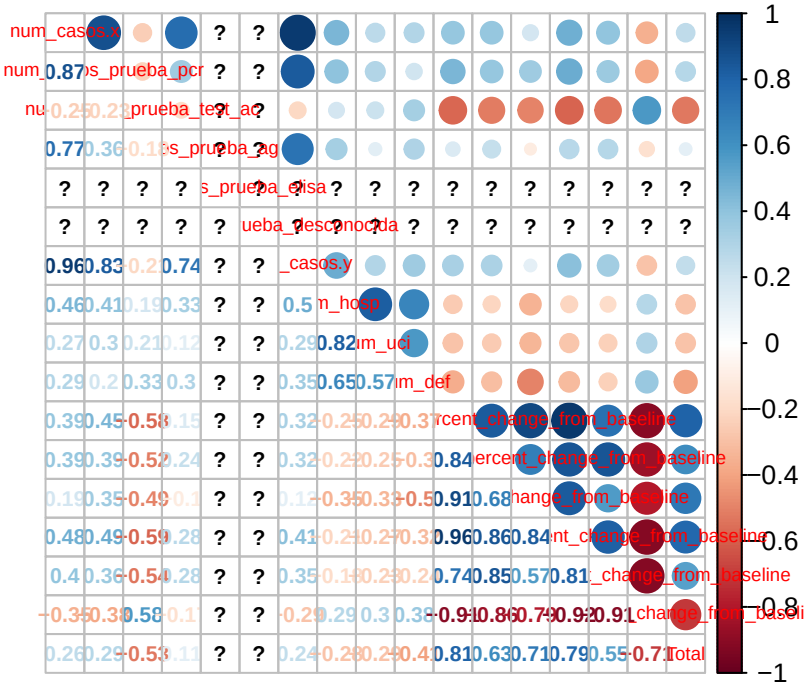



```
# C sub_region_2 == "Barcelona" by month
Total_ts %>% filter(sub_region_2 == "Barcelona") %>%
  gg_season(num_casos.x, period = "month", labels = "both") +
  theme(legend.position = "top") +
  labs(y="Nº of Cases", title="Barcelona - Infections by Month")
```

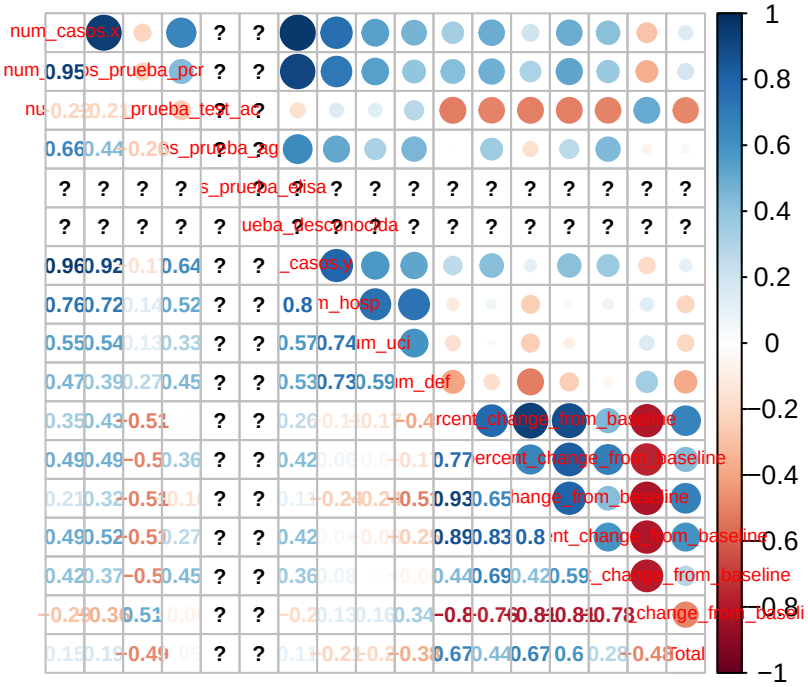


2.3.3 Correlation plots (from dataframe)

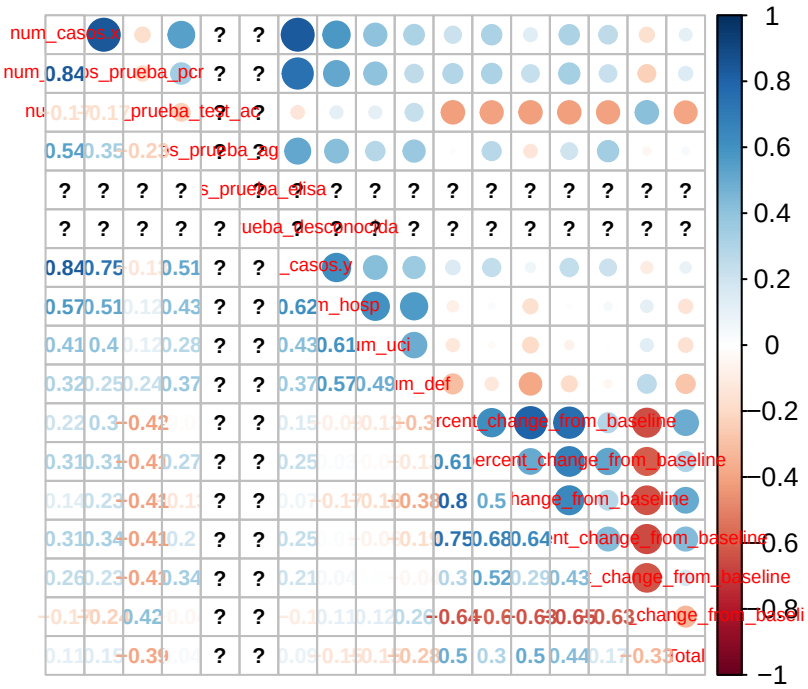
```
# Filter to "sub_region_2" == "Barcelona" or "Málaga"
# Character / date columns are eliminated
#library(corrplot)
#### Málaga
# pearson
Total.res<-Total %>%
  filter(sub_region_2 == "Málaga")
Total.res<-cor(Total.res[,c(-1,-2,-3)],method="pearson")
corrplot.mixed(Total.res,upper="circle",number.cex=.65,tl.cex=.6, title="Málaga -
               pearson ")
```



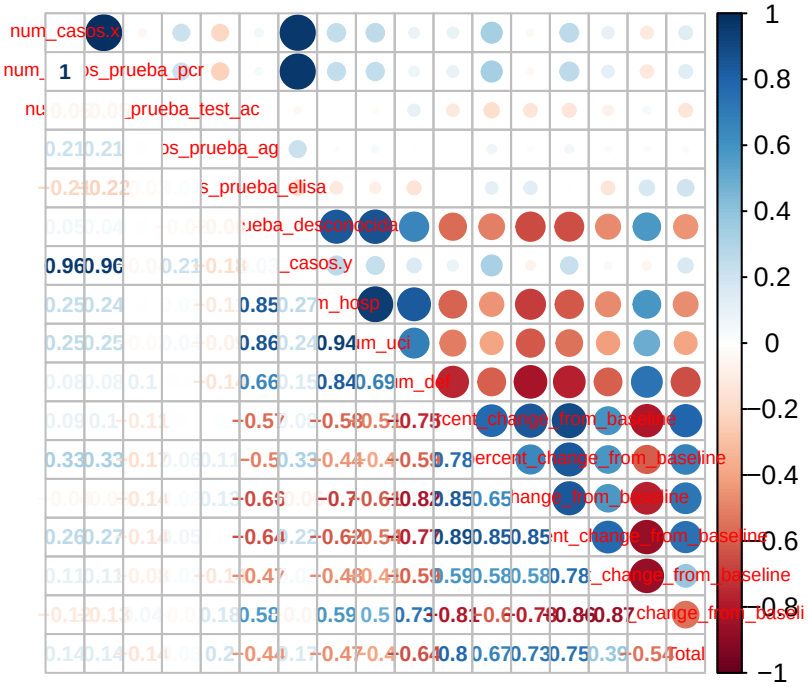

```
# spearman
Total.res<-Total %>%
  filter(sub_region_2 == "Málaga")
Total.res<-cor(Total.res[,c(-1,-2,-3)],method="spearman")
corrplot.mixed(Total.res,upper="circle",number.cex=.65,tl.cex=.6, title="Málaga -
               spearman ")
```



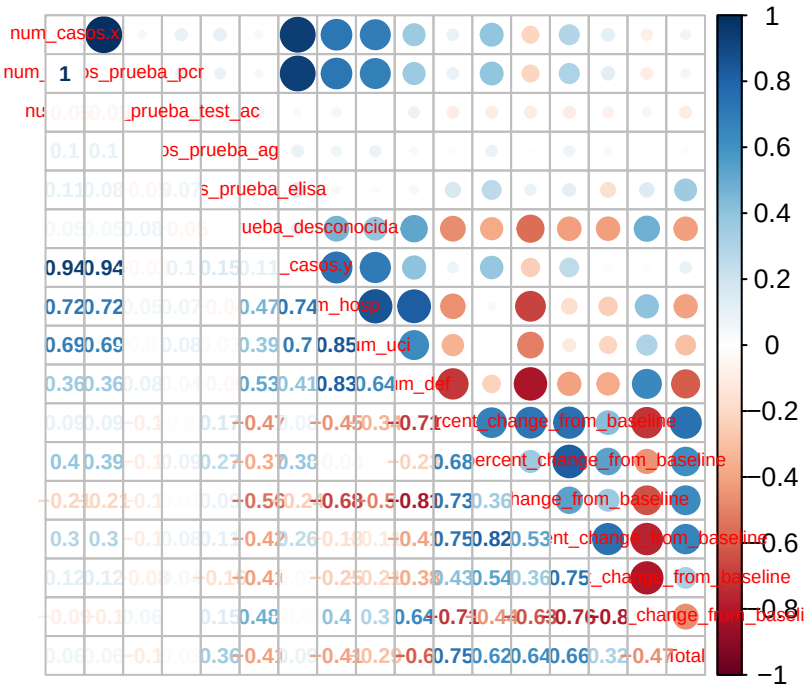

```
# kendall
Total.res<-Total %>%
  filter(sub_region_2 == "Málaga")
Total.res<-cor(Total.res[,c(-1,-2,-3)],method="kendall")
corrplot.mixed(Total.res,upper="circle",number.cex=.65,tl.cex=.6, title="Málaga -
               kendall ")
```



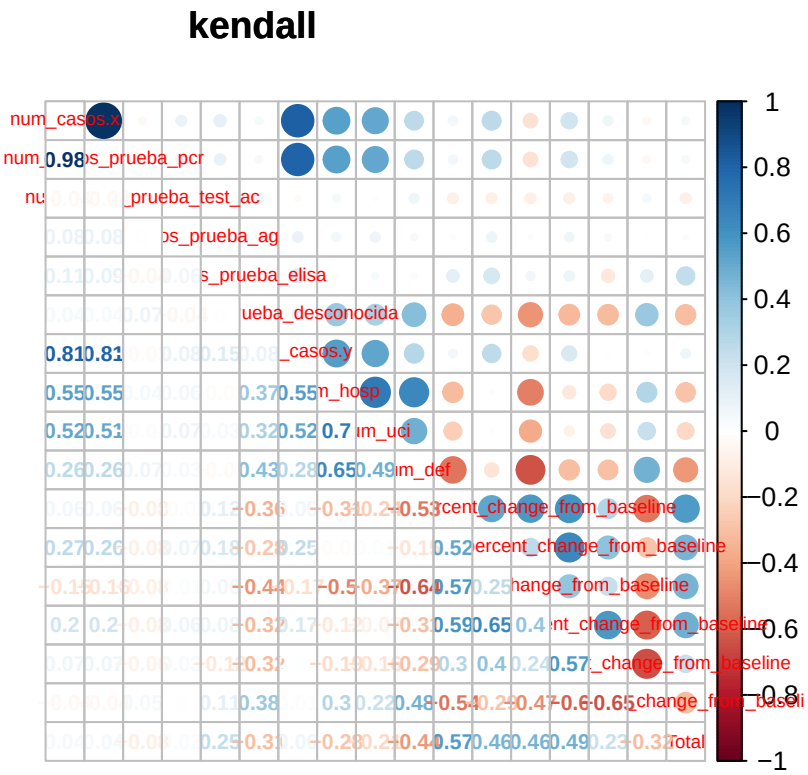

```
#### Barcelona
# pearson
Total.res<-Total %>%
  filter(sub_region_2 == "Barcelona")
Total.res<-cor(Total.res[,c(-1,-2,-3)],method="pearson")
corrplot.mixed(Total.res,upper="circle",number.cex=.65,tl.cex=.6, title="Barcelona -
               pearson ")
```




```
# spearman
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, title="Barcelona -
               spearman ")
```




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



2.3.4 PCA (Barcelona)

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

```
## Importance of components:
##                           PC1    PC2     PC3     PC4     PC5     PC6     PC7
## Standard deviation     3.0590 1.8914 1.12142 1.02409 0.83504 0.57825 0.46266
## Proportion of Variance 0.5504 0.2104 0.07398 0.06169 0.04102 0.01967 0.01259
## Cumulative Proportion  0.5504 0.7609 0.83485 0.89655 0.93756 0.95723 0.96982
##                           PC8     PC9     PC10    PC11    PC12    PC13    PC14
## Standard deviation     0.41006 0.33620 0.28445 0.21986 0.17734 0.16911 0.15372
## Proportion of Variance 0.00989 0.00665 0.00476 0.00284 0.00185 0.00168 0.00139
## Cumulative Proportion  0.97971 0.98636 0.99112 0.99397 0.99582 0.99750 0.99889
##                           PC15    PC16      PC17
## Standard deviation     0.1369 0.01274 1.826e-17
## Proportion of Variance 0.0011 0.00001 0.000e+00
## Cumulative Proportion  1.0000 1.00000 1.000e+00
```

```
pca$rotation
```

```
##                                                 PC1          PC2
## num_casos.x                             -0.1354826901 -0.469400471
## num_casos_prueba_pcr                    -0.1356873829 -0.469237915
## num_casos_prueba_test_ac                -0.0782958432  0.237502756
## num_casos_prueba_ag                      0.0005323686  0.008790618
```

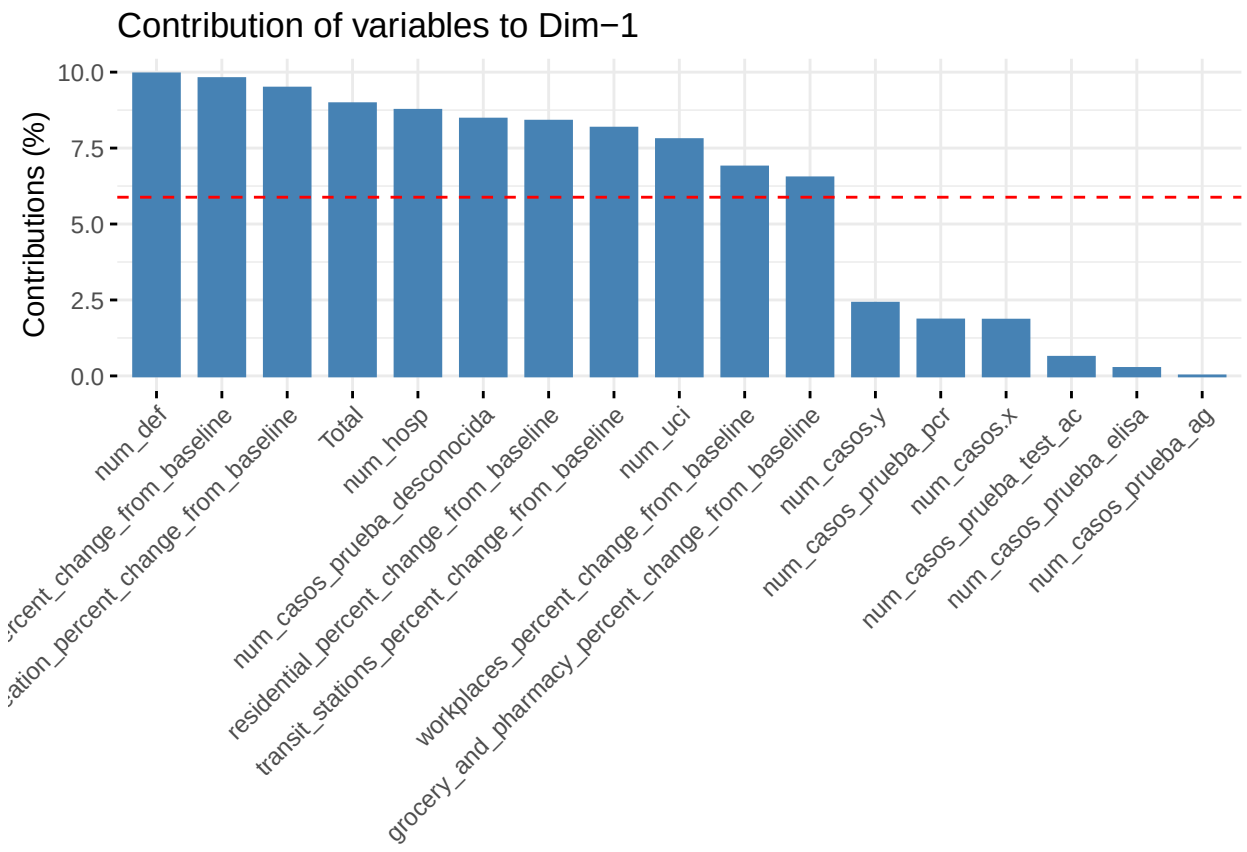
```
## num_casos_prueba_elisa                                0.0495912937  0.004385553
## num_casos_prueba_desconocida                         -0.2907430443  0.113686282
## num_casos.y                                          -0.1546876637 -0.450080493
## num_hosp                                             -0.2956764064 -0.199498016
## num_uci                                              -0.2788863801 -0.230508957
## num_def                                              -0.3153112111 -0.030904089
## retail_and_recreation_percent_change_from_baseline    0.3077977291 -0.116093786
## grocery_and_pharmacy_percent_change_from_baseline     0.2553316609 -0.261732823
## parks_percent_change_from_baseline                    0.3128404870  0.012776948
## transit_stations_percent_change_from_baseline         0.2855716515 -0.218931952
## workplaces_percent_change_from_baseline               0.2622358364 -0.170838668
## residential_percent_change_from_baseline             -0.2895648649  0.166332144
## Total                                                 0.2993175108 -0.081611685
##                                                              PC3          PC4
## num_casos.x                                          -0.002875288 -0.028445983
## num_casos_prueba_pcr                                 -0.012292151 -0.026795983
## num_casos_prueba_test_ac                             -0.392712472 -0.268237834
## num_casos_prueba_ag                                  -0.034460138  0.950253303
## num_casos_prueba_elisa                                0.811470962 -0.060011278
## num_casos_prueba_desconocida                          0.019674417 -0.078105637
## num_casos.y                                           0.041668217 -0.036946432
## num_hosp                                             -0.051419434 -0.010413059
## num_uci                                              -0.018126448  0.006323566
## num_def                                              -0.031133681  0.009747098
## retail_and_recreation_percent_change_from_baseline    0.033200491 -0.075398568
## grocery_and_pharmacy_percent_change_from_baseline     0.027494995 -0.030995413
## parks_percent_change_from_baseline                    0.029299658 -0.011018427
## transit_stations_percent_change_from_baseline        -0.099387689 -0.018021579
## workplaces_percent_change_from_baseline              -0.303553292  0.028981871
## residential_percent_change_from_baseline              0.211975965  0.003369575
## Total                                                 0.173800838 -0.065471155
##                                                              PC5          PC6
## num_casos.x                                          -0.15653475  0.16549669
## num_casos_prueba_pcr                                 -0.15256567  0.17028866
## num_casos_prueba_test_ac                             -0.81534671 -0.10365823
## num_casos_prueba_ag                                  -0.25969423 -0.01360833
## num_casos_prueba_elisa                               -0.34805371 -0.37185910
## num_casos_prueba_desconocida                          0.20580692 -0.11429059
## num_casos.y                                          -0.15827091  0.15297764
## num_hosp                                              0.03855580 -0.11688342
## num_uci                                               0.06172358 -0.06173530
## num_def                                               0.08791553 -0.26888200
## retail_and_recreation_percent_change_from_baseline -0.02731712  0.18700422
## grocery_and_pharmacy_percent_change_from_baseline     0.01445198 -0.34534708
## parks_percent_change_from_baseline                   -0.01705528  0.39173313
## transit_stations_percent_change_from_baseline         0.03520761 -0.26003250
## workplaces_percent_change_from_baseline               0.10943614 -0.48832683
## residential_percent_change_from_baseline              0.03104587  0.13040337
## Total                                                -0.05468582  0.19337305
##                                                              PC7          PC8
## num_casos.x                                           0.11538168  0.07515692
## num_casos_prueba_pcr                                  0.11048811  0.07713501
## num_casos_prueba_test_ac                             -0.08510797 -0.12117026
## num_casos_prueba_ag                                  -0.03926649 -0.14832473
```

```
## num_casos_prueba_elisa                                 0.24859208  0.01374512
## num_casos_prueba_desconocida                           0.19845835 -0.75630827
## num_casos.y                                            0.04117476 -0.02860659
## num_hosp                                              -0.11367668 -0.07611704
## num_uci                                               -0.02723992 -0.20583241
## num_def                                               -0.20890547  0.15436921
## retail_and_recreation_percent_change_from_baseline -0.10130686 -0.31700087
## grocery_and_pharmacy_percent_change_from_baseline  -0.63305922 -0.04093499
## parks_percent_change_from_baseline                     0.15076652  0.04293438
## transit_stations_percent_change_from_baseline      -0.06852096 -0.19335324
## workplaces_percent_change_from_baseline                0.37588850  0.19906444
## residential_percent_change_from_baseline           -0.39494991  0.23079899
## Total                                                 -0.26415699 -0.26912855
##                                                              PC9         PC10
## num_casos.x                                           -0.204798939 -0.059620970
## num_casos_prueba_pcr                                  -0.206074966 -0.057649643
## num_casos_prueba_test_ac                               0.031408747  0.010328003
## num_casos_prueba_ag                                   -0.027397924 -0.004813823
## num_casos_prueba_elisa                                 0.085159377 -0.047189805
## num_casos_prueba_desconocida                          -0.349092565 -0.125363275
## num_casos.y                                           -0.130984317  0.031574368
## num_hosp                                               0.283065654  0.067094187
## num_uci                                                0.717067401  0.169083317
## num_def                                               -0.009119052  0.013475201
## retail_and_recreation_percent_change_from_baseline  0.099531350 -0.317145228
## grocery_and_pharmacy_percent_change_from_baseline  -0.110976209 -0.296856620
## parks_percent_change_from_baseline                     0.283874181 -0.240873233
## transit_stations_percent_change_from_baseline          0.094114251 -0.074265913
## workplaces_percent_change_from_baseline               -0.125028631  0.240735868
## residential_percent_change_from_baseline              -0.178700468  0.013386663
## Total                                                 -0.118124812  0.793981499
##                                                             PC11          PC12
## num_casos.x                                           -0.049617465 -0.0988357734
## num_casos_prueba_pcr                                  -0.044726847 -0.1058640000
## num_casos_prueba_test_ac                              -0.042562355 -0.0389190655
## num_casos_prueba_ag                                    0.003758095 -0.0008550931
## num_casos_prueba_elisa                                 0.023430627 -0.0013867741
## num_casos_prueba_desconocida                          -0.154872738 -0.1615965585
## num_casos.y                                            0.033429358  0.1359821524
## num_hosp                                               0.302911164  0.0671255962
## num_uci                                               -0.400459562  0.0477114671
## num_def                                                0.553043315 -0.1950704924
## retail_and_recreation_percent_change_from_baseline  0.286708424  0.6275693247
## grocery_and_pharmacy_percent_change_from_baseline  -0.348092535 -0.0594956464
## parks_percent_change_from_baseline                    -0.082227368 -0.4958947989
## transit_stations_percent_change_from_baseline          0.264287632 -0.4433548371
## workplaces_percent_change_from_baseline               -0.216784094  0.2008296543
## residential_percent_change_from_baseline              -0.278596900  0.0313367951
## Total                                                  0.074087201 -0.0830357636
##                                                             PC13         PC14
## num_casos.x                                            0.3503737964 -0.03447444
## num_casos_prueba_pcr                                   0.3691954013 -0.03383423
## num_casos_prueba_test_ac                              -0.0023721487 -0.01431289
## num_casos_prueba_ag                                    0.0009495141 -0.01895981
```

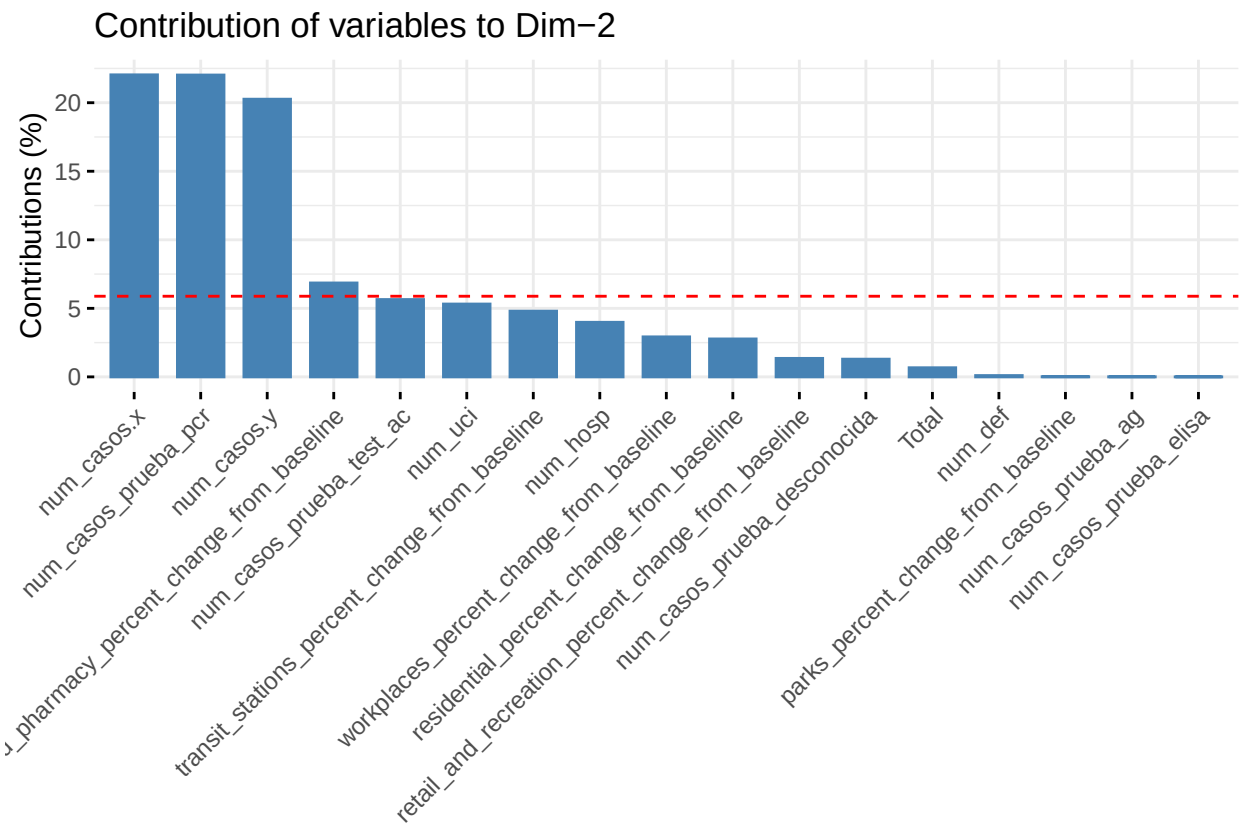
```
## num_casos_prueba_elisa                                0.0189278939 -0.03470038
## num_casos_prueba_desconocida                         -0.0341231415 -0.11380732
## num_casos.y                                          -0.8087585769  0.15136854
## num_hosp                                             -0.0093409355 -0.32920173
## num_uci                                               0.0905105752  0.12476243
## num_def                                              -0.0179131471 -0.20425404
## retail_and_recreation_percent_change_from_baseline    0.1591640063  0.05248551
## grocery_and_pharmacy_percent_change_from_baseline    -0.0689717137 -0.30356466
## parks_percent_change_from_baseline                   -0.1967768342 -0.33947866
## transit_stations_percent_change_from_baseline         0.0373896719  0.66046288
## workplaces_percent_change_from_baseline              -0.0493969622 -0.09490414
## residential_percent_change_from_baseline              0.0240600499  0.34670086
## Total                                                 0.0590314137 -0.13712447
##                                                              PC15          PC16
## num_casos.x                                           0.021886709 -0.710827710
## num_casos_prueba_pcr                                  0.020989875  0.696614910
## num_casos_prueba_test_ac                              0.002128322 -0.009045443
## num_casos_prueba_ag                                  -0.001031653 -0.006169593
## num_casos_prueba_elisa                               -0.019875868  0.004055133
## num_casos_prueba_desconocida                         -0.000227830 -0.014131490
## num_casos.y                                           0.065935929  0.012850260
## num_hosp                                             -0.738022542 -0.005532761
## num_uci                                               0.291185664 -0.005062923
## num_def                                               0.517898894 -0.032682612
## retail_and_recreation_percent_change_from_baseline    0.103782290 -0.031882076
## grocery_and_pharmacy_percent_change_from_baseline     0.033876519  0.014999252
## parks_percent_change_from_baseline                   -0.032945065 -0.039812604
## transit_stations_percent_change_from_baseline        -0.169052448 -0.008281975
## workplaces_percent_change_from_baseline              -0.059237981 -0.040905347
## residential_percent_change_from_baseline             -0.223342981 -0.056238440
## Total                                                 0.040900018 -0.009746369
##                                                              PC17
## num_casos.x                                          -0.04694046
## num_casos_prueba_pcr                                  0.08912178
## num_casos_prueba_test_ac                              0.09544863
## num_casos_prueba_ag                                   0.05828430
## num_casos_prueba_elisa                                0.04498527
## num_casos_prueba_desconocida                          0.16508413
## num_casos.y                                          -0.01242631
## num_hosp                                              0.04584112
## num_uci                                               0.06322805
## num_def                                               0.30912666
## retail_and_recreation_percent_change_from_baseline    0.33484091
## grocery_and_pharmacy_percent_change_from_baseline    -0.13871900
## parks_percent_change_from_baseline                    0.41803506
## transit_stations_percent_change_from_baseline         0.04834211
## workplaces_percent_change_from_baseline               0.44739326
## residential_percent_change_from_baseline              0.57600490
## Total                                                 0.07657033
```

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

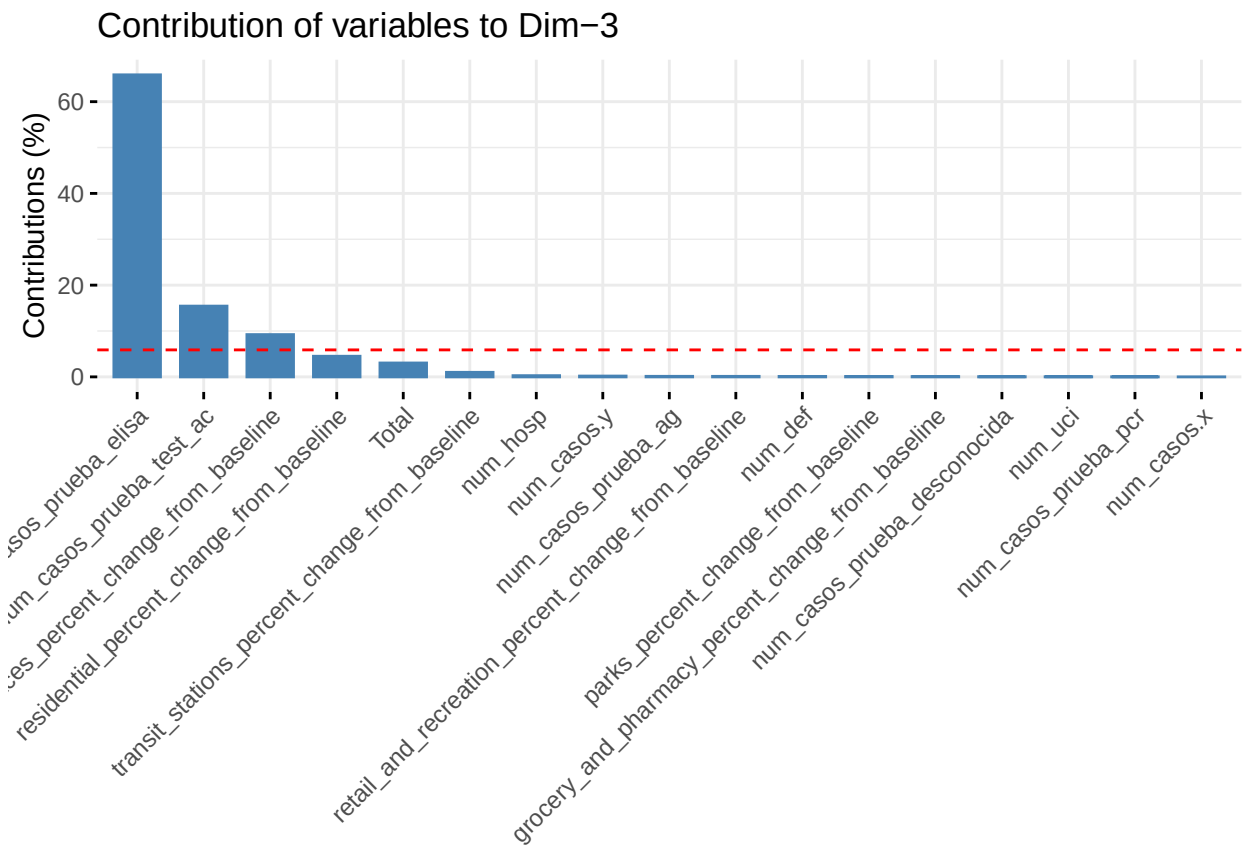
```
    install.packages('factoextra', repos='http://cran.us.r-project.org')
    library(factoextra)}

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



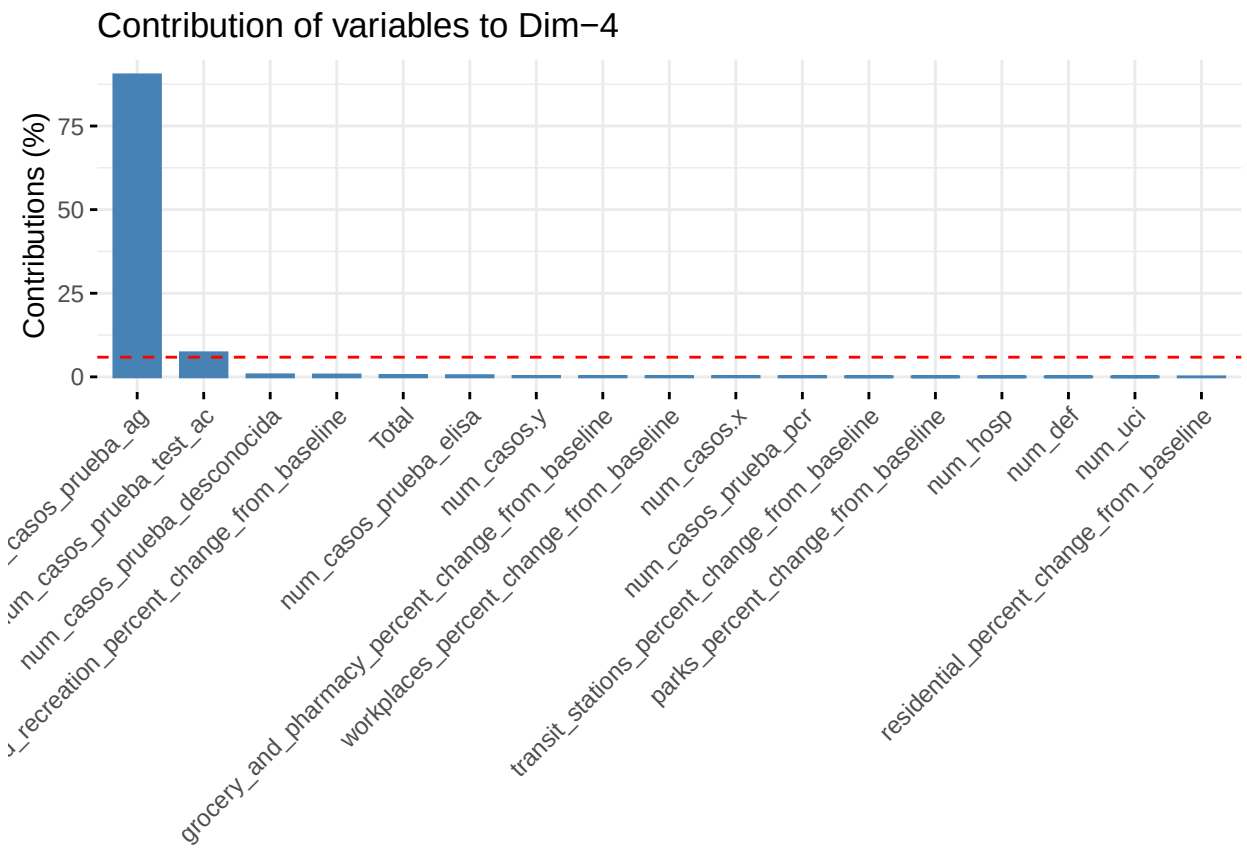

```
fviz_contrib(pca, choice = "var", axes = 2)
```



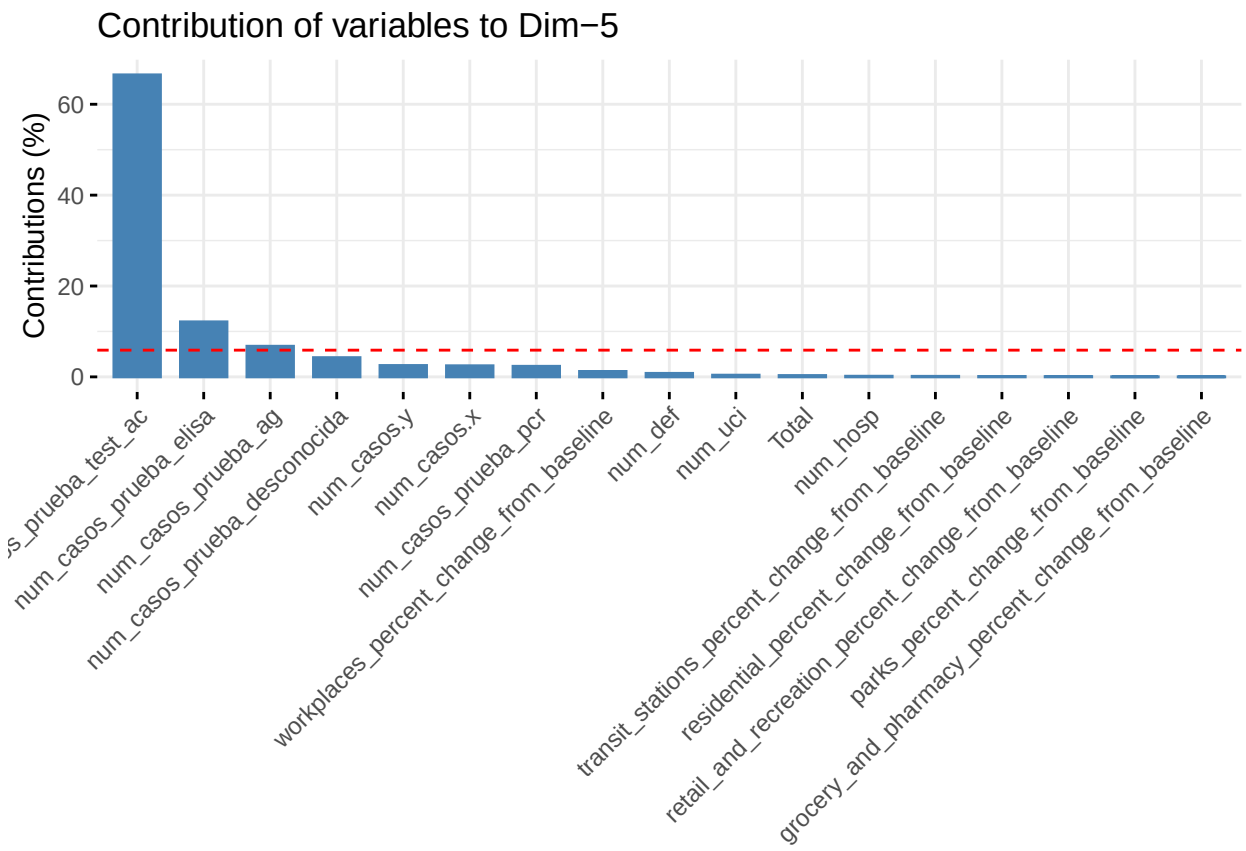

```
fviz_contrib(pca, choice = "var", axes = 3)
```




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

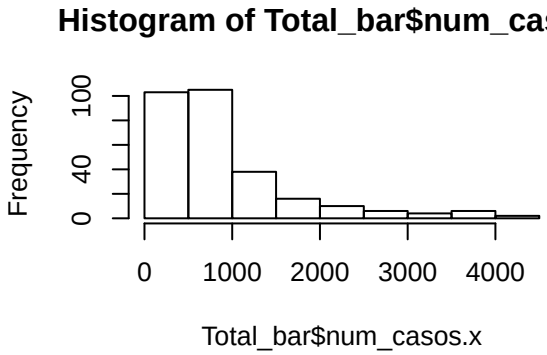


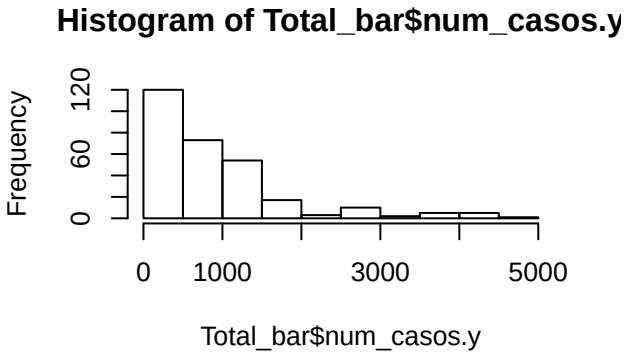

```
fviz_contrib(pca, choice = "var", axes = 5)
```

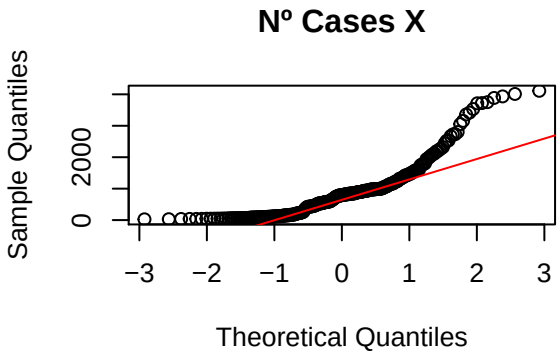


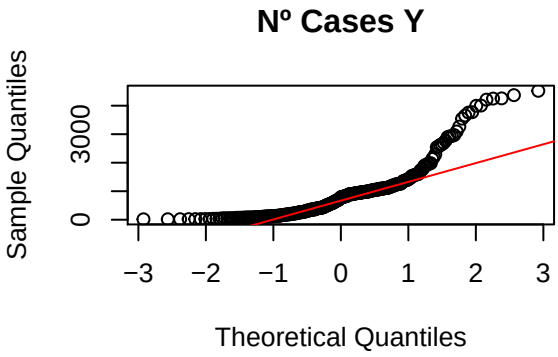
2.3.5 Review normality (Barcelona)

```
# Check for Barcelona
# Raw
Total %>%
  filter(sub_region_2 == "Barcelona") -> Total_bar

par(mfrow=c(2,2))

hist(Total_bar$num_casos.x)
hist(Total_bar$num_casos.y)

qqnorm(Total_bar$num_casos.x, main="Nº Cases X")
qqline(Total_bar$num_casos.x,col=2)

qqnorm(Total_bar$num_casos.y, main="Nº Cases Y")
qqline(Total_bar$num_casos.y,col=2)
```

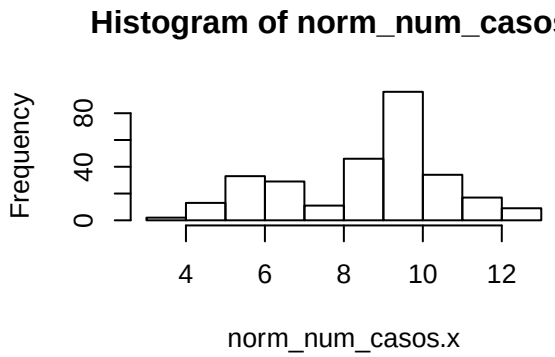


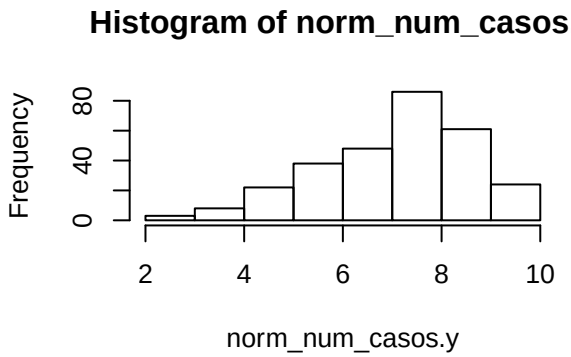


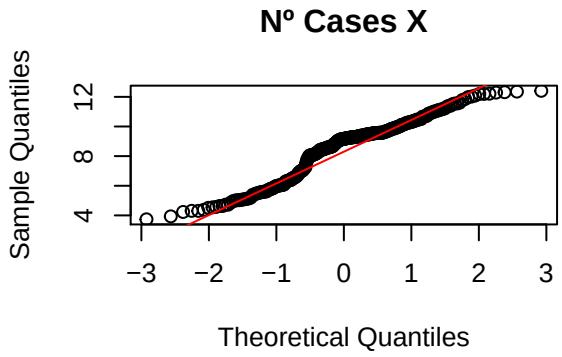


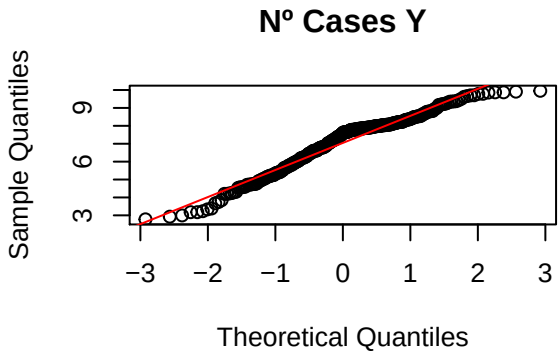



```r
# Normalize
library(DescTools)
norm_num_casos.x <- BoxCox(Total_bar$num_casos.x, lambda =
                           BoxCoxLambda(Total_bar$num_casos.x))
norm_num_casos.y <- BoxCox(Total_bar$num_casos.y, lambda =
                           BoxCoxLambda(Total_bar$num_casos.y))

hist(norm_num_casos.x)
hist(norm_num_casos.y)

qqnorm(norm_num_casos.x, main="Nº Cases X")
qqline(norm_num_casos.x,col=2)

qqnorm(norm_num_casos.y, main="Nº Cases Y")
qqline(norm_num_casos.y,col=2)
```










```
# Columns removal according PCA results and SME knowledge
Total <- Total[c(-3,-6,-7,-8,-10)]
Total_bar <- Total_bar[c(-3,-6,-7,-8,-10)]
Total_ts <- Total_ts[c(-4,-5,-6,-8)]
Total_ts_b <- Total_ts_b[c(-4,-5,-6,-8)]
table(Total_ts$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
```

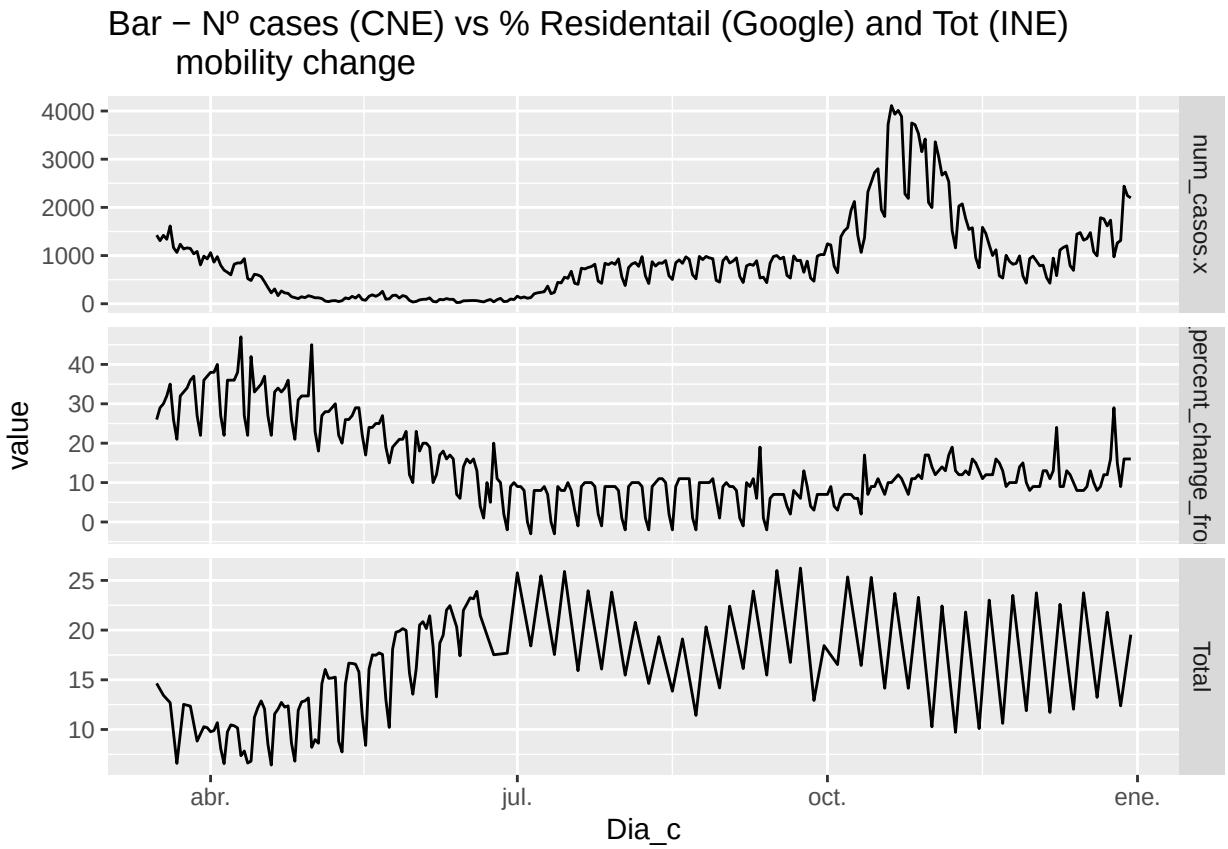
```
#str(Total_ts)
summary(Total_ts)
```

```
##  sub_region_2        num_casos.x    num_casos_prueba_pcr
##  Length:15080       Min.   :   0   Min.   :   0.0
##  Class :character   1st Qu.:   5   1st Qu.:   5.0
##  Mode  :character   Median :  39   Median :  35.0
##                     Mean   : 126   Mean   : 110.2
##                     3rd Qu.: 120   3rd Qu.: 105.0
##                     Max.   :6565   Max.   :6546.0
##  num_casos_prueba_desconocida    num_hosp          num_uci
##  Min.   : 0.0000              Min.   :   0.00   Min.   :  0.000
##  1st Qu.: 0.0000              1st Qu.:   1.00   1st Qu.:  0.000
##  Median : 0.0000              Median :   4.00   Median :  0.000
##  Mean   : 0.1317              Mean   :  14.86   Mean   :  1.281
##  3rd Qu.: 0.0000              3rd Qu.:  12.00   3rd Qu.:  1.000
##  Max.   :65.0000              Max.   :1930.00   Max.   :135.000
##     num_def        retail_and_recreation_percent_change_from_baseline
##  Min.   :  0.000   Min.   :-97.00
##  1st Qu.:  0.000   1st Qu.:-57.00
##  Median :  1.000   Median :-30.00
##  Mean   :  3.437   Mean   :-37.29
##  3rd Qu.:  3.000   3rd Qu.:-17.00
##  Max.   :334.000   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
```

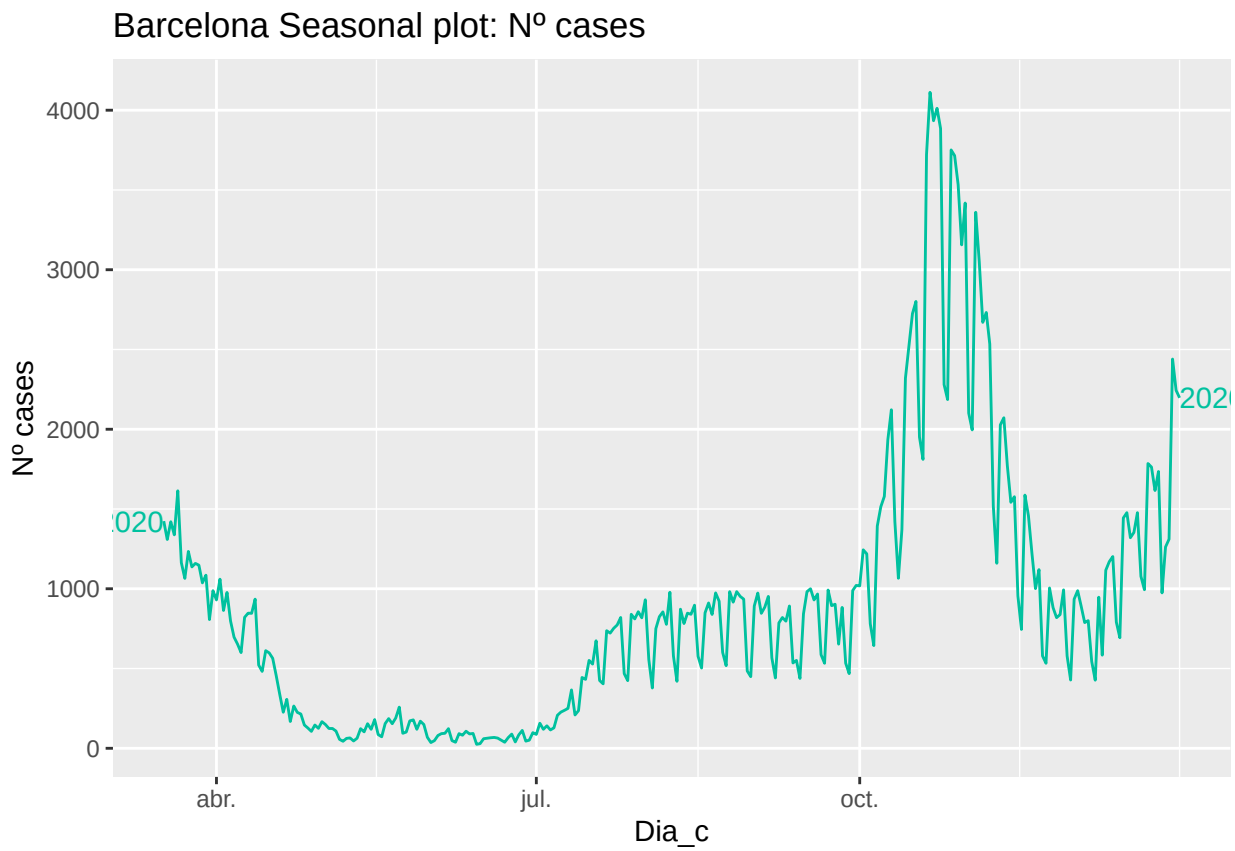
```
##  3rd Qu.: 30.000
##  Max.   :543.000
##  transit_stations_percent_change_from_baseline
##  Min.   :-100.00
##  1st Qu.: -53.00
##  Median : -31.00
##  Mean   : -35.19
##  3rd Qu.: -17.00
##  Max.   :  74.00
##  workplaces_percent_change_from_baseline
##  Min.   :-92.00
##  1st Qu.:-43.00
##  Median :-26.00
##  Mean   :-29.08
##  3rd Qu.:-13.00
##  Max.   : 55.00
##  residential_percent_change_from_baseline     Total           Dia_c
##  Min.   :-10.00                           Min.   : 1.95   Min.   :2020-03-16
##  1st Qu.:  4.00                           1st Qu.:11.36   1st Qu.:2020-05-27
##  Median :  7.00                           Median :14.39   Median :2020-08-07
##  Mean   : 10.14                           Mean   :14.20   Mean   :2020-08-07
##  3rd Qu.: 14.00                           3rd Qu.:17.11   3rd Qu.:2020-10-19
##  Max.   : 48.00                           Max.   :29.00   Max.   :2020-12-30
```

2.3.6 Final plots (Barcelona and others)

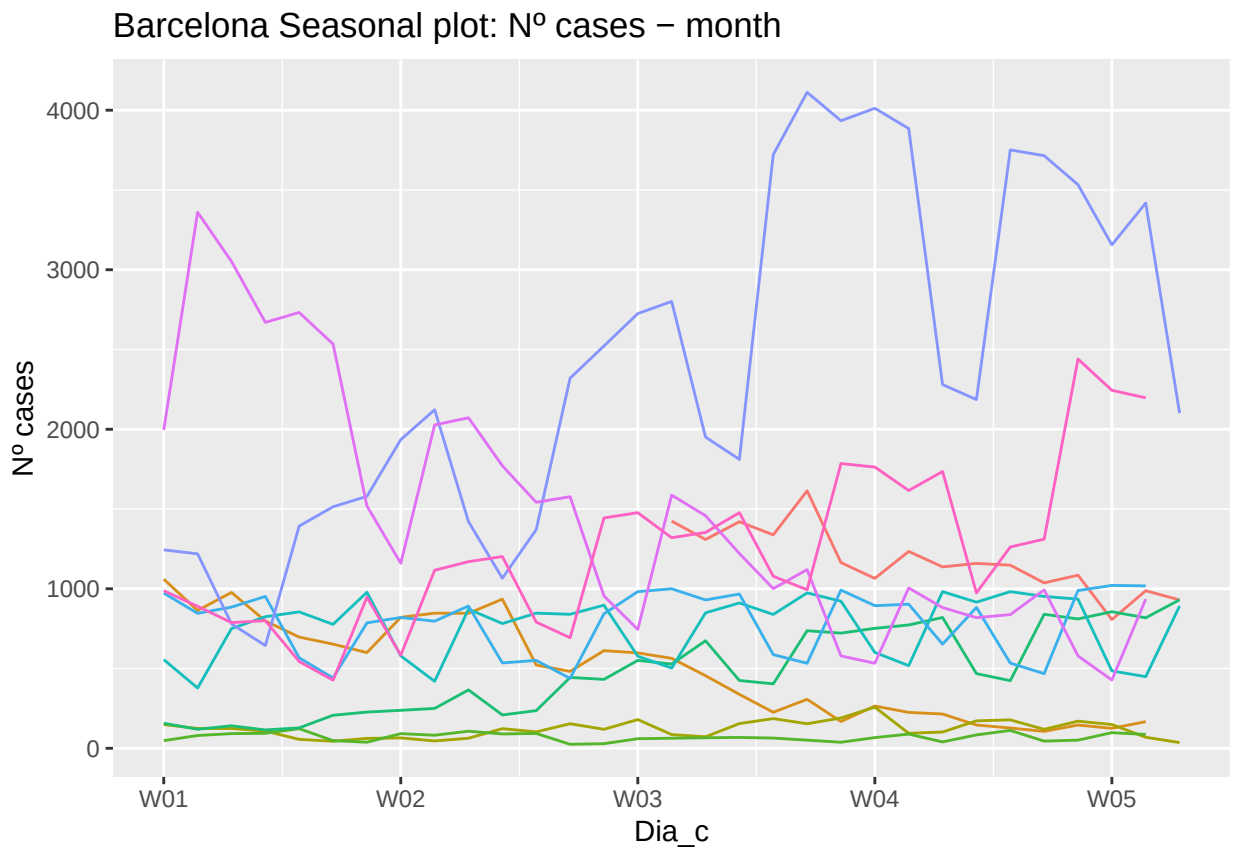
```
# Total_ts plots for the selected variables
# % of mobility reported by INE and Google (EM3 study)
Total_ts_b %>%
  filter(sub_region_2 == "Barcelona") %>%
  pivot_longer(c(2,13,14)) %>%
  ggplot(aes(x = Dia_c, y = value)) +
  geom_line() +
  facet_grid(vars(name), scales = "free_y")+
  labs(title = "Bar - Nº cases (CNE) vs % Residentail (Google) and Tot (INE)
       mobility change")
```




```
# Barcelona Seasonal plot: Nº cases
Total_ts_b %>%
  filter(sub_region_2 == "Barcelona") %>%
  gg_season(num_casos.x, labels = "both") +
  labs(y = "Nº cases",
       title = "Barcelona Seasonal plot: Nº cases")
```

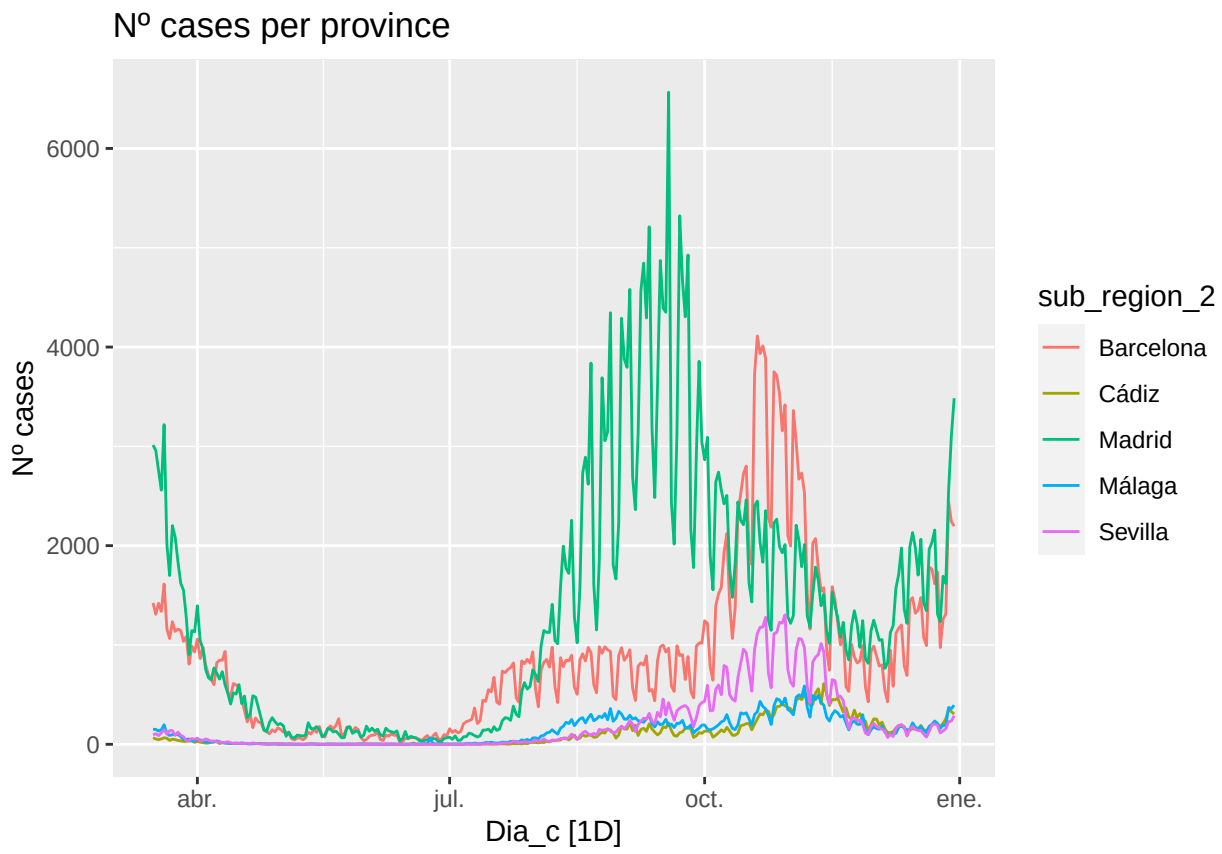



```
# Barcelona Seasonal plot: Nº cases by month
Total_ts_b %>%
  filter(sub_region_2 == "Barcelona") %>%
  gg_season(num_casos.x, period = "month") +
  theme(legend.position = "none") +
  labs(y="Nº cases", title="Barcelona Seasonal plot: Nº cases - month")
```

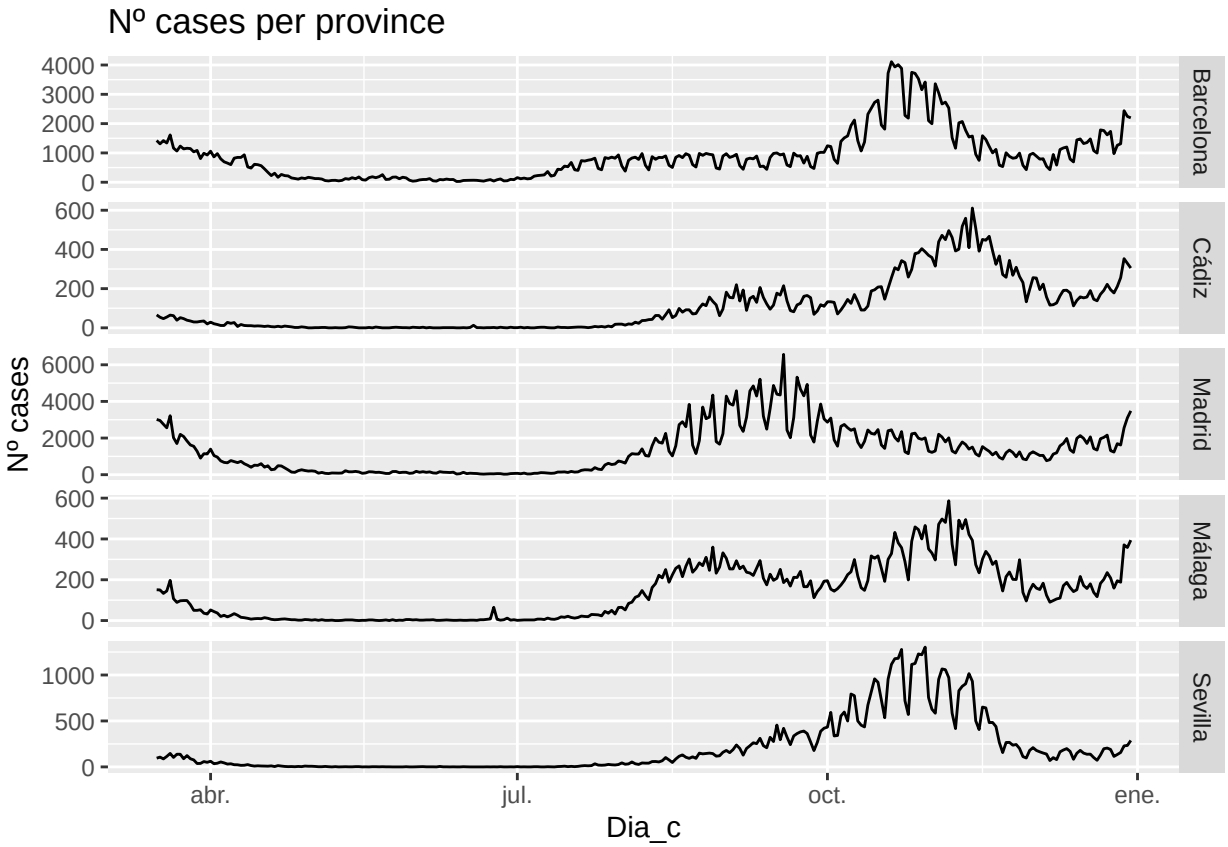



```
# Barcelona scatter plot Nº cases vs residential_percent_change
Total_ts_b %>%
  filter(sub_region_2 == "Barcelona") %>%
  ggplot(aes(x = num_casos.x, y = residential_percent_change_from_baseline )) +
  geom_point() +
  labs(x = "num_casos.x)",
       y = "residential_percent_change",
       title="Barcelona scatter plot Nº cases vs residential_percent_chang")
```

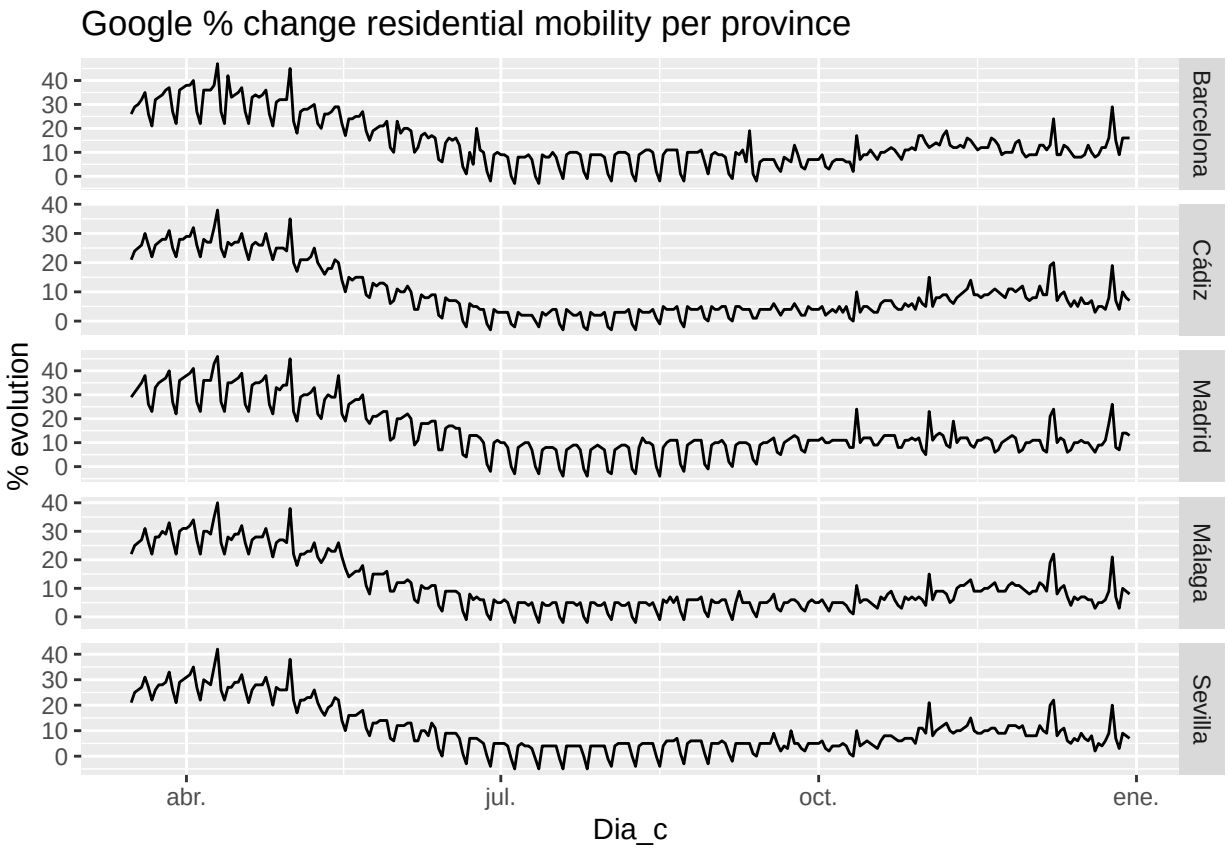

```
########################################
# A - Nº cases per province (Barcelona, Madrid, Málaga, Córdoba and Cádiz)
autoplot(Total_ts_b, num_casos.x) +
  labs(y = "Nº cases",
       title = "Nº cases per province")
```



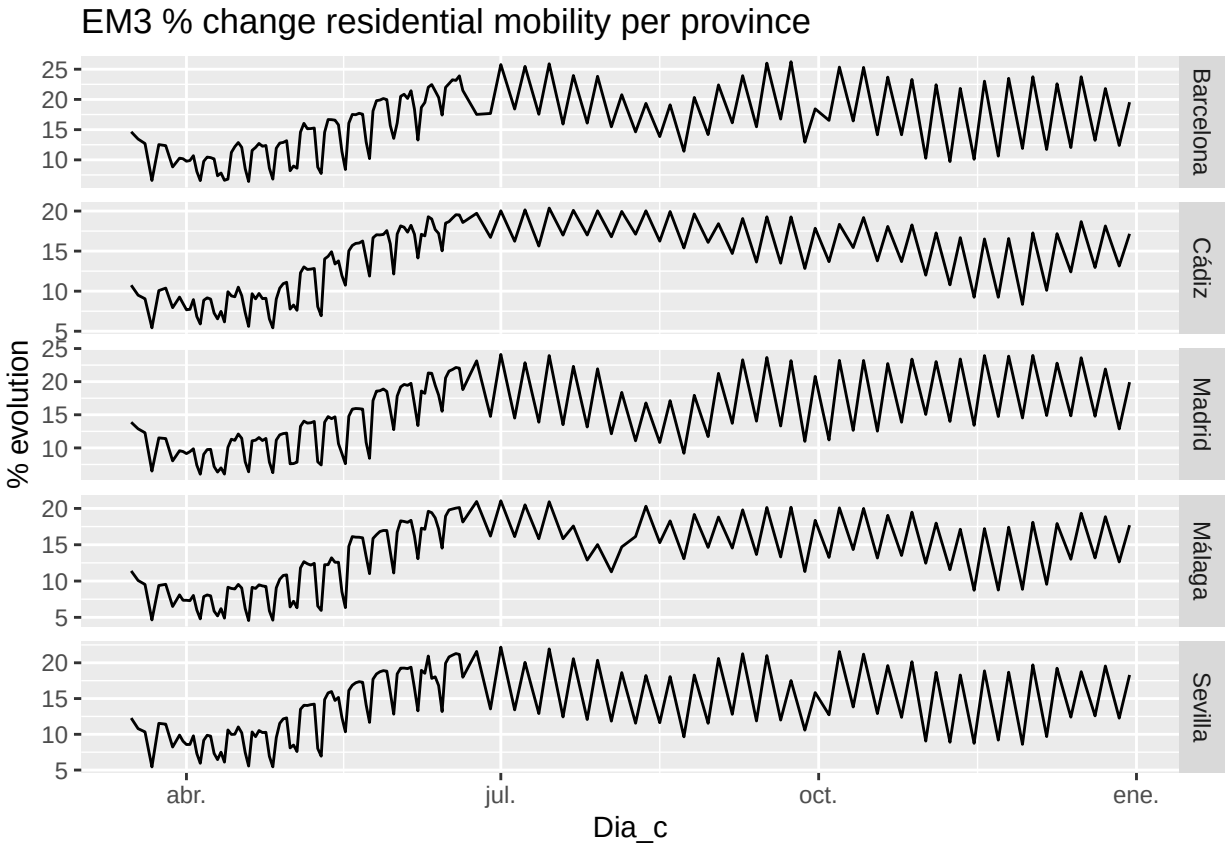

```
# B - Nº cases per province (Barcelona, Madrid, Málaga, Córdoba and Cádiz)
Total_ts_b %>%
  group_by(sub_region_2) %>%
  summarise(CASOS = sum(num_casos.x))%>%
  ggplot(aes(x = Dia_c, y = CASOS)) +
  geom_line() +
  facet_grid(vars(sub_region_2), scales = "free_y") +
  labs(title = "Nº cases per province", y= "Nº cases")
```



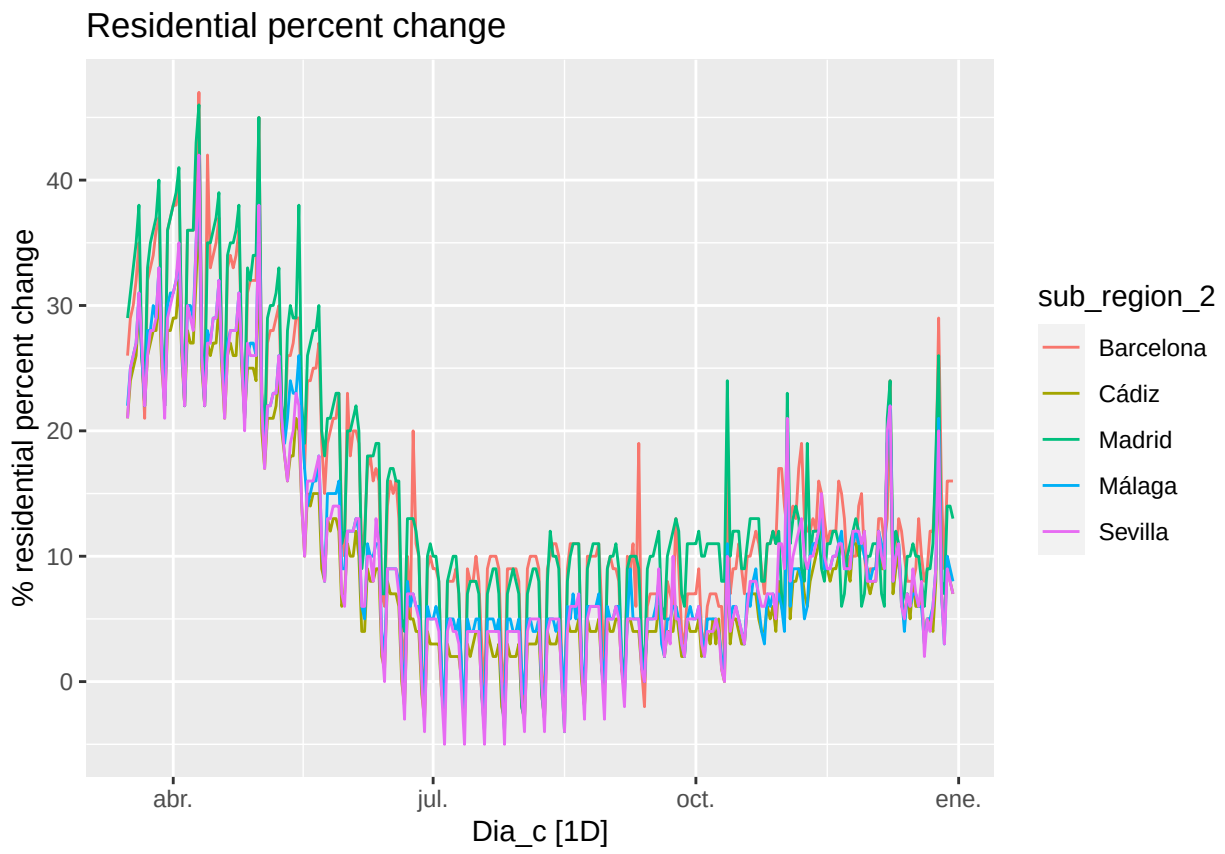

```
# B.b - Google % change residential mobility per province (Barcelona, Madrid, Málaga, Cádiz and Sevilla
Total_ts_b %>%
  group_by(sub_region_2) %>%
  summarise(per_c = (residential_percent_change_from_baseline))%>%
  ggplot(aes(x = Dia_c, y = per_c)) +
  geom_line() +
  facet_grid(vars(sub_region_2), scales = "free_y") +
  labs(title = "Google % change residential mobility per province", y= "% evolution")
```



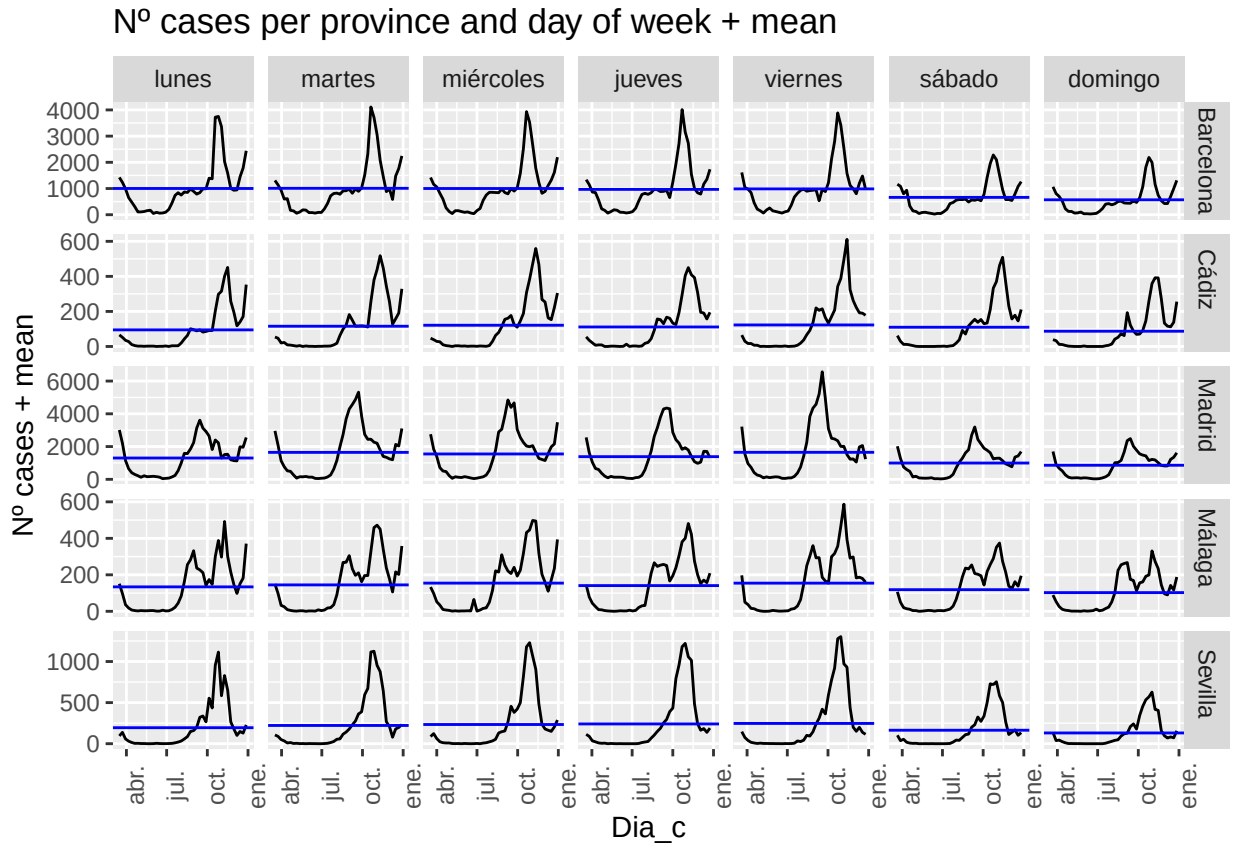

```
# B.c - EM3 % change residential mobility per province (Barcelona, Madrid, Málaga, Cádiz and Sevilla)
Total_ts_b %>%
  group_by(sub_region_2) %>%
  summarise(per_c = (Total))%>%
  ggplot(aes(x = Dia_c, y = per_c)) +
  geom_line() +
  facet_grid(vars(sub_region_2), scales = "free_y") +
  labs(title = "EM3 % change residential mobility per province", y= "% evolution")
```



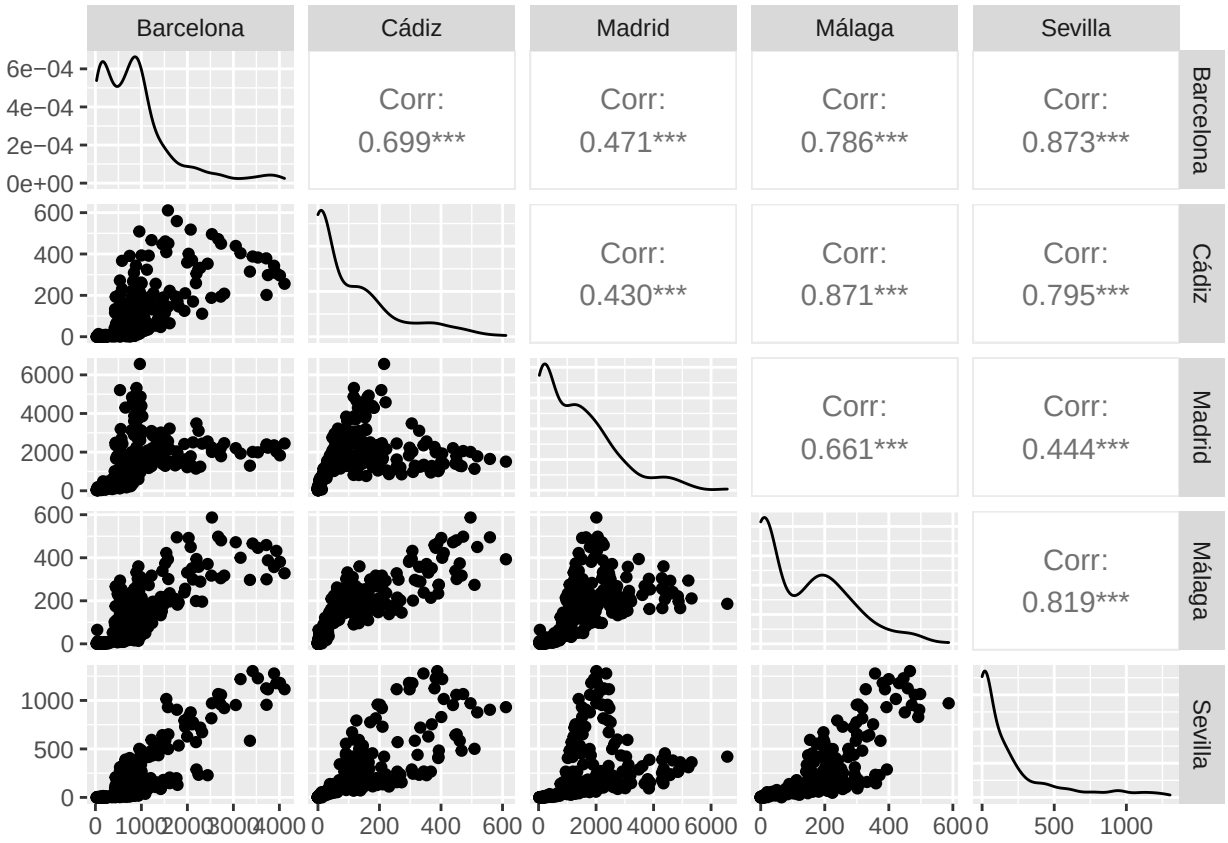

```
# % residential percent change (Barcelona, Madrid, Málaga, Cádiz and Sevilla)
autoplot(Total_ts_b, residential_percent_change_from_baseline ) +
  labs(y = "% residential percent change",
       title = "Residential percent change")
```



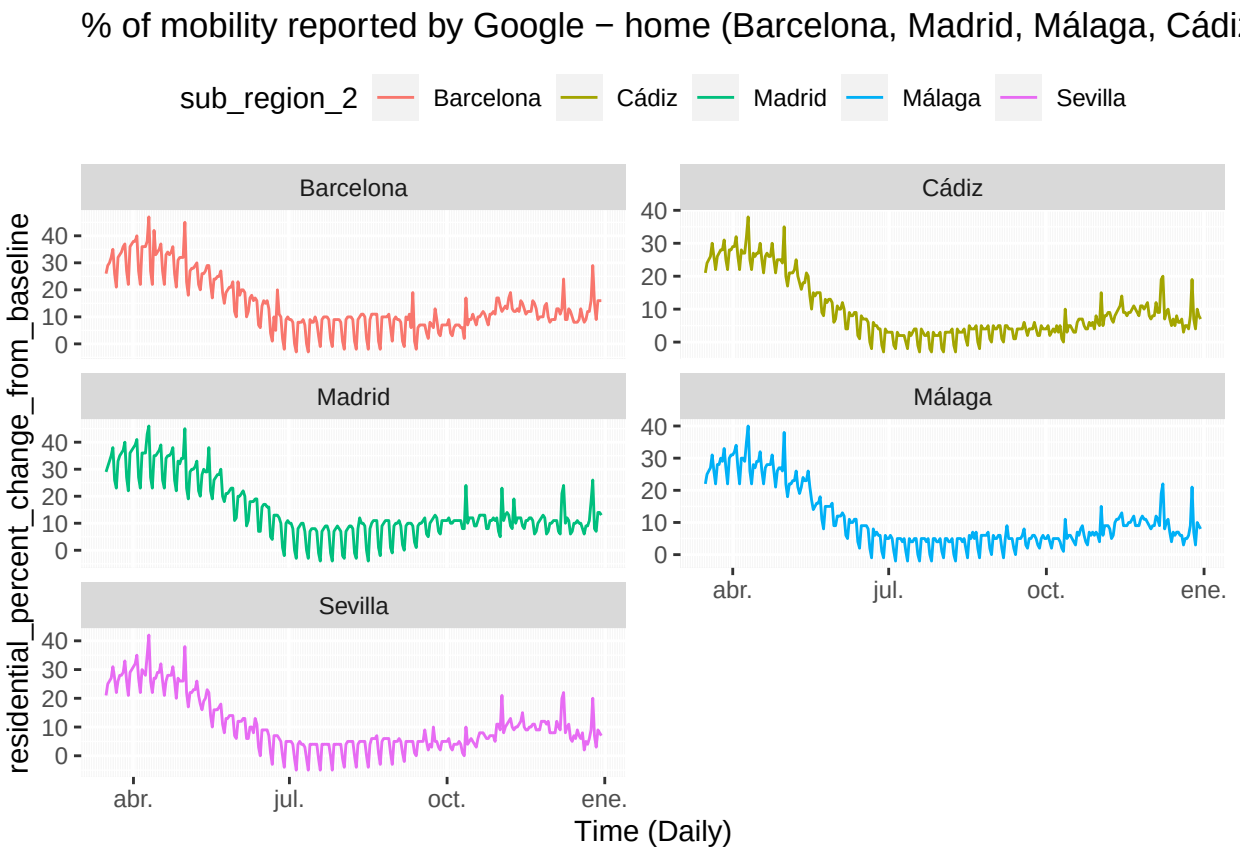

```
# Nº cases per province and day of week + mean
Total_ts_b %>%
  gg_subseries(num_casos.x, period = "week") +
  labs(y = "Nº cases + mean",
       title = "Nº cases per province and day of week + mean")
```




```
# Correlation plot / nº cases by province
Total_ts_b %>%
  group_by(sub_region_2) %>%
  summarise(CASOS = sum(num_casos.x))%>%
  pivot_wider(values_from=CASOS, names_from=sub_region_2) %>%
  GGally::ggpairs(2:6)
```




```
# % of mobility reported by Google - residential_percent_change
autoplot(Total_ts_b, residential_percent_change_from_baseline) +
  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 = "% of mobility reported by Google - home (Barcelona, Madrid, Málaga, Cádiz and Sevilla
```



3 ARIMA - fpp3 library

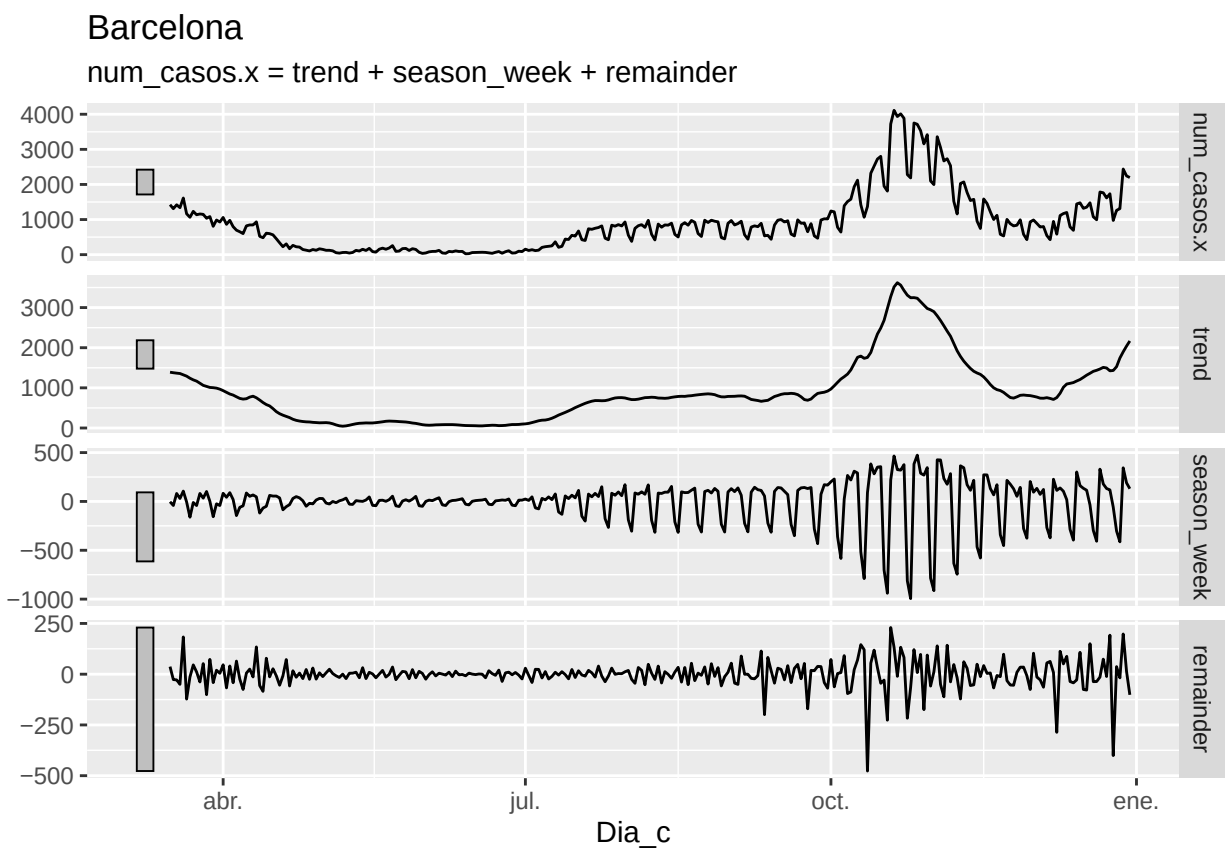
3.1 STL (Seasonal and Trend decomposition using Loess - Barcelona, Madrid, Málaga, Cádiz and Sevilla)

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

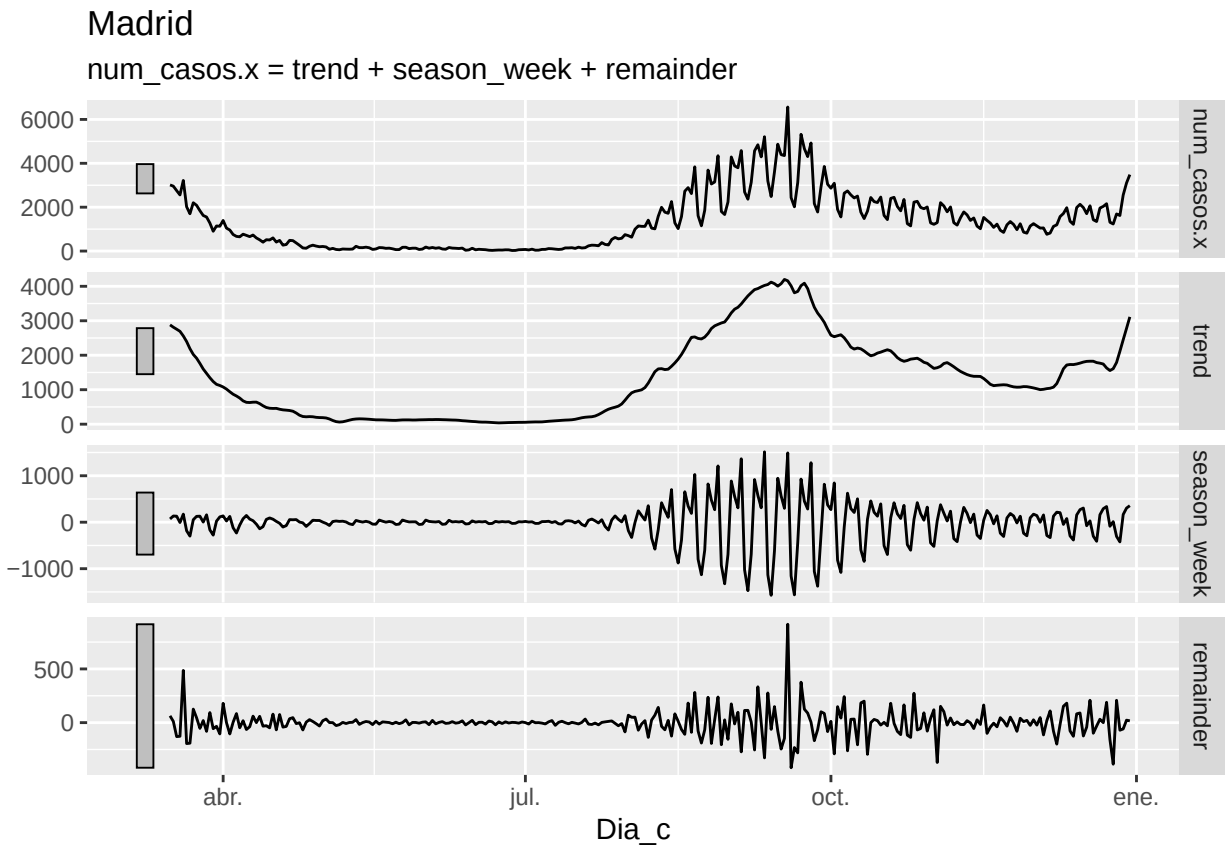
- Unlike SEATS and X-11, STL will handle any type of seasonality, not only monthly and quarterly data.
- The seasonal component is allowed to change over time, and the rate of change can be controlled by the user.
- The smoothness of the trend-cycle can also be controlled by the user.
- It can be robust 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"...

```
# Check Seasonal and trend
#Total_ts %>%
#  filter(sub_region_2 == "Barcelona") %>%
#  model(STL(num_casos.x)) %>%
#  components() %>%
#  autoplot()

#Total_ts %>%
#  filter(sub_region_2 == "Barcelona") %>%
#  model(STL(num_casos.x ~ season(window = 7))) %>%
```

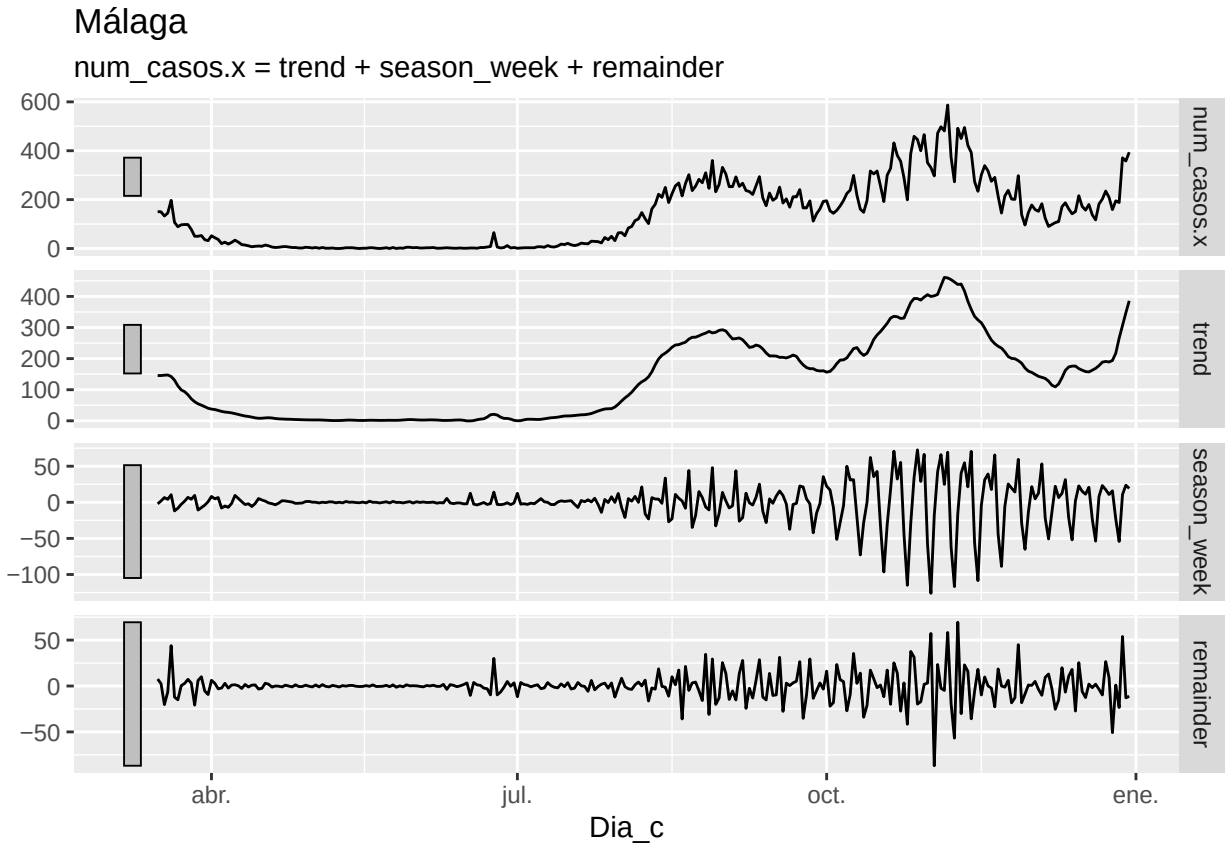
```
#  components() %>%
#  autoplot()

Total_ts %>%
  #filter_index("2020-09-1" ~ "2020-12-31")  %>%
  filter(sub_region_2 == "Barcelona") %>%
  model(STL(num_casos.x ~ season(window = 7) +
              trend(window = 7))) %>%
  components() %>%
  autoplot() + labs(title="Barcelona")
```



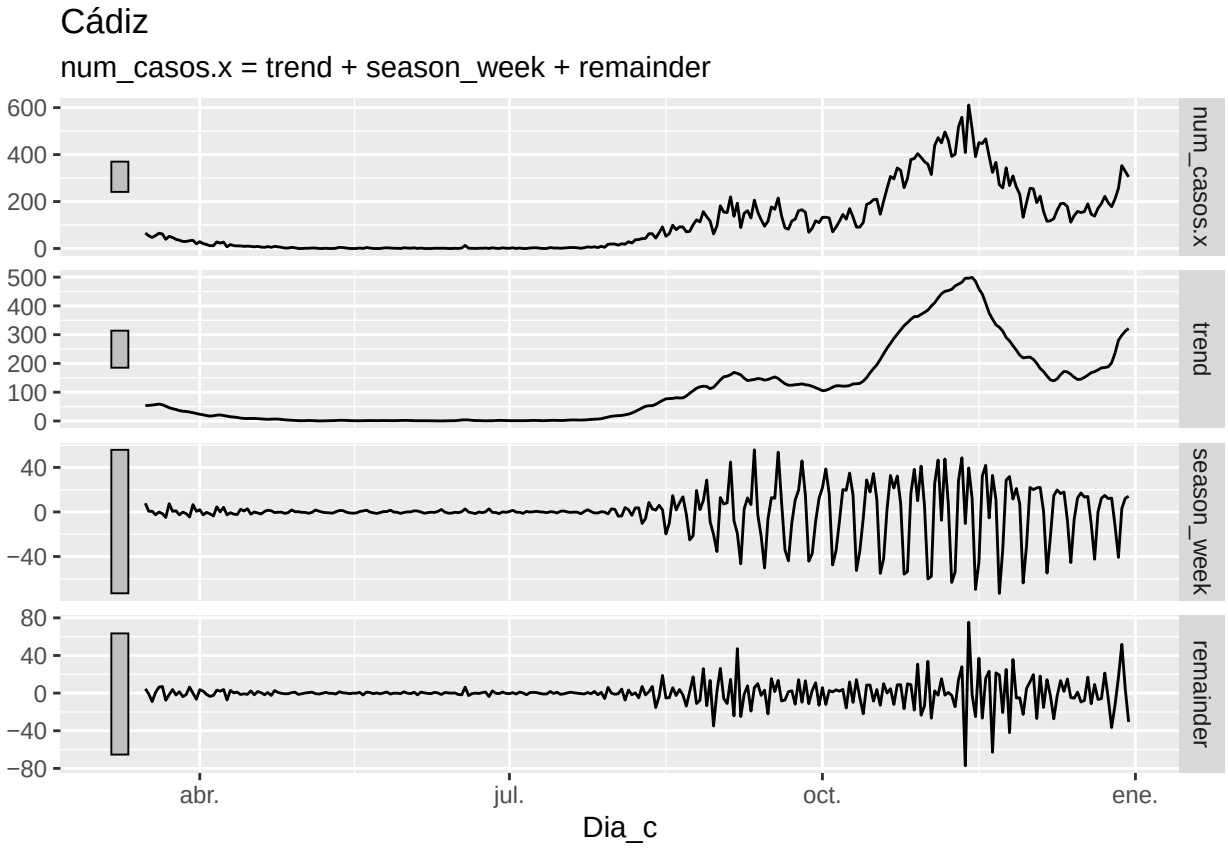

```
Total_ts %>%
  #filter_index("2020-09-1" ~ "2020-12-31")  %>%
  filter(sub_region_2 == "Madrid") %>%
  model(STL(num_casos.x ~ season(window = 7) +
              trend(window = 7))) %>%
  components() %>%
  autoplot() + labs(title="Madrid")
```



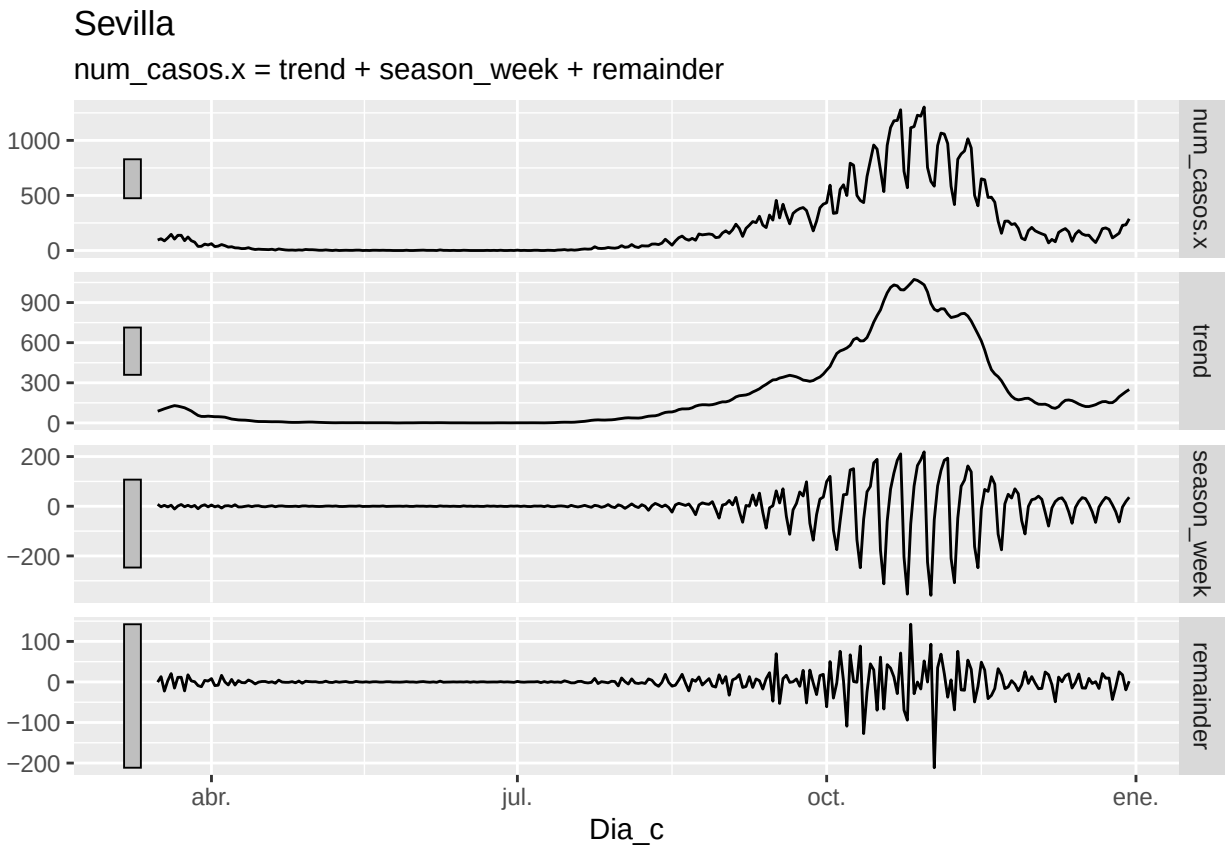

```
Total_ts %>%
  #filter_index("2020-09-1" ~ "2020-12-31")  %>%
  filter(sub_region_2 == "Málaga") %>%
  model(STL(num_casos.x ~ season(window = 7) +
              trend(window = 7))) %>%
  components() %>%
  autoplot() + labs(title="Málaga")
```




```
Total_ts %>%
  #filter_index("2020-09-1" ~ "2020-12-31")  %>%
  filter(sub_region_2 == "Cádiz") %>%
  model(STL(num_casos.x ~ season(window = 7) +
              trend(window = 7))) %>%
  components() %>%
  autoplot() + labs(title="Cádiz")
```




```
Total_ts %>%
  #filter_index("2020-09-1" ~ "2020-12-31")  %>%
  filter(sub_region_2 == "Sevilla") %>%
  model(STL(num_casos.x ~ season(window = 7) +
              trend(window = 7))) %>%
  components() %>%
  autoplot() + labs(title="Sevilla")
```



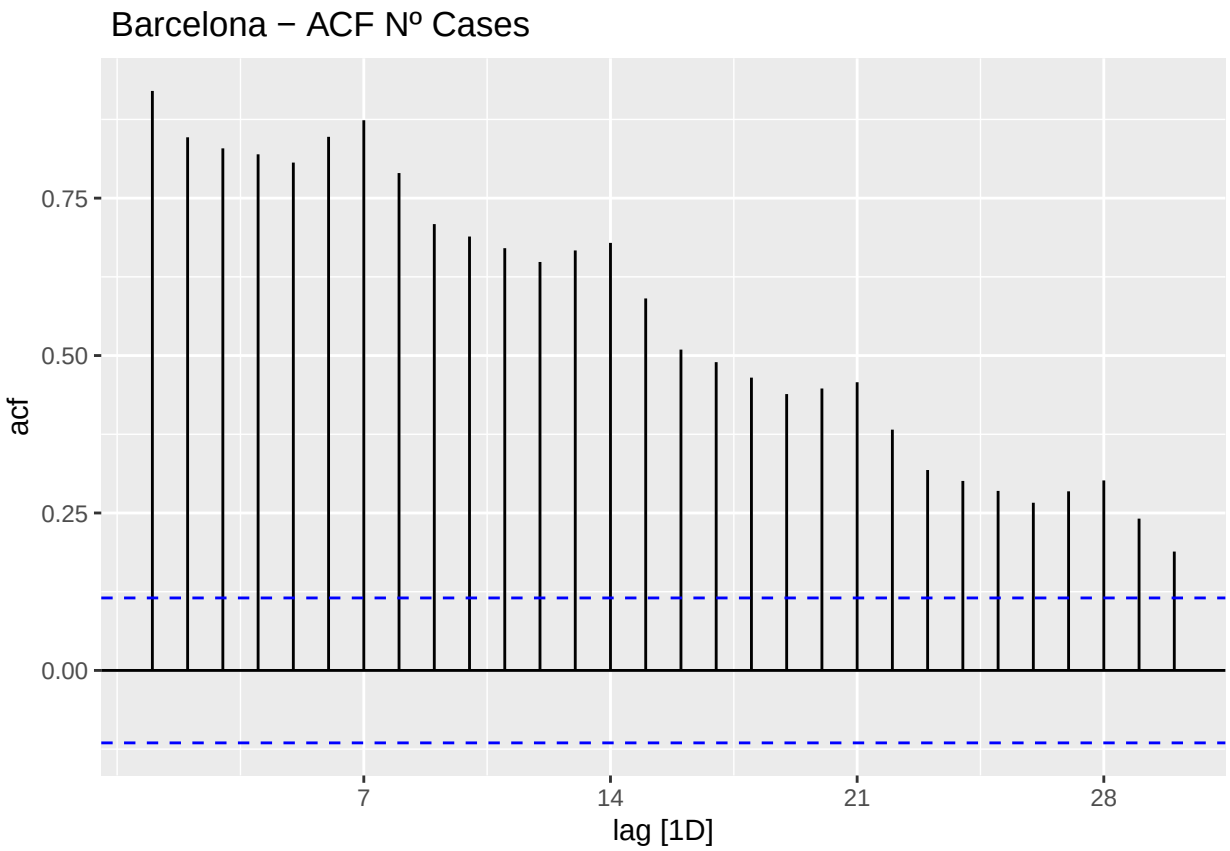
3.2 ACF and PACF (Barcelona, Madrid, Málaga, Córdoba and Cádiz)

As stated by (Hyndman and Athanasopoulos 2021)... "ACF plot is also useful for identifying non-stationary time series. For a stationary time series, the ACF will drop to zero relatively quickly, while the ACF of non-stationary data decreases slowly.

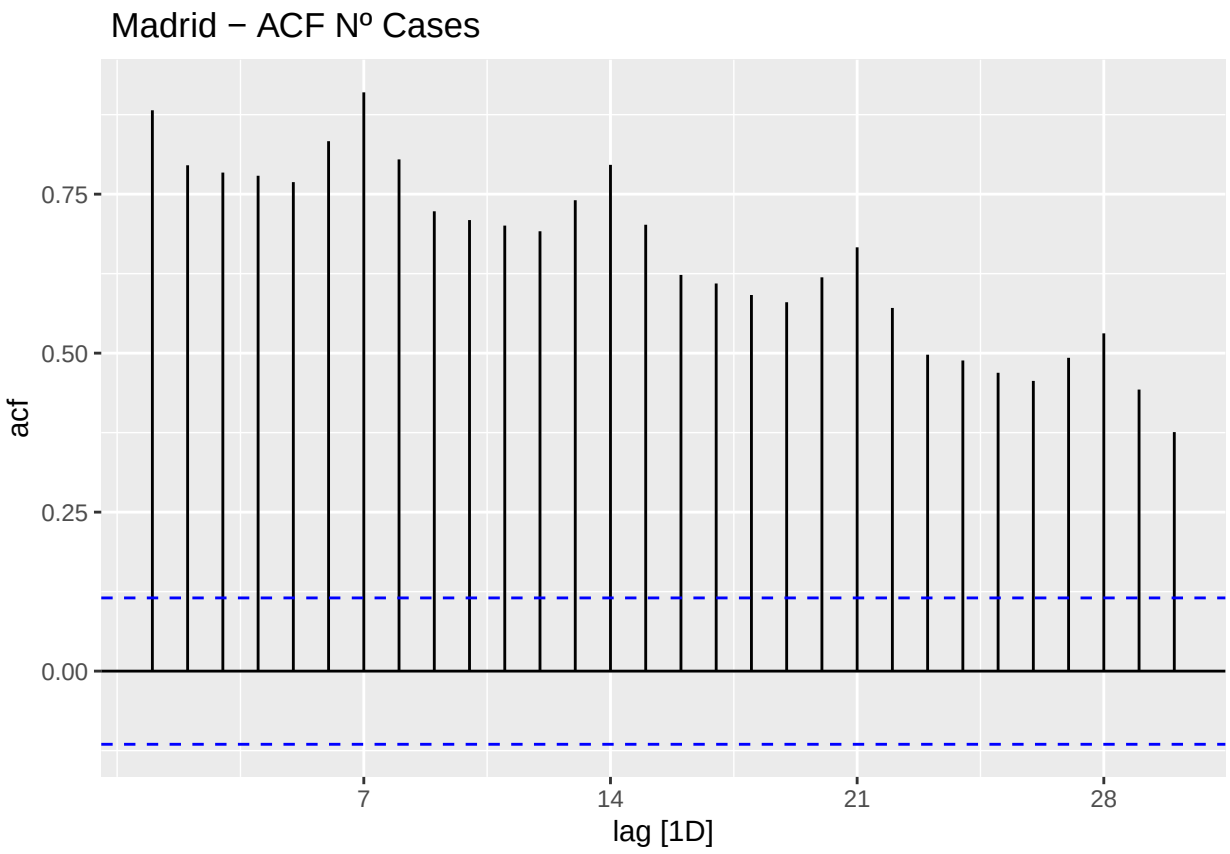
- Our time-series for Bar is non-stationary

```
# New time-series for Bar, Mad, Mal, Cor and, Cad
Total_ts %>%
  filter_index("2020-03-15" ~ "2020-12-31")  %>%
  filter(sub_region_2 == "Barcelona")-> Bar_N_cases #%>%
Total_ts %>%
  filter_index("2020-03-15" ~ "2020-12-31")  %>%
  filter(sub_region_2 == "Madrid")-> Mad_N_cases #%>%
Total_ts %>%
  filter_index("2020-03-15" ~ "2020-12-31")  %>%
  filter(sub_region_2 == "Málaga")-> Mal_N_cases #%>%
Total_ts %>%
  filter_index("2020-03-15" ~ "2020-12-31")  %>%
  filter(sub_region_2 == "Cádiz")-> Cad_N_cases #%>%
Total_ts %>%
  filter_index("2020-03-15" ~ "2020-12-31")  %>%
  filter(sub_region_2 == "Sevilla")-> Sev_N_cases #%>%

# ACF
Bar_N_cases %>%
```

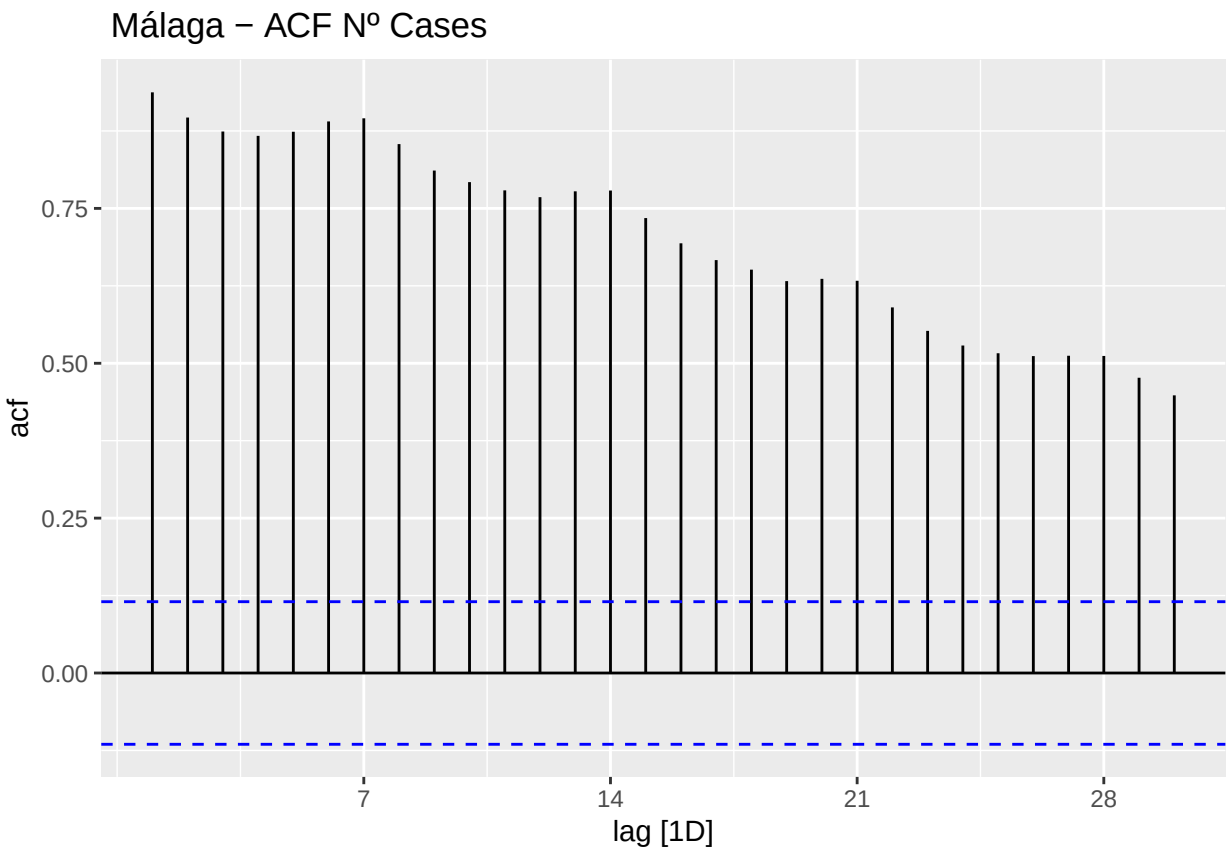
```
  ACF(num_casos.x, lag_max = 30) %>%
  autoplot() +
  labs(title=" Barcelona - ACF Nº Cases")
```



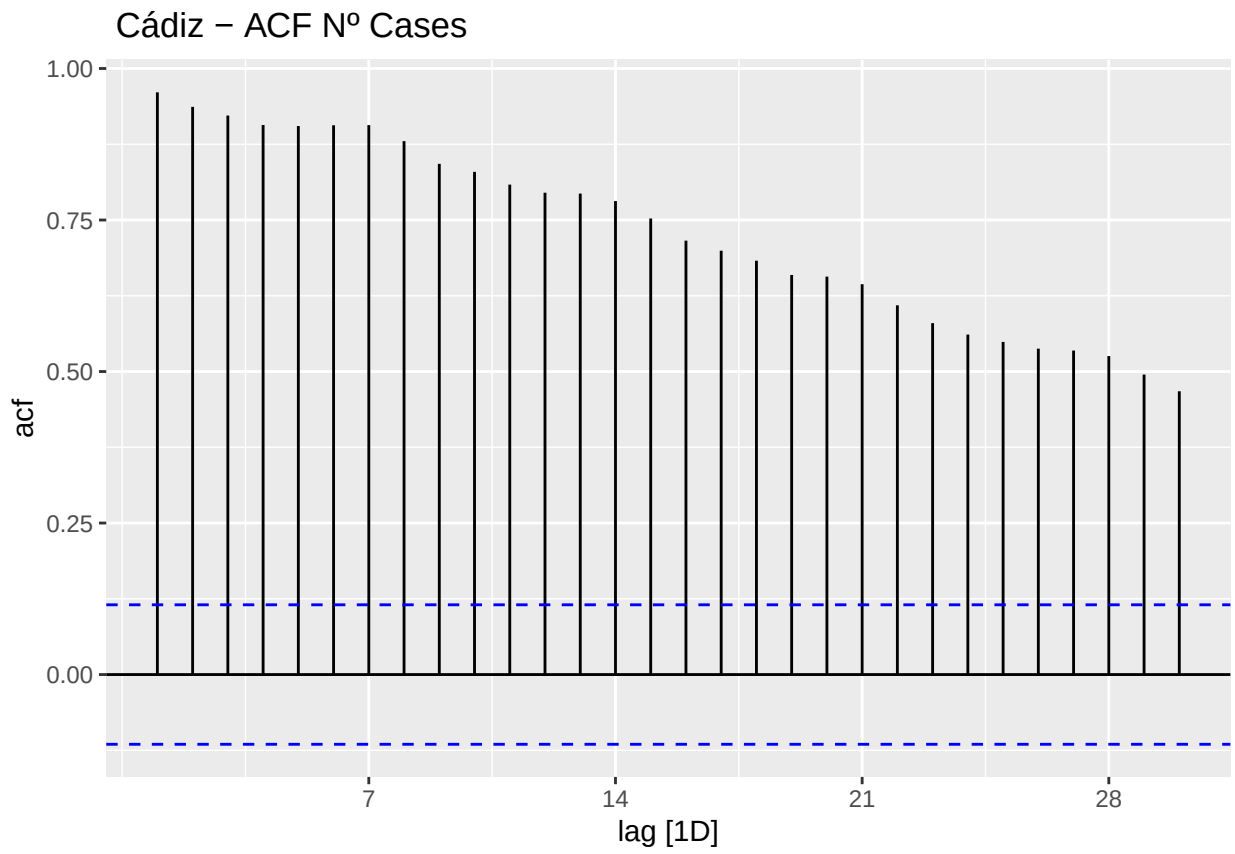

```
Mad_N_cases %>%
  ACF(num_casos.x, lag_max = 30) %>%
  autoplot() +
  labs(title=" Madrid - ACF Nº Cases")
```



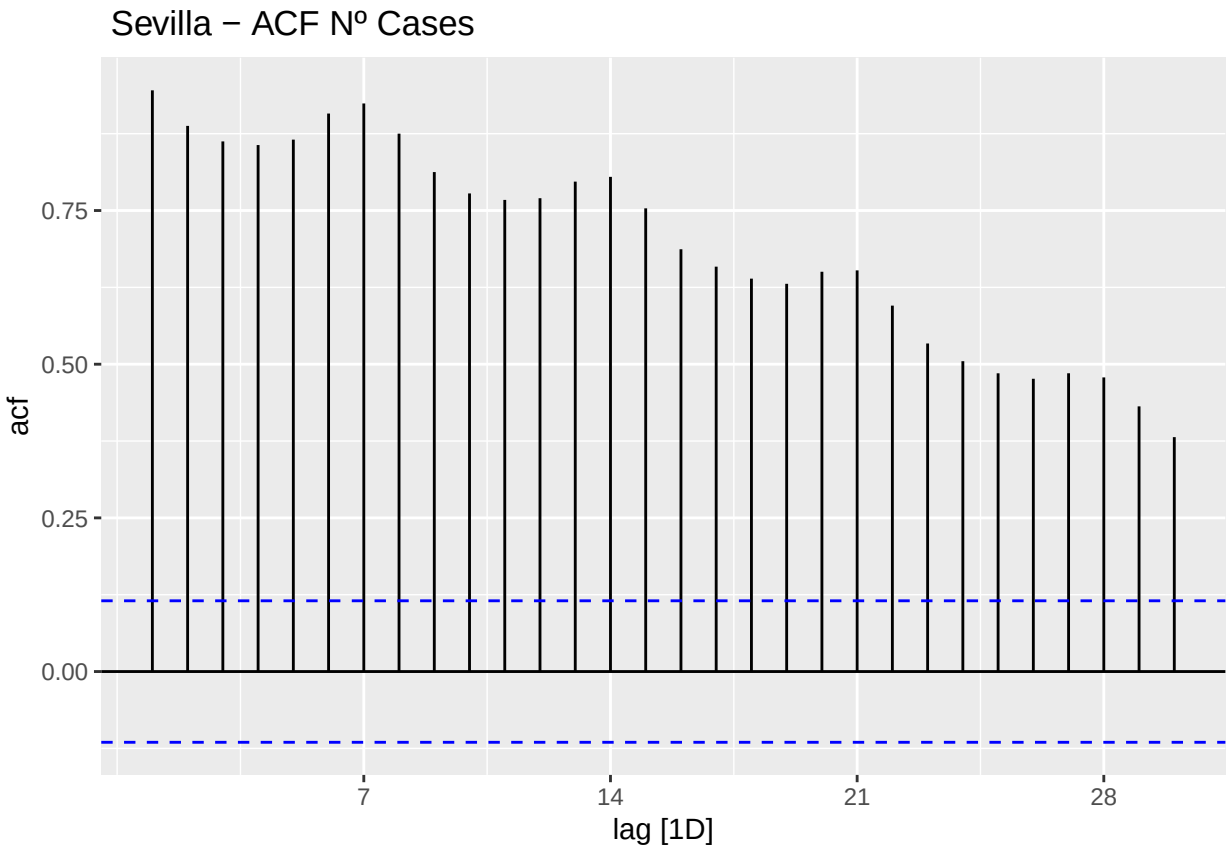

```
Mal_N_cases %>%
  ACF(num_casos.x, lag_max = 30) %>%
  autoplot() +
  labs(title=" Málaga - ACF Nº Cases")
```



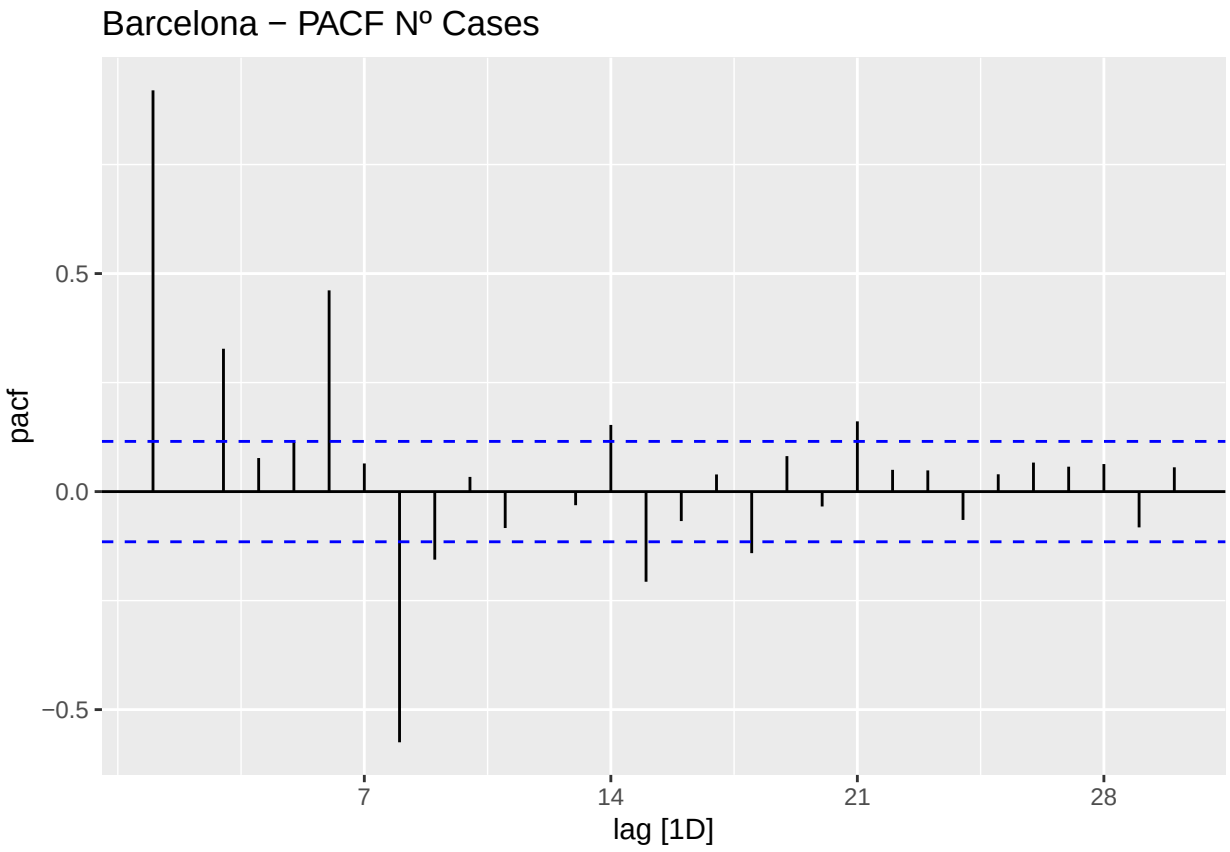

```
Cad_N_cases %>%
  ACF(num_casos.x, lag_max = 30) %>%
  autoplot() +
  labs(title=" Cádiz - ACF Nº Cases")
```



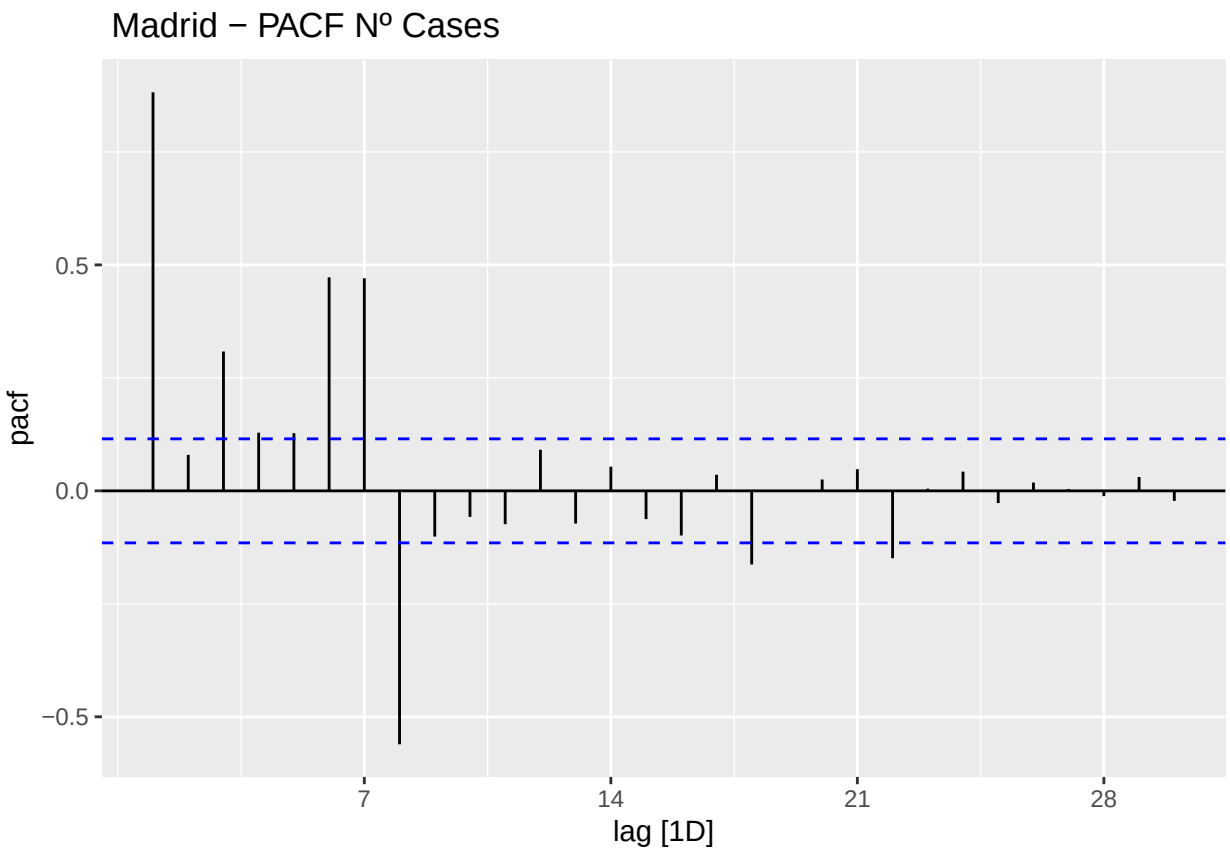

```
Sev_N_cases %>%
  ACF(num_casos.x, lag_max = 30) %>%
  autoplot() +
  labs(title=" Sevilla - ACF Nº Cases")
```



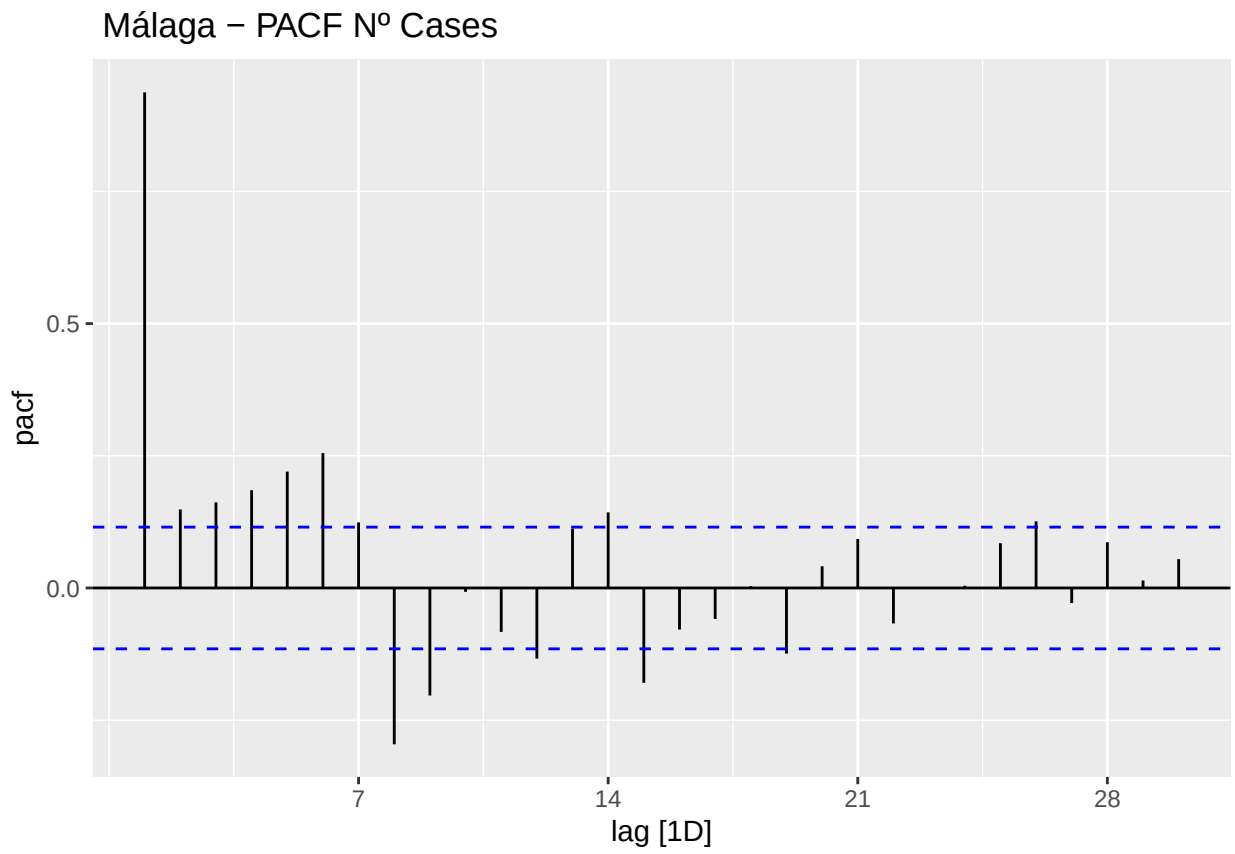

```
# PACF
Bar_N_cases %>%
  PACF(num_casos.x, lag_max = 30) %>%
  autoplot() +
  labs(title="Barcelona - PACF Nº Cases")
```



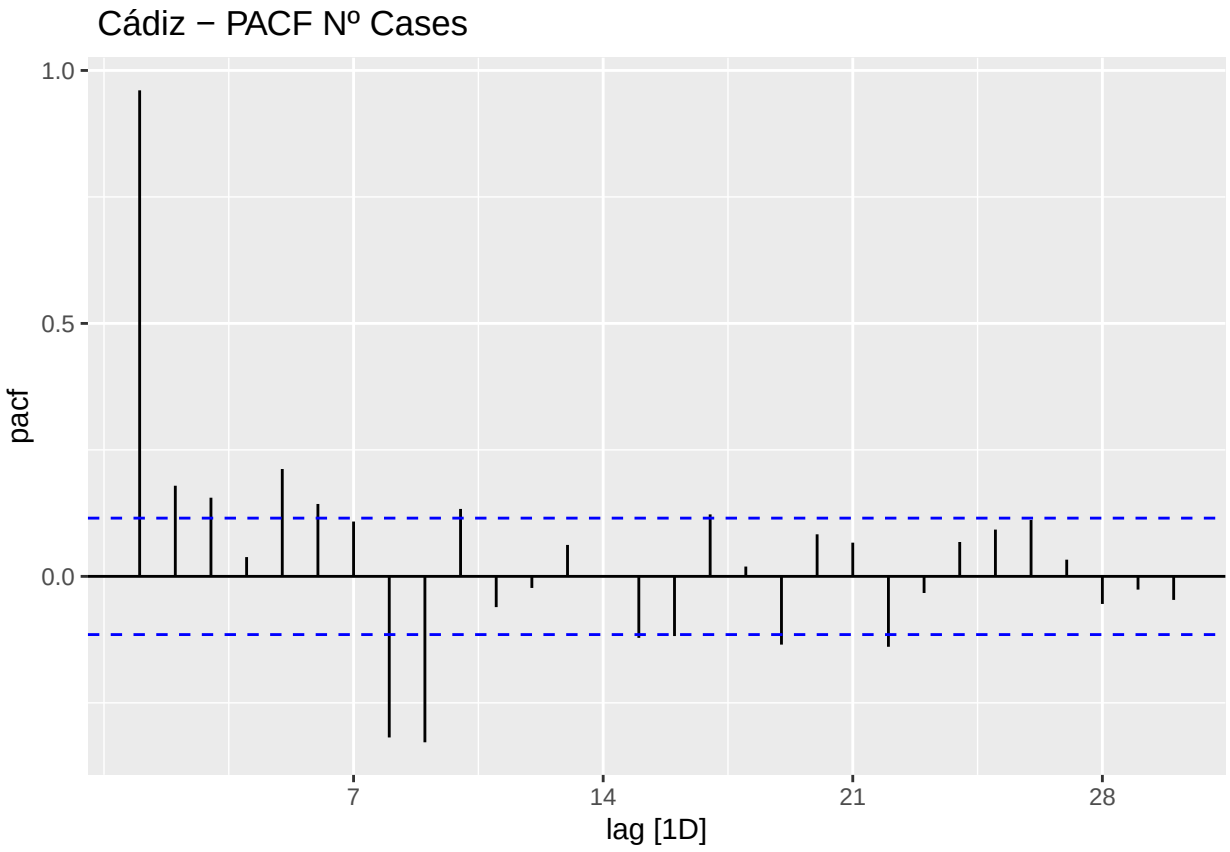

```
Mad_N_cases %>%
  PACF(num_casos.x, lag_max = 30) %>%
  autoplot() +
  labs(title=" Madrid - PACF Nº Cases")
```



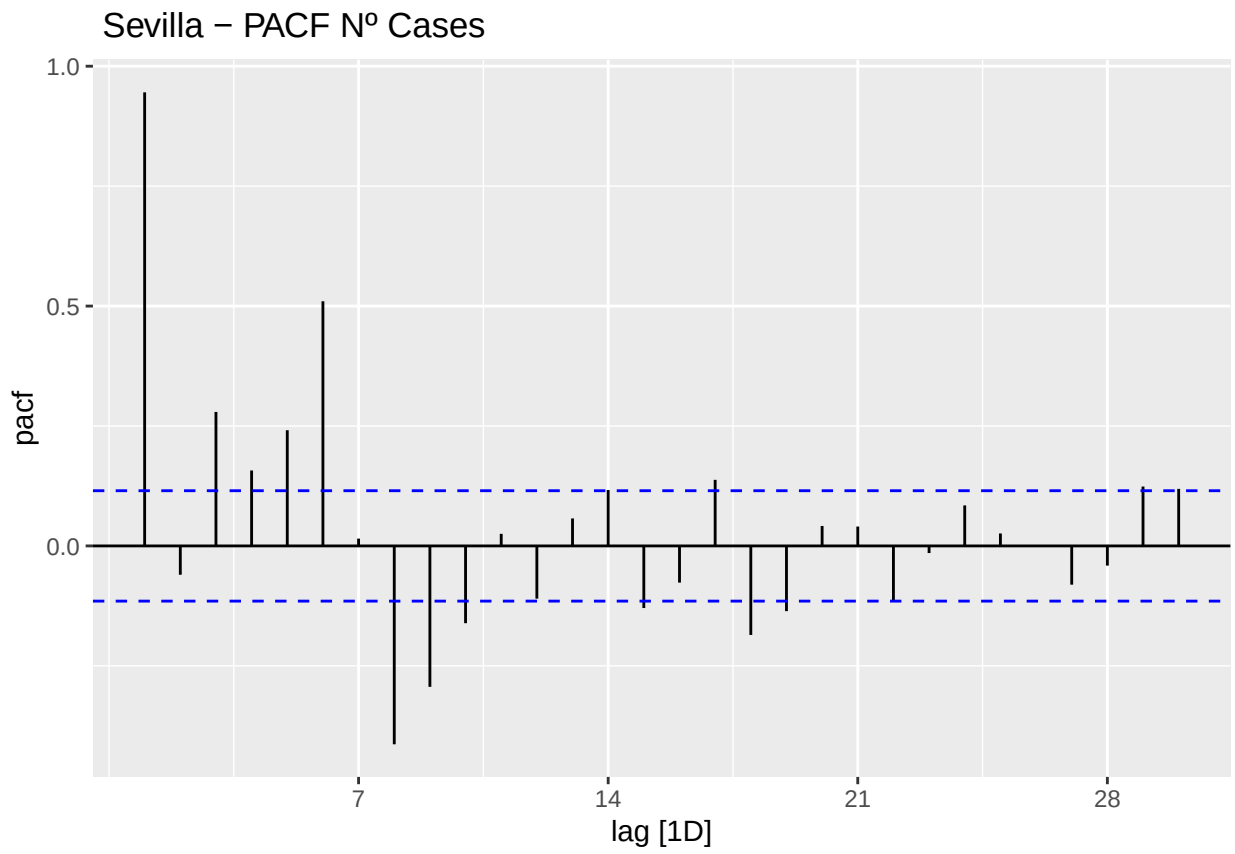

```
Mal_N_cases %>%
  PACF(num_casos.x, lag_max = 30) %>%
  autoplot() +
  labs(title=" Málaga - PACF Nº Cases")
```




```
Cad_N_cases %>%
  PACF(num_casos.x, lag_max = 30) %>%
  autoplot() +
  labs(title=" Cádiz - PACF Nº Cases")
```

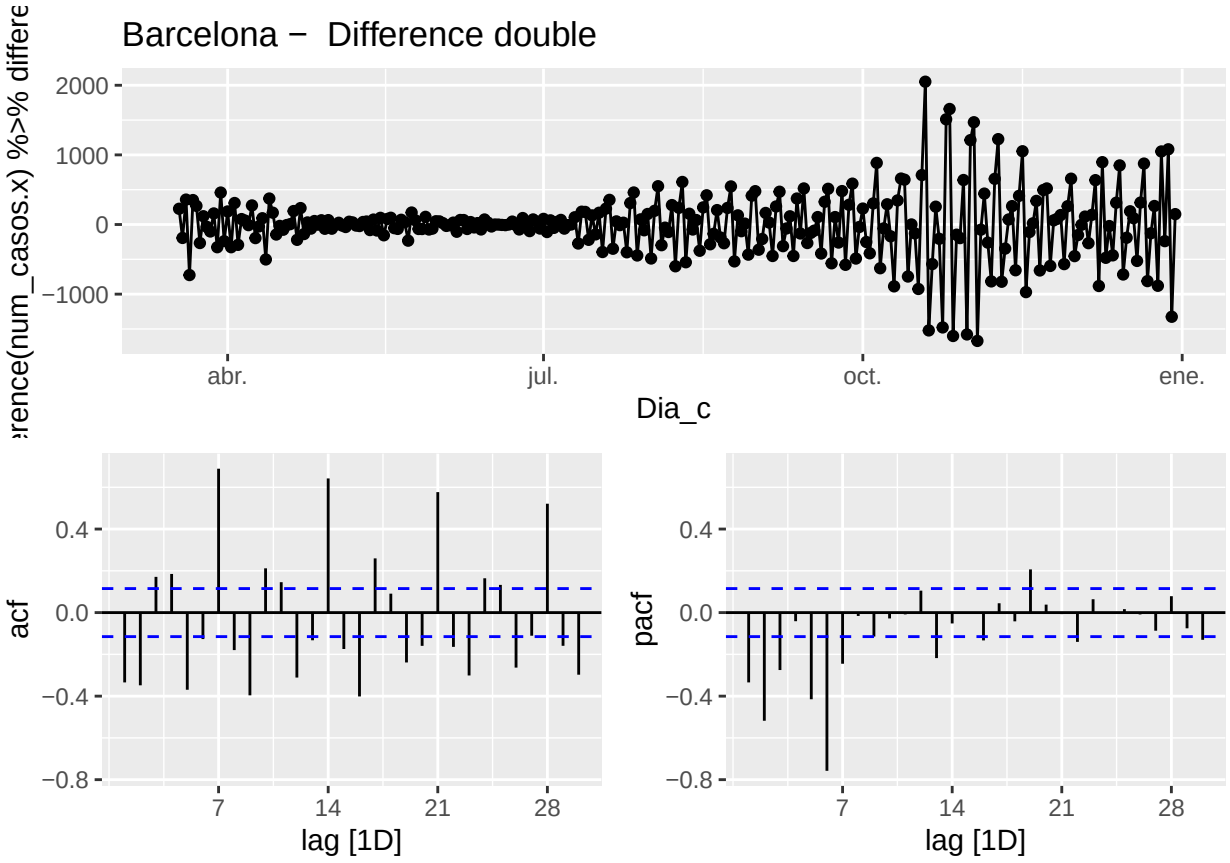



```
Sev_N_cases %>%
  PACF(num_casos.x, lag_max = 30) %>%
  autoplot() +
  labs(title=" Sevilla - PACF Nº Cases")
```

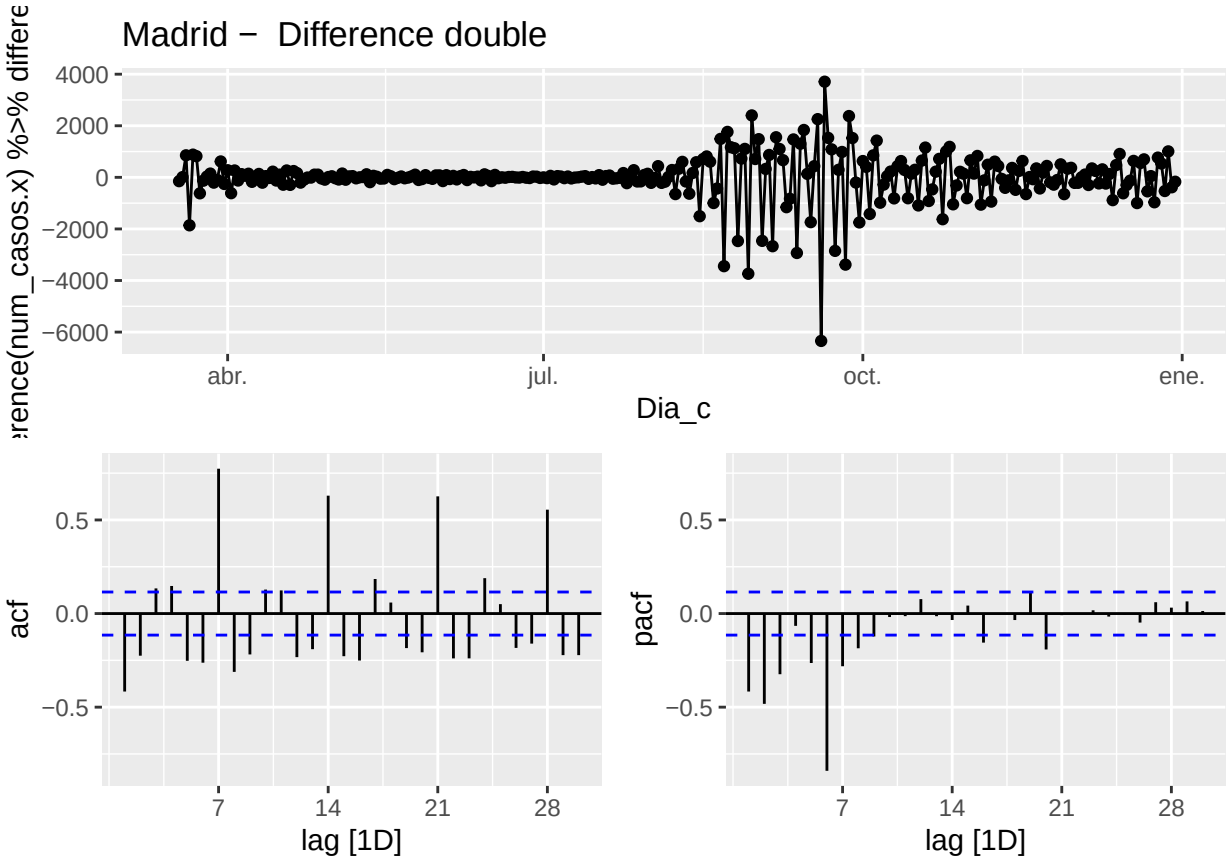


Double difference is plotted.

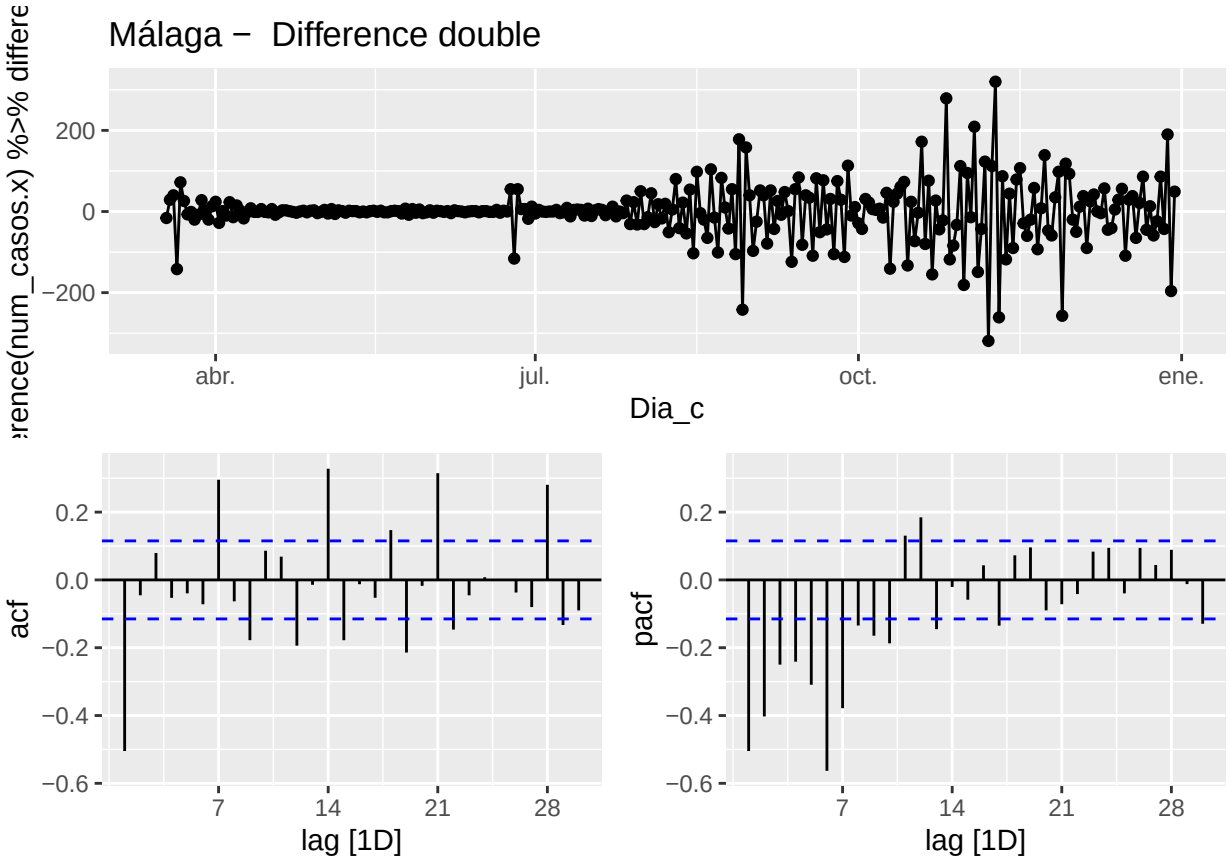
```
# Difference
#Bar_N_cases %>%
#  gg_tsdisplay(difference(num_casos.x),
#               plot_type='partial', lag_max = 30)

#Bar_N_cases %>%
#  gg_tsdisplay(difference(log(num_casos.x)),
#               plot_type='partial', lag_max = 30)

# Difference double
Bar_N_cases %>%
  gg_tsdisplay(difference(num_casos.x) %>%
               difference(),
               plot_type='partial', lag_max = 30)+
  labs(title="Barcelona -  Difference double")
```



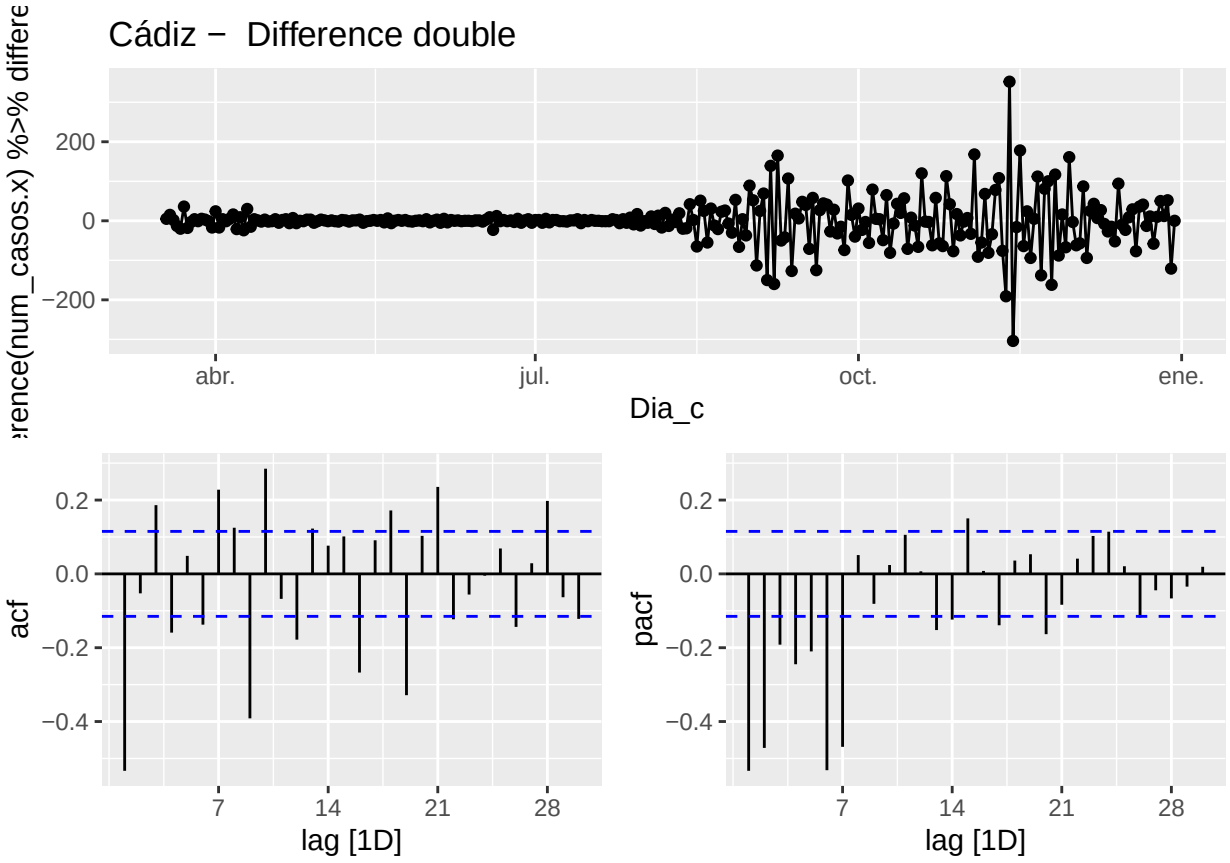

```
Mad_N_cases %>%
  gg_tsdisplay(difference(num_casos.x) %>%
                 difference(),
                 plot_type='partial', lag_max = 30)+
  labs(title="Madrid -  Difference double")
```



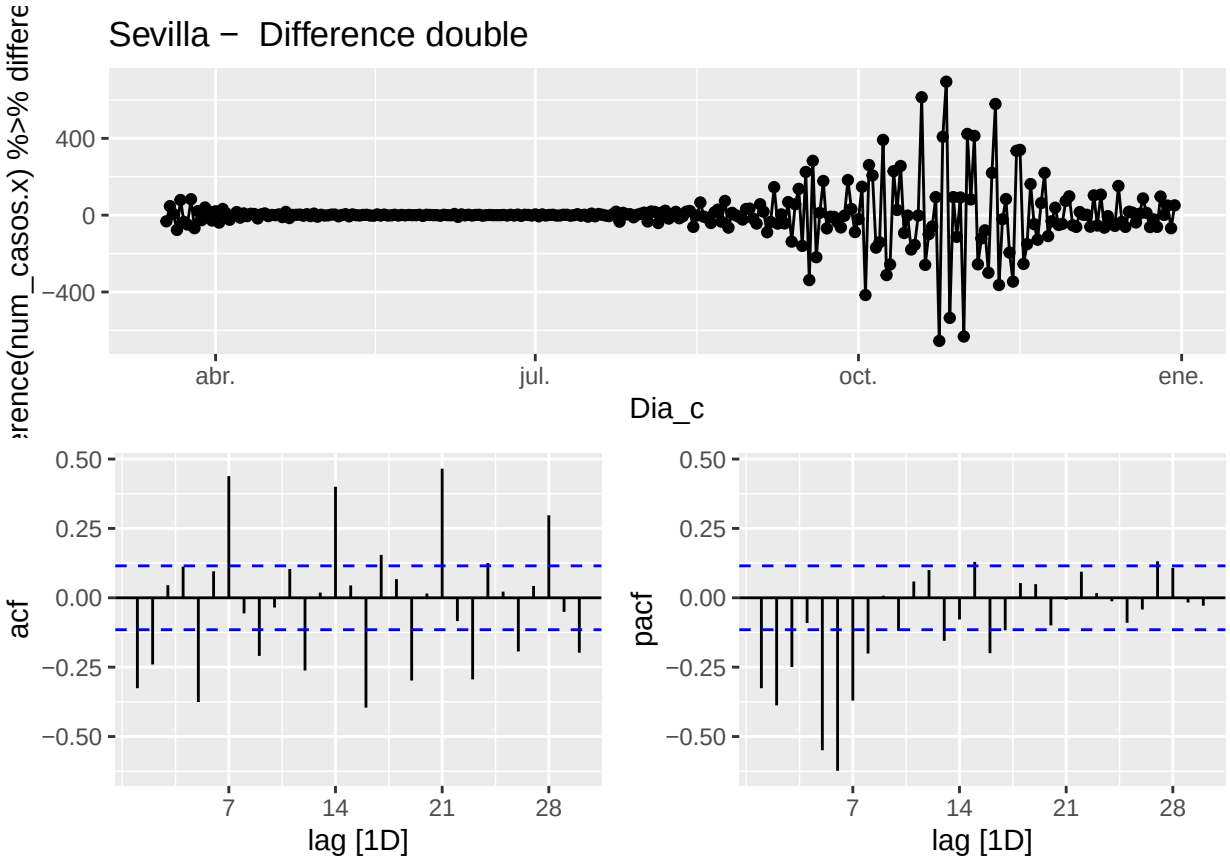

```
Mal_N_cases %>%
  gg_tsdisplay(difference(num_casos.x) %>%
                 difference(),
                 plot_type='partial', lag_max = 30)+
  labs(title="Málaga -  Difference double")
```




```
Cad_N_cases %>%
  gg_tsdisplay(difference(num_casos.x) %>%
                 difference(),
                 plot_type='partial', lag_max = 30)+
  labs(title="Cádiz -  Difference double")
```




```
Sev_N_cases %>%
  gg_tsdisplay(difference(num_casos.x) %>%
                 difference(),
                 plot_type='partial', lag_max = 30)+
  labs(title="Sevilla -  Difference double")
```



3.3 Model and Forecast (Barcelona, Madrid, Málaga, Córdoba and Cádiz)

3.3.1 Univariate (7, 14, 21 days) Barcelona

As stated by (Hyndman and Athanasopoulos 2021)... "The ARIMA() function uses unitroot_nsdiffs() to determine D (the number of seasonal differences to use), and unitroot_ndiffs() to determine d (the number of ordinary differences to use), when these are not specified."

```
# Train and test ts
Bar_N_cases_tr <- Bar_N_cases %>%
  filter_index("2020-03-15" ~ "2020-12-9")
Bar_N_cases_tt <- Bar_N_cases %>%
  filter_index("2020-12-10" ~ "2020-12-31")

# Model train
fit_model <- Bar_N_cases_tr %>%
  model(
    SNaive = SNAIVE(num_casos.x),
    arima_man = ARIMA(num_casos.x ~ pdq(2,1,2) + PDQ(1,1,1)),
    arima_at1 = ARIMA(num_casos.x),
    arima_at2 = ARIMA(num_casos.x, stepwise = FALSE, approx = FALSE))

# Show and report model
fit_model
```

```
## # A mable: 1 x 5
## # Key:     sub_region_2 [1]
```

```
##   sub_region_2   SNaive                arima_man                arima_at1
##   <chr>         <model>                  <model>                  <model>
## 1 Barcelona    <SNAIVE> <ARIMA(2,1,2)(1,1,1)[7]> <ARIMA(1,0,2)(1,1,0)[7]>
## # ... with 1 more variable: arima_at2 <model>
```

```
report(fit_model)
```

```
## # A tibble: 4 x 9
##   sub_region_2 .model     sigma2 log_lik   AIC  AICc   BIC ar_roots  ma_roots
##   <chr>        <chr>       <dbl>   <dbl> <dbl> <dbl> <dbl> <list>    <list>
## 1 Barcelona    SNaive    148096.      NA    NA    NA    NA  <NULL>    <NULL>
## 2 Barcelona    arima_man  35350.  -1735. 3484. 3485. 3509. <cpl [9]> <cpl [9]>
## 3 Barcelona    arima_at1  36260.  -1746. 3502. 3502. 3520. <cpl [8]> <cpl [2]>
## 4 Barcelona    arima_at2  33389.  -1735. 3485. 3485. 3510. <cpl [4]> <cpl [2]>
```

```
# Good model >> Less Sigma / More BIC or AIC
fit_model %>% pivot_longer(!sub_region_2,
                           names_to = "Model name",
                           values_to = "Orders")
```

```
## # A mable: 4 x 3
## # Key:     sub_region_2, Model name [4]
##   sub_region_2 `Model name`                   Orders
##   <chr>        <chr>                         <model>
## 1 Barcelona    SNaive                       <SNAIVE>
## 2 Barcelona    arima_man    <ARIMA(2,1,2)(1,1,1)[7]>
## 3 Barcelona    arima_at1    <ARIMA(1,0,2)(1,1,0)[7]>
## 4 Barcelona    arima_at2    <ARIMA(4,0,2)(0,1,0)[7]>
```

```
glance(fit_model) %>% arrange(AICc) %>% select(.model:BIC)
```

```
## # A tibble: 4 x 6
##   .model     sigma2 log_lik   AIC  AICc   BIC
##   <chr>       <dbl>   <dbl> <dbl> <dbl> <dbl>
## 1 arima_man  35350.  -1735. 3484. 3485. 3509.
## 2 arima_at2  33389.  -1735. 3485. 3485. 3510.
## 3 arima_at1  36260.  -1746. 3502. 3502. 3520.
## 4 SNaive    148096.     NA    NA    NA    NA
```

```
# We use a Ljung-Box test >> large p-value, confirmins residuals are similar to white noise.
augment(fit_model) %>%
  features(.innov, ljung_box, lag=7)
```

```
## # A tibble: 4 x 4
##   sub_region_2 .model    lb_stat lb_pvalue
##   <chr>        <chr>       <dbl>     <dbl>
## 1 Barcelona    arima_at1    19.6   0.00646
## 2 Barcelona    arima_at2    10.2   0.175
## 3 Barcelona    arima_man    16.2   0.0235
## 4 Barcelona    SNaive      827.    0
```

```
augment(fit_model) %>%
  features(.innov, ljung_box, lag=14)
```

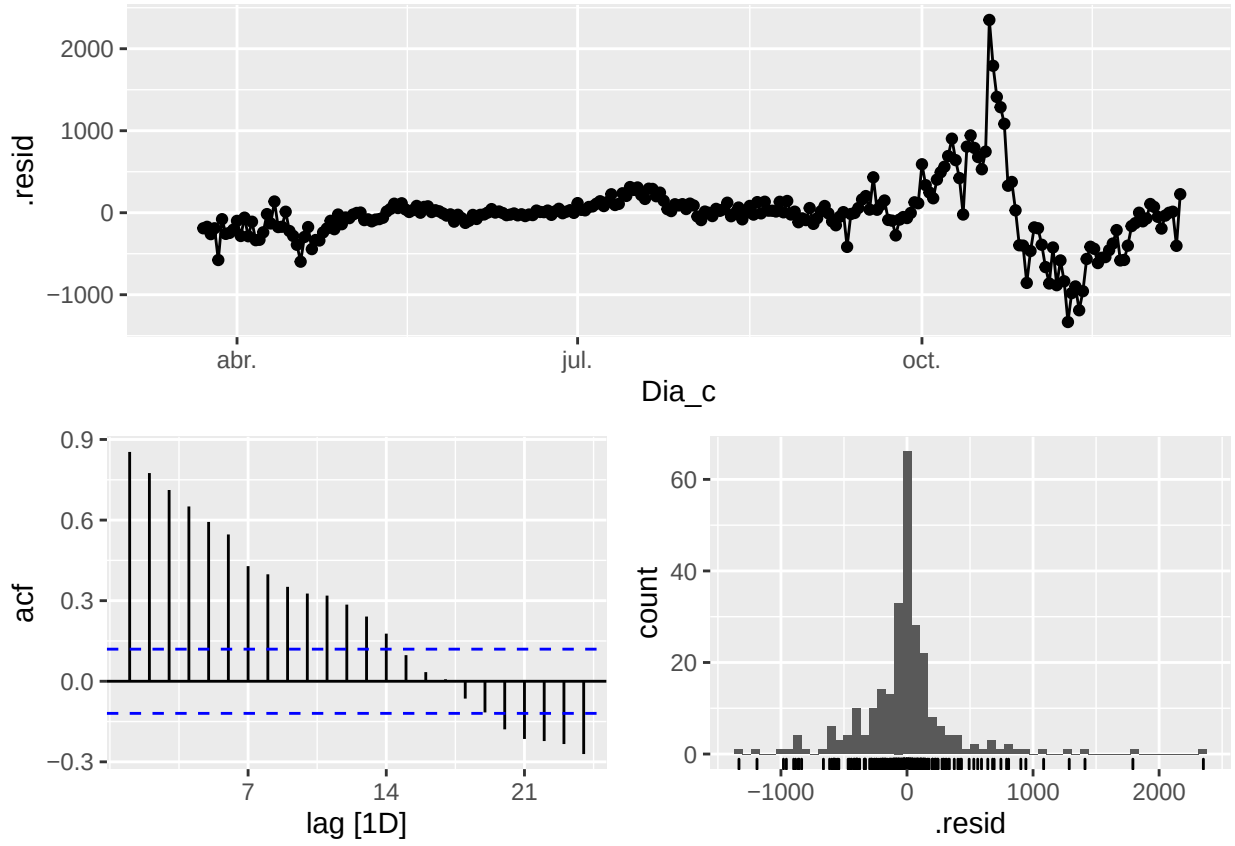
```
## # A tibble: 4 x 4
##   sub_region_2 .model    lb_stat lb_pvalue
##   <chr>        <chr>       <dbl>     <dbl>
## 1 Barcelona    arima_at1    35.1   0.00140
```

```
## 2 Barcelona    arima_at2    24.2   0.0438
## 3 Barcelona    arima_man    21.4   0.0907
## 4 Barcelona    SNaive     1009.    0
```

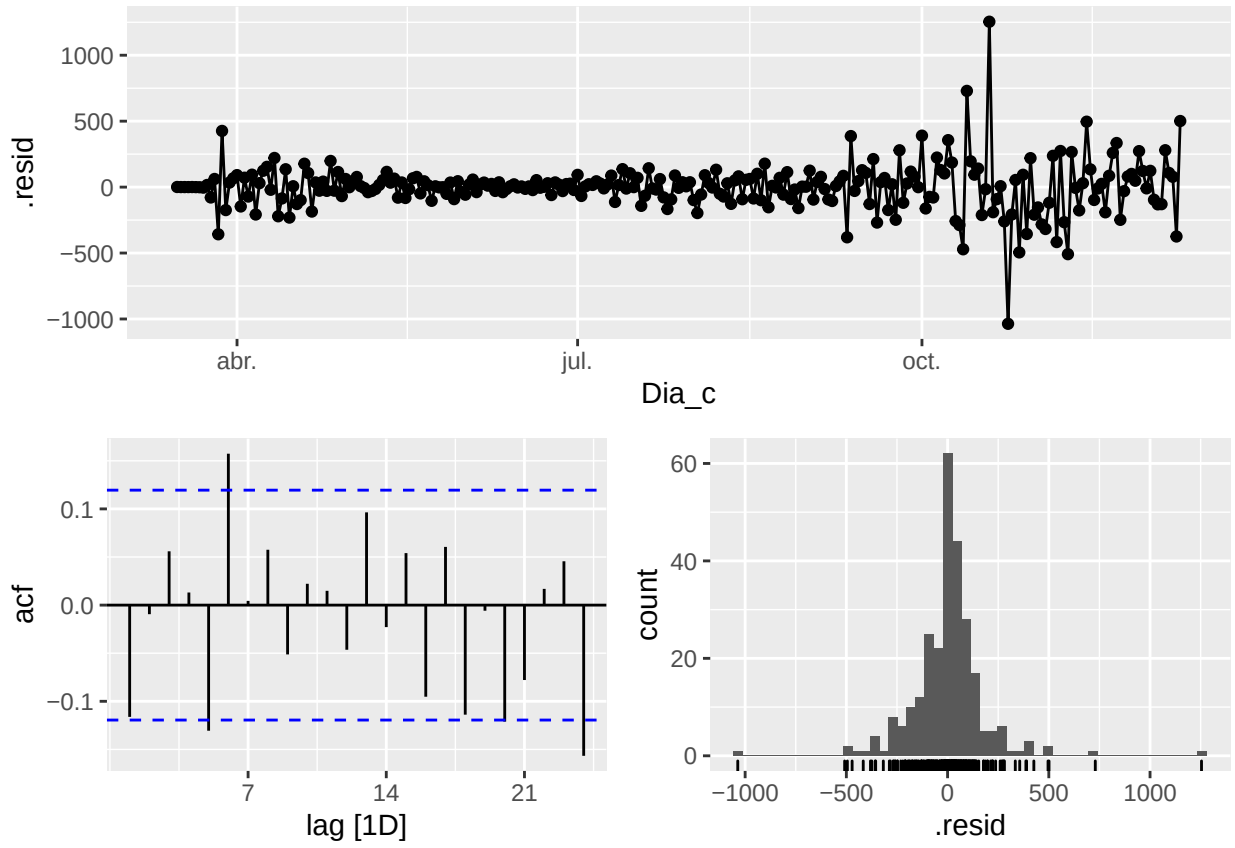
```
augment(fit_model) %>%
  features(.innov, ljung_box, lag=21)
```

```
## # A tibble: 4 x 4
##   sub_region_2 .model    lb_stat lb_pvalue
##   <chr>        <chr>       <dbl>     <dbl>
## 1 Barcelona    arima_at1    54.0 0.0000974
## 2 Barcelona    arima_at2    38.9 0.0100
## 3 Barcelona    arima_man    35.8 0.0229
## 4 Barcelona    SNaive     1039.  0
```

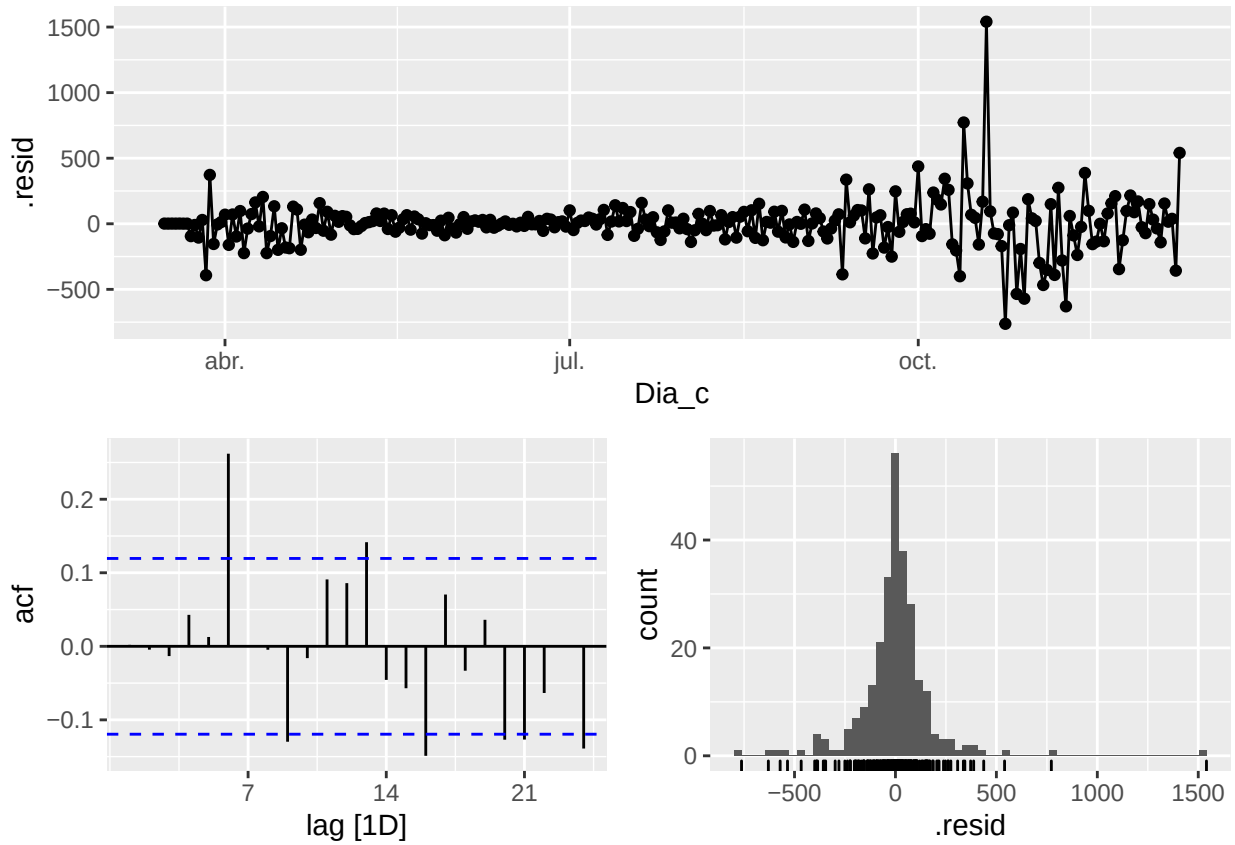
```
fit_model %>% select(SNaive) %>% gg_tsresiduals()
```



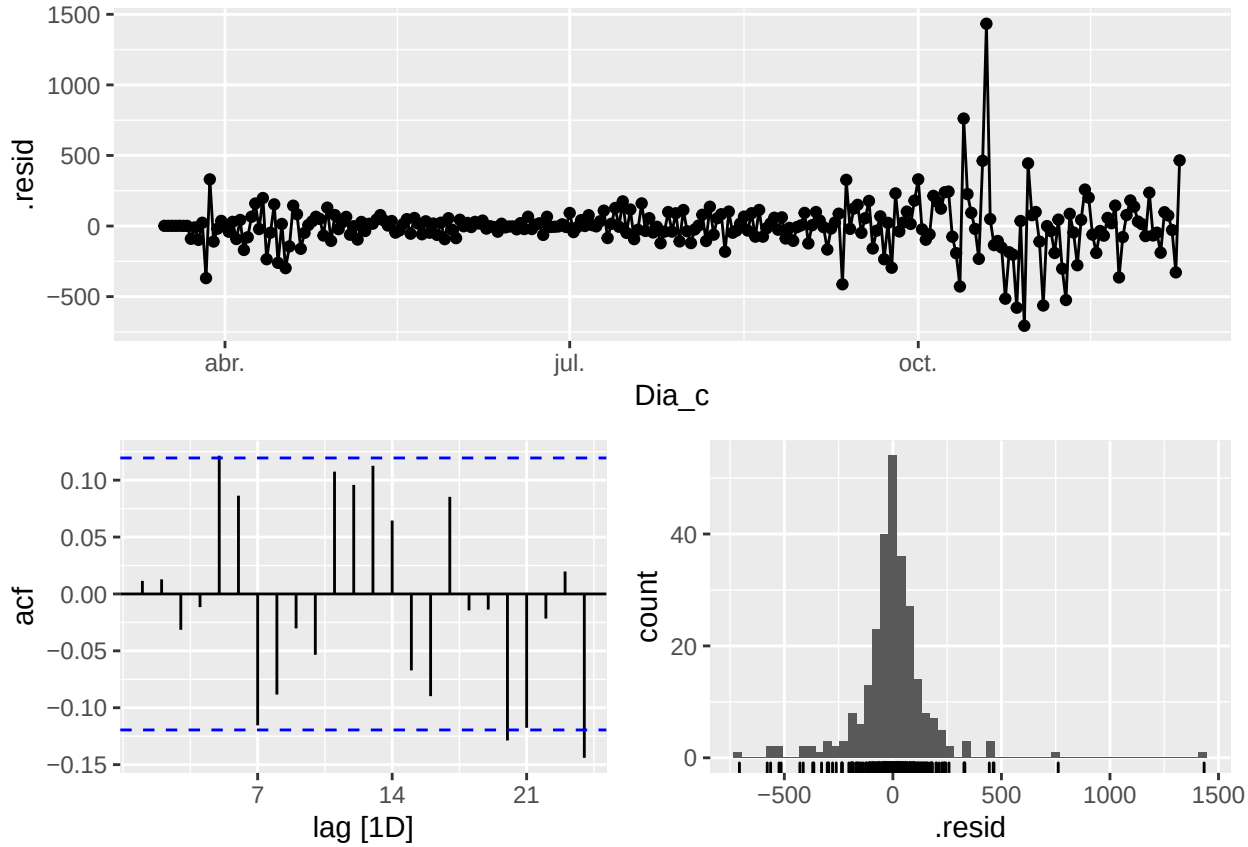

```
fit_model %>% select(arima_man) %>% gg_tsresiduals()
```




```
fit_model %>% select(arima_at1) %>% gg_tsresiduals()
```




```
fit_model %>% select(arima_at2) %>% gg_tsresiduals()
```




```
# Significant spikes (at lag 6, 15, etc.) out of 30 is still consistent with white noise.
# To be sure, use a Ljung-Box test, which has a large p-value, confirming that
# the residuals are similar to white noise.
# Note that the alternative models also pass this test.

# Forecast
fc_h7<-fabletools::forecast(fit_model, h=7)
fc_h14<-fabletools::forecast(fit_model, h=14)
fc_h21<-fabletools::forecast(fit_model, h=21)

# Accuracy
fabletools::accuracy(fc_h7, Bar_N_cases_tt)
```

```
## # A tibble: 4 x 11
##   .model    sub_region_2 .type    ME  RMSE   MAE   MPE  MAPE  MASE RMSSE    ACF1
##   <chr>     <chr>        <chr> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>   <dbl>
## 1 arima_at1 Barcelona    Test   285.  339.  285.  23.5  23.5   NaN   NaN  0.107
## 2 arima_at2 Barcelona    Test   333.  390.  333.  26.9  26.9   NaN   NaN  0.0700
## 3 arima_man Barcelona    Test   204.  277.  204.  17.3  17.3   NaN   NaN  0.155
## 4 SNaive    Barcelona    Test   413   467.  413   35.1  35.1   NaN   NaN -0.138
```

```
fabletools::accuracy(fc_h14, Bar_N_cases_tt)
```

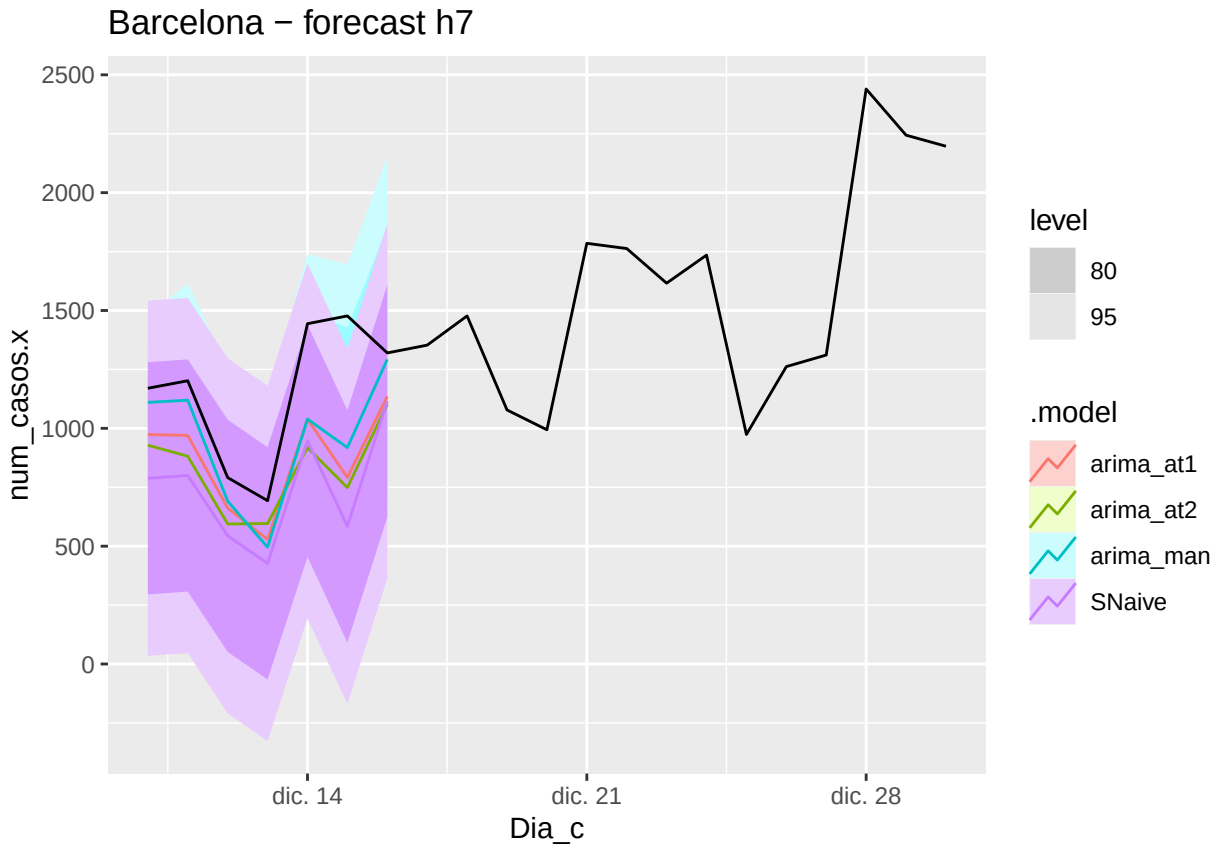
```
## # A tibble: 4 x 11
##   .model    sub_region_2 .type    ME  RMSE   MAE   MPE  MAPE  MASE RMSSE  ACF1
##   <chr>     <chr>        <chr> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
## 1 arima_at1 Barcelona    Test   411.  472.  411.  30.2  30.2   NaN   NaN 0.376
```

```
## 2 arima_at2 Barcelona    Test   449.  512.  449.  32.7  32.7   NaN   NaN 0.321
## 3 arima_man Barcelona    Test   293.  367.  293.  22.1  22.1   NaN   NaN 0.355
## 4 SNaive    Barcelona    Test   554.  612.  554.  41.8  41.8   NaN   NaN 0.189
```

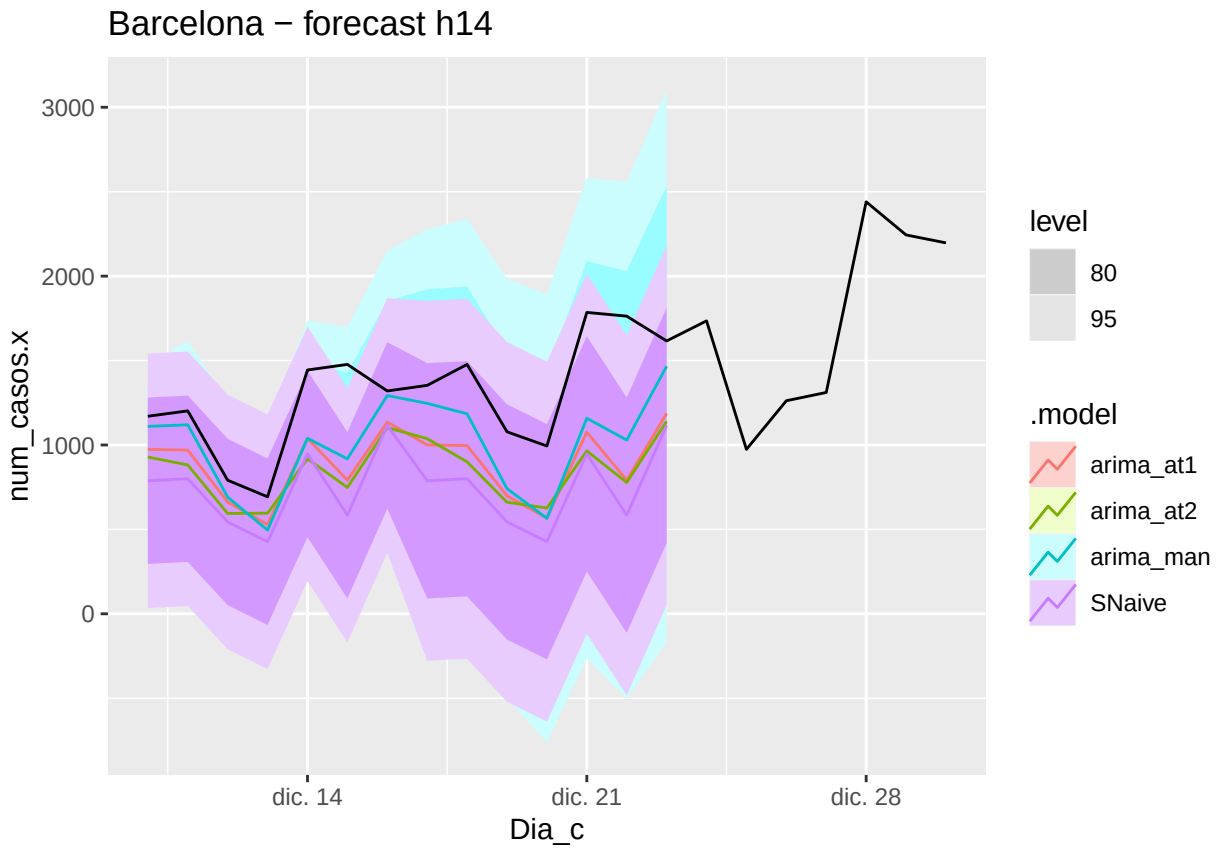
```
fabletools::accuracy(fc_h21, Bar_N_cases_tt)
```

```
## # A tibble: 4 x 11
##   .model    sub_region_2 .type    ME  RMSE   MAE   MPE  MAPE  MASE RMSSE  ACF1
##   <chr>     <chr>        <chr> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
## 1 arima_at1 Barcelona    Test   540.  659.  546.  34.0  34.6   NaN   NaN 0.531
## 2 arima_at2 Barcelona    Test   580.  697.  580.  36.6  36.6   NaN   NaN 0.526
## 3 arima_man Barcelona    Test   379.  507.  409.  23.8  26.9   NaN   NaN 0.479
## 4 SNaive    Barcelona    Test   700.  806.  700.  46.0  46.0   NaN   NaN 0.455
```

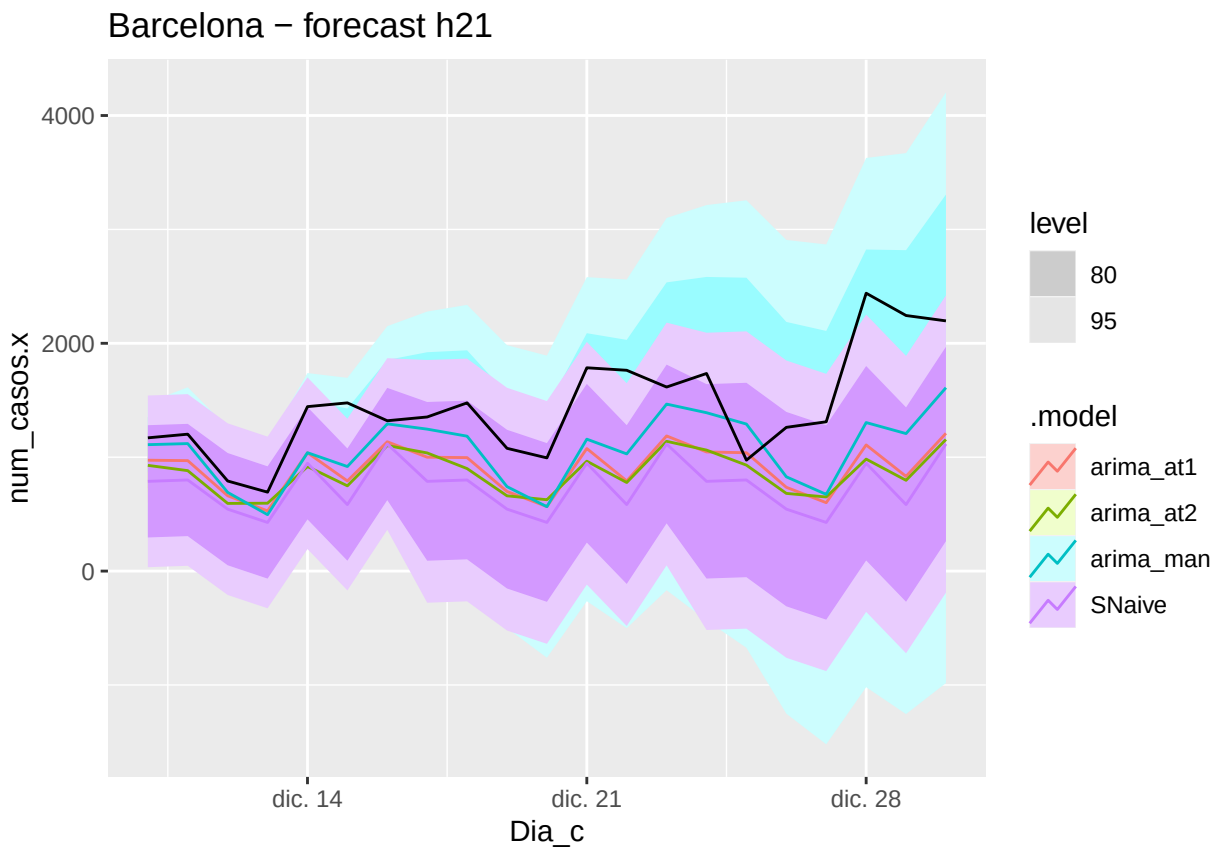
```
# Plots
fc_h7 %>%
  #filter(.model=='arima_at1'|.model=='arima_at2'|.model=='SNaive') %>%
  autoplot(Bar_N_cases_tt) +
  labs(title="Barcelona - forecast h7")
```




```
fc_h14 %>%
  #filter(.model=='arima_at1'|.model=='arima_at2'|.model=='SNaive') %>%
  autoplot(Bar_N_cases_tt) +
  labs(title="Barcelona - forecast h14")
```




```
fc_h21 %>%
  #filter(.model=='arima_at1'|.model=='arima_at2'|.model=='SNaive') %>%
  autoplot(Bar_N_cases_tt) +
  labs(title="Barcelona - forecast h21")
```



3.3.2 Multivariate (7, 14, 21 days) Barcelona

```
# Model train
# We have added mobility variables to models
fit_model <- Bar_N_cases_tr %>%
  model(
    SNaive = SNAIVE(num_casos.x),
    arima_man = ARIMA(num_casos.x ~ retail_and_recreation_percent_change_from_baseline +
                        grocery_and_pharmacy_percent_change_from_baseline +
                        parks_percent_change_from_baseline +
                        transit_stations_percent_change_from_baseline +
                        workplaces_percent_change_from_baseline +
                        residential_percent_change_from_baseline + Total + pdq(2,1,2) +
                        PDQ(1,1,1)),
    arima_at1 = ARIMA(num_casos.x~ retail_and_recreation_percent_change_from_baseline +
                        grocery_and_pharmacy_percent_change_from_baseline +
                        parks_percent_change_from_baseline +
                        transit_stations_percent_change_from_baseline +
                        workplaces_percent_change_from_baseline +
                        residential_percent_change_from_baseline + Total),
    arima_at2 = ARIMA(num_casos.x~ retail_and_recreation_percent_change_from_baseline +
                        grocery_and_pharmacy_percent_change_from_baseline +
                        parks_percent_change_from_baseline +
                        transit_stations_percent_change_from_baseline +
                        workplaces_percent_change_from_baseline +
```

```
                        residential_percent_change_from_baseline + Total,
                      stepwise = FALSE,approx = FALSE))

# Show and report model
fit_model
```

```
## # A mable: 1 x 5
## # Key:     sub_region_2 [1]
##   sub_region_2   SNaive                                arima_man
##   <chr>         <model>                                  <model>
## 1 Barcelona    <SNAIVE> <LM w/ ARIMA(2,1,2)(1,1,1)[7] errors>
## # ... with 2 more variables: arima_at1 <model>, arima_at2 <model>
```

```
report(fit_model)
```

```
## # A tibble: 4 x 9
##   sub_region_2 .model     sigma2 log_lik   AIC  AICc   BIC ar_roots   ma_roots
##   <chr>        <chr>       <dbl>   <dbl> <dbl> <dbl> <dbl> <list>     <list>
## 1 Barcelona    SNaive    148096.      NA    NA    NA    NA  <NULL>     <NULL>
## 2 Barcelona    arima_man  24852.  -1688. 3405. 3407. 3455. <cpl [9]>  <cpl [9]>
## 3 Barcelona    arima_at1  27061.  -1756. 3535. 3536. 3574. <cpl [8]>  <cpl [1]>
## 4 Barcelona    arima_at2  26350.  -1752. 3527. 3528. 3570. <cpl [15]> <cpl [0]>
```

```
# Good model >> Less Sigma - More BIC or AIC
fit_model %>% pivot_longer(!sub_region_2,
                           names_to = "Model name",
                           values_to = "Orders")
```

```
## # A mable: 4 x 3
## # Key:     sub_region_2, Model name [4]
##   sub_region_2 `Model name`                                  Orders
##   <chr>        <chr>                                        <model>
## 1 Barcelona    SNaive                                      <SNAIVE>
## 2 Barcelona    arima_man    <LM w/ ARIMA(2,1,2)(1,1,1)[7] errors>
## 3 Barcelona    arima_at1    <LM w/ ARIMA(1,0,1)(1,0,0)[7] errors>
## 4 Barcelona    arima_at2    <LM w/ ARIMA(1,0,0)(2,0,0)[7] errors>
```

```
glance(fit_model) %>% arrange(AICc) %>% select(.model:BIC)
```

```
## # A tibble: 4 x 6
##   .model     sigma2 log_lik   AIC  AICc   BIC
##   <chr>       <dbl>   <dbl> <dbl> <dbl> <dbl>
## 1 arima_man  24852.  -1688. 3405. 3407. 3455.
## 2 arima_at2  26350.  -1752. 3527. 3528. 3570.
## 3 arima_at1  27061.  -1756. 3535. 3536. 3574.
## 4 SNaive    148096.     NA    NA    NA    NA
```

```
# We use a Ljung-Box test >> large p-value, confirmins residuals are similar to white noise.
augment(fit_model) %>%
  features(.innov, ljung_box, lag=7)
```

```
## # A tibble: 4 x 4
##   sub_region_2 .model    lb_stat lb_pvalue
##   <chr>        <chr>       <dbl>     <dbl>
## 1 Barcelona    arima_at1   17.3     0.0158
## 2 Barcelona    arima_at2   16.2     0.0232
## 3 Barcelona    arima_man    9.22    0.237
```

```
## 4 Barcelona    SNaive     827.      0
```

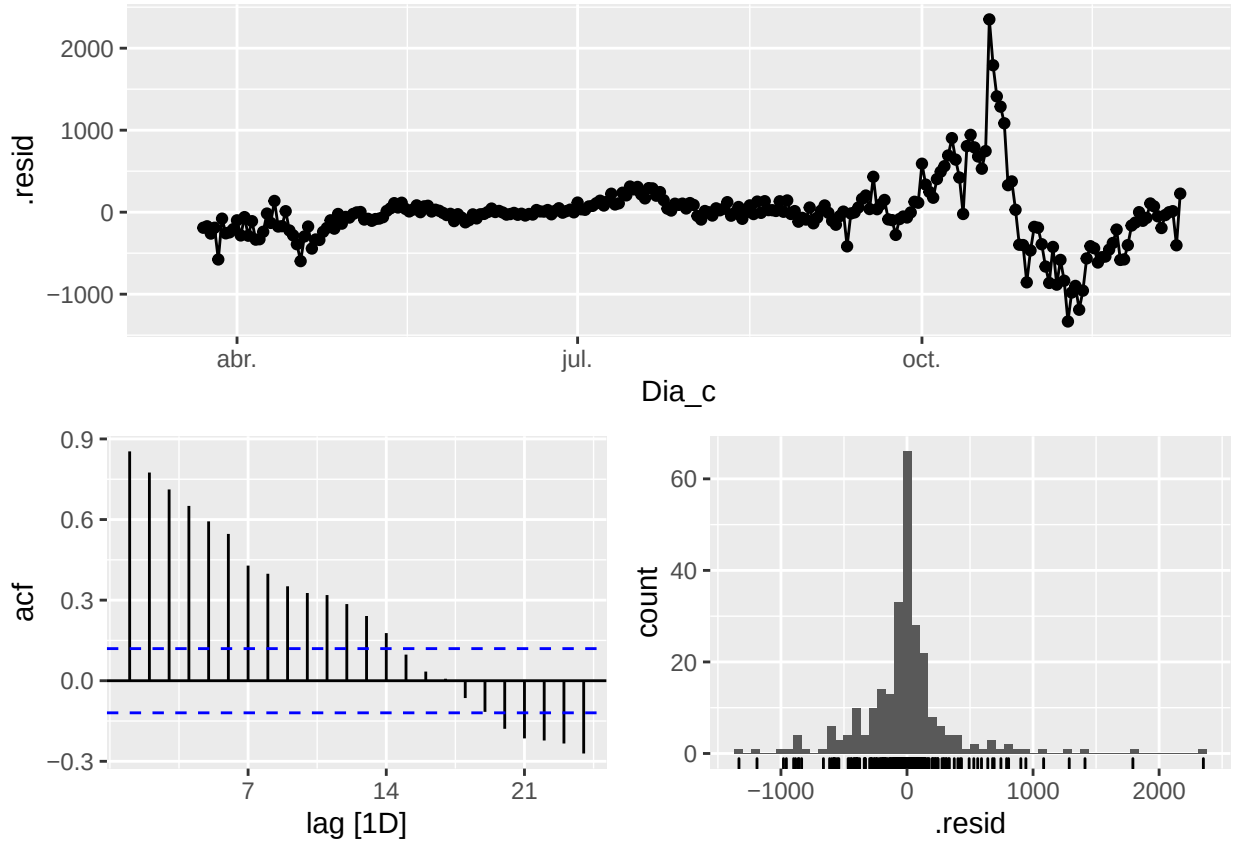
```
augment(fit_model) %>%
  features(.innov, ljung_box, lag=14)
```

```
## # A tibble: 4 x 4
##   sub_region_2 .model    lb_stat lb_pvalue
##   <chr>        <chr>       <dbl>     <dbl>
## 1 Barcelona    arima_at1    40.4  0.000221
## 2 Barcelona    arima_at2    39.7  0.000284
## 3 Barcelona    arima_man    32.0  0.00394
## 4 Barcelona    SNaive     1009.   0
```

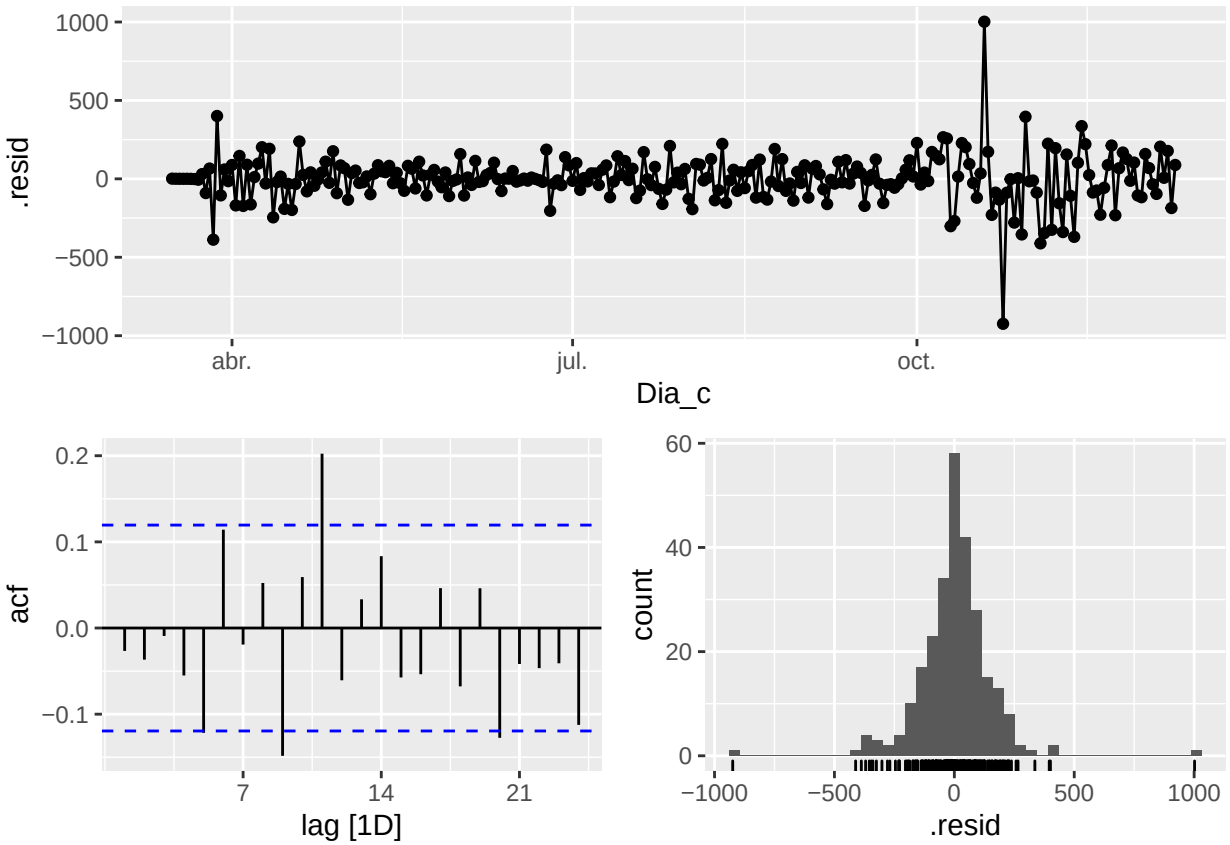
```
augment(fit_model) %>%
  features(.innov, ljung_box, lag=21)
```

```
## # A tibble: 4 x 4
##   sub_region_2 .model    lb_stat lb_pvalue
##   <chr>        <chr>       <dbl>     <dbl>
## 1 Barcelona    arima_at1    52.0  0.000191
## 2 Barcelona    arima_at2    49.9  0.000372
## 3 Barcelona    arima_man    41.7  0.00464
## 4 Barcelona    SNaive     1039.   0
```

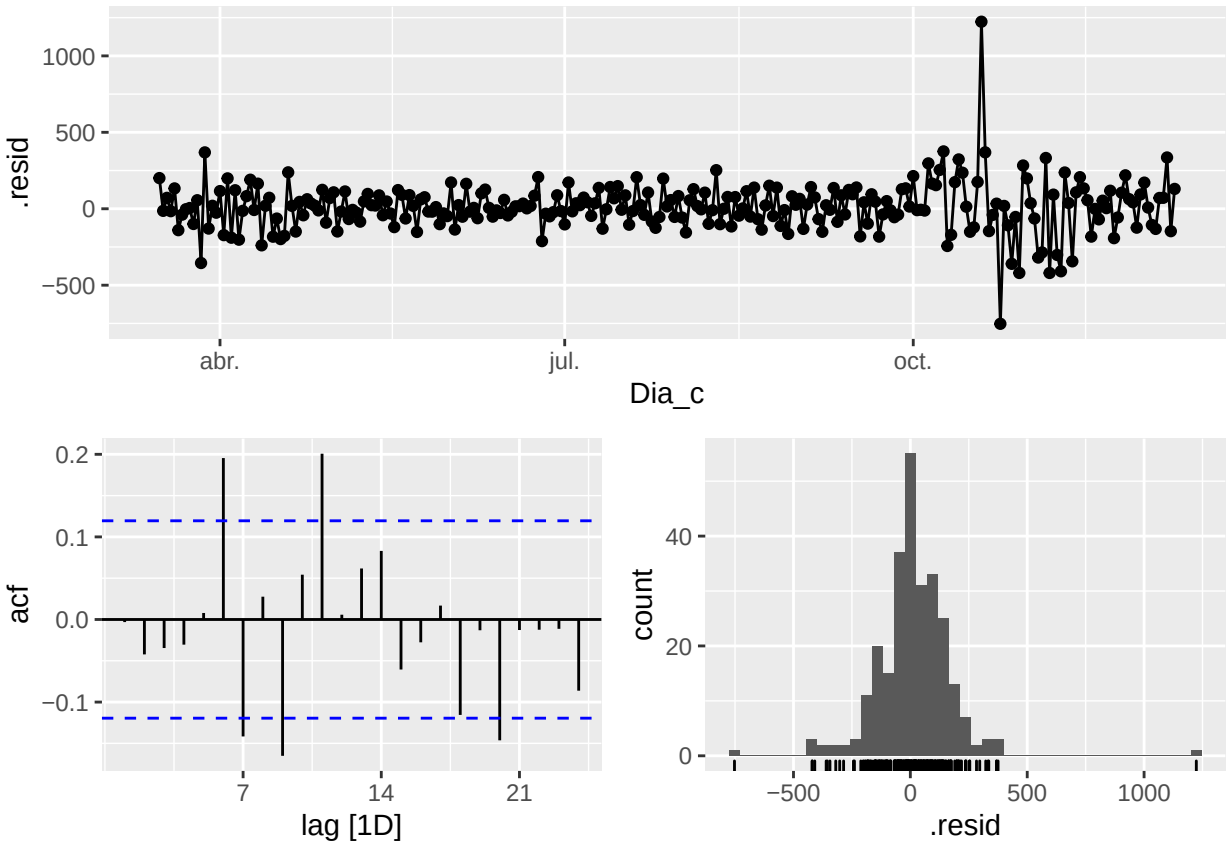
```
fit_model %>% select(SNaive) %>% gg_tsresiduals()
```



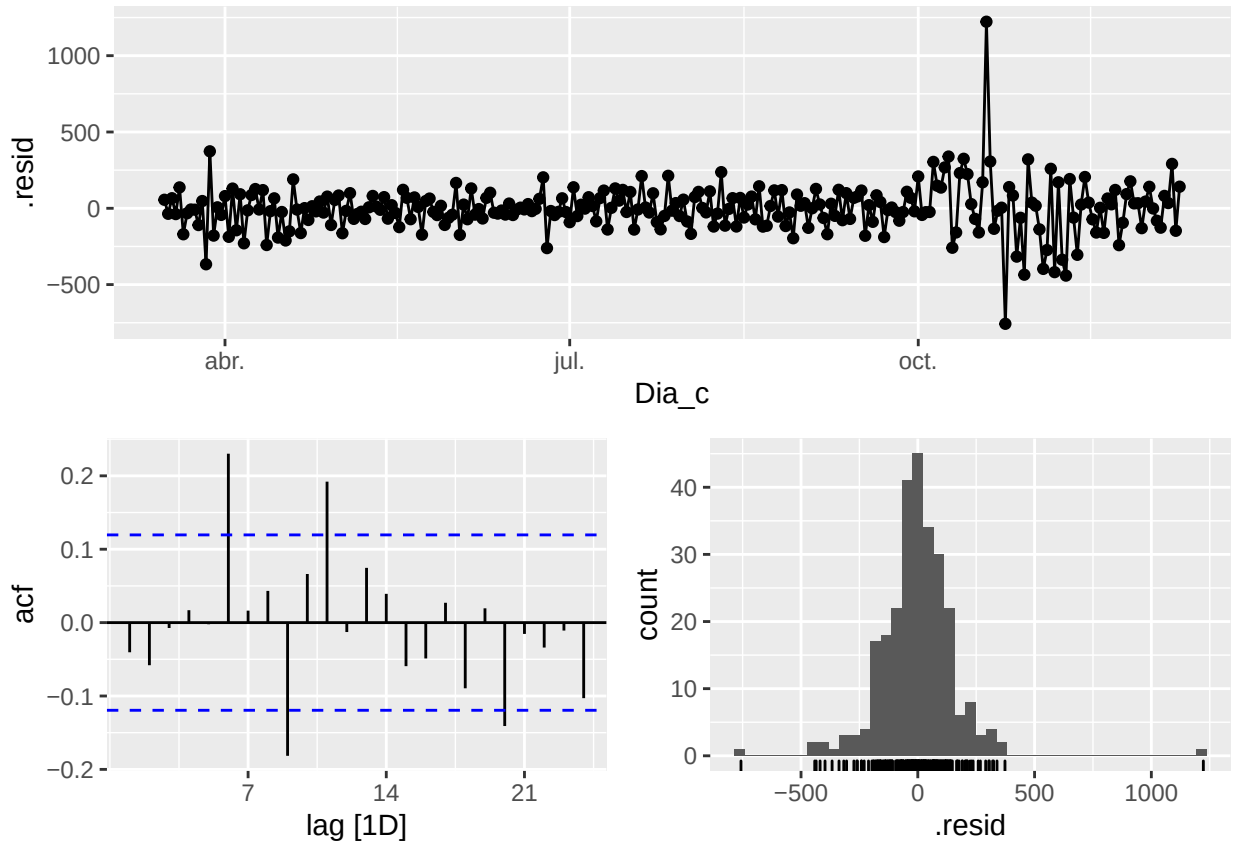

```
fit_model %>% select(arima_man) %>% gg_tsresiduals()
```




```
fit_model %>% select(arima_at1) %>% gg_tsresiduals()
```




```
fit_model %>% select(arima_at2) %>% gg_tsresiduals()
```




```
# Significant spikes out of 30 is still consistent with white noise.
# To be sure, use a Ljung-Box test, which has a large p-value, confirming that the
# residuals are similar to white noise.
# Note that the alternative models also pass this test.

# New data (dynamic regression)
# Here it is needed generate future values for the exogenous variables
# Foir simplicity we select a rand number included into the 2nd and 3rd quantile for
# the variable
# h7
Bar_N_cases_fr7 <- new_data(Bar_N_cases_tr, 7) %>%
  mutate(retail_and_recreation_percent_change_from_baseline =
           runif(7,quantile(Bar_N_cases_tt$retail_and_recreation_percent_change_from_baseline,
                            0.25),
                 quantile(Bar_N_cases_tt$retail_and_recreation_percent_change_from_baseline,
                          0.75)),
         grocery_and_pharmacy_percent_change_from_baseline =
           runif(7,quantile(Bar_N_cases_tt$grocery_and_pharmacy_percent_change_from_baseline,
                            0.25),
                 quantile(Bar_N_cases_tt$grocery_and_pharmacy_percent_change_from_baseline,
                          0.75)),
         parks_percent_change_from_baseline =
           runif(7,quantile(Bar_N_cases_tr$parks_percent_change_from_baseline,
                            0.25),
                 quantile(Bar_N_cases_tt$parks_percent_change_from_baseline,
                          0.75)),
```

```
          transit_stations_percent_change_from_baseline =
            runif(7,quantile(Bar_N_cases_tt$transit_stations_percent_change_from_baseline,
                             0.25),
                  quantile(Bar_N_cases_tt$transit_stations_percent_change_from_baseline,
                           0.75)),
          workplaces_percent_change_from_baseline =
            runif(7,quantile(Bar_N_cases_tt$workplaces_percent_change_from_baseline,
                             0.25),
                  quantile(Bar_N_cases_tt$workplaces_percent_change_from_baseline,
                           0.75)),
          residential_percent_change_from_baseline =
            runif(7,quantile(Bar_N_cases_tt$residential_percent_change_from_baseline,
                             0.25),
                  quantile(Bar_N_cases_tt$residential_percent_change_from_baseline,
                           0.75)),
          Total = runif(7,quantile(Bar_N_cases_tt$Total,0.25),
                        quantile(Bar_N_cases_tt$Total,0.75)))

# h14
Bar_N_cases_fr14 <- new_data(Bar_N_cases_tr, 14) %>%
  mutate(retail_and_recreation_percent_change_from_baseline =
            runif(14,quantile(Bar_N_cases_tt$retail_and_recreation_percent_change_from_baseline,
                              0.25),
                  quantile(Bar_N_cases_tt$retail_and_recreation_percent_change_from_baseline,
                           0.75)),
          grocery_and_pharmacy_percent_change_from_baseline =
            runif(14,quantile(Bar_N_cases_tt$grocery_and_pharmacy_percent_change_from_baseline,
                              0.25),
                  quantile(Bar_N_cases_tt$grocery_and_pharmacy_percent_change_from_baseline,
                           0.75)),
          parks_percent_change_from_baseline =
            runif(14,quantile(Bar_N_cases_tt$parks_percent_change_from_baseline,
                              0.25),
                  quantile(Bar_N_cases_tt$parks_percent_change_from_baseline,
                           0.75)),
          transit_stations_percent_change_from_baseline =
            runif(14,quantile(Bar_N_cases_tt$transit_stations_percent_change_from_baseline,
                              0.25),
                  quantile(Bar_N_cases_tt$transit_stations_percent_change_from_baseline,
                           0.75)),
          workplaces_percent_change_from_baseline =
            runif(14,quantile(Bar_N_cases_tt$workplaces_percent_change_from_baseline,
                              0.25),
                  quantile(Bar_N_cases_tt$workplaces_percent_change_from_baseline,
                           0.75)),
          residential_percent_change_from_baseline =
            runif(14,quantile(Bar_N_cases_tt$residential_percent_change_from_baseline,
                              0.25),
                  quantile(Bar_N_cases_tt$residential_percent_change_from_baseline,
                           0.75)),
          Total = runif(14,quantile(Bar_N_cases_tt$Total,0.25),
                        quantile(Bar_N_cases_tt$Total,0.75)))
```

```
# h21
Bar_N_cases_fr21 <- new_data(Bar_N_cases_tr, 21) %>%
  mutate(retail_and_recreation_percent_change_from_baseline =
           runif(21,quantile(Bar_N_cases_tt$retail_and_recreation_percent_change_from_baseline,
                             0.25),
                 quantile(Bar_N_cases_tt$retail_and_recreation_percent_change_from_baseline,
                          0.75)),
         grocery_and_pharmacy_percent_change_from_baseline =
           runif(21,quantile(Bar_N_cases_tt$grocery_and_pharmacy_percent_change_from_baseline,
                             0.25),
                 quantile(Bar_N_cases_tt$grocery_and_pharmacy_percent_change_from_baseline,
                          0.75)),
         parks_percent_change_from_baseline =
           runif(21,quantile(Bar_N_cases_tt$parks_percent_change_from_baseline,
                             0.25),
                 quantile(Bar_N_cases_tt$parks_percent_change_from_baseline,
                          0.75)),
         transit_stations_percent_change_from_baseline =
           runif(21,quantile(Bar_N_cases_tt$transit_stations_percent_change_from_baseline,
                             0.25),
                 quantile(Bar_N_cases_tt$transit_stations_percent_change_from_baseline,
                          0.75)),
         workplaces_percent_change_from_baseline =
           runif(21,quantile(Bar_N_cases_tt$workplaces_percent_change_from_baseline,
                             0.25),
                 quantile(Bar_N_cases_tt$workplaces_percent_change_from_baseline,
                          0.75)),
         residential_percent_change_from_baseline =
           runif(21,quantile(Bar_N_cases_tt$residential_percent_change_from_baseline,
                             0.25),
                 quantile(Bar_N_cases_tt$residential_percent_change_from_baseline,
                          0.75)),
         Total = runif(21,quantile(Bar_N_cases_tt$Total,0.25),
                       quantile(Bar_N_cases_tt$Total,0.75)))

# Forecast
fc_fh7<-fabletools::forecast(fit_model, new_data = Bar_N_cases_fr7)
fc_fh14<-fabletools::forecast(fit_model, new_data = Bar_N_cases_fr14)
fc_fh21<-fabletools::forecast(fit_model, new_data = Bar_N_cases_fr21)

# Accuracy
fabletools::accuracy(fc_fh7, Bar_N_cases)
```

```
## # A tibble: 4 x 11
##   .model    sub_region_2 .type    ME  RMSE   MAE   MPE  MAPE  MASE RMSSE    ACF1
##   <chr>     <chr>        <chr> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>   <dbl>
## 1 arima_at1 Barcelona    Test   242.  272.  242.  20.6  20.6 1.07  0.708  0.0321
## 2 arima_at2 Barcelona    Test   191.  233.  191.  15.5  15.5 0.848 0.605  0.222
## 3 arima_man Barcelona    Test   252.  287.  252.  25.5  25.5 1.12  0.747  0.0519
## 4 SNaive    Barcelona    Test   413   467.  413   35.1  35.1 1.83  1.21  -0.138
```

```
fabletools::accuracy(fc_fh14, Bar_N_cases)
```

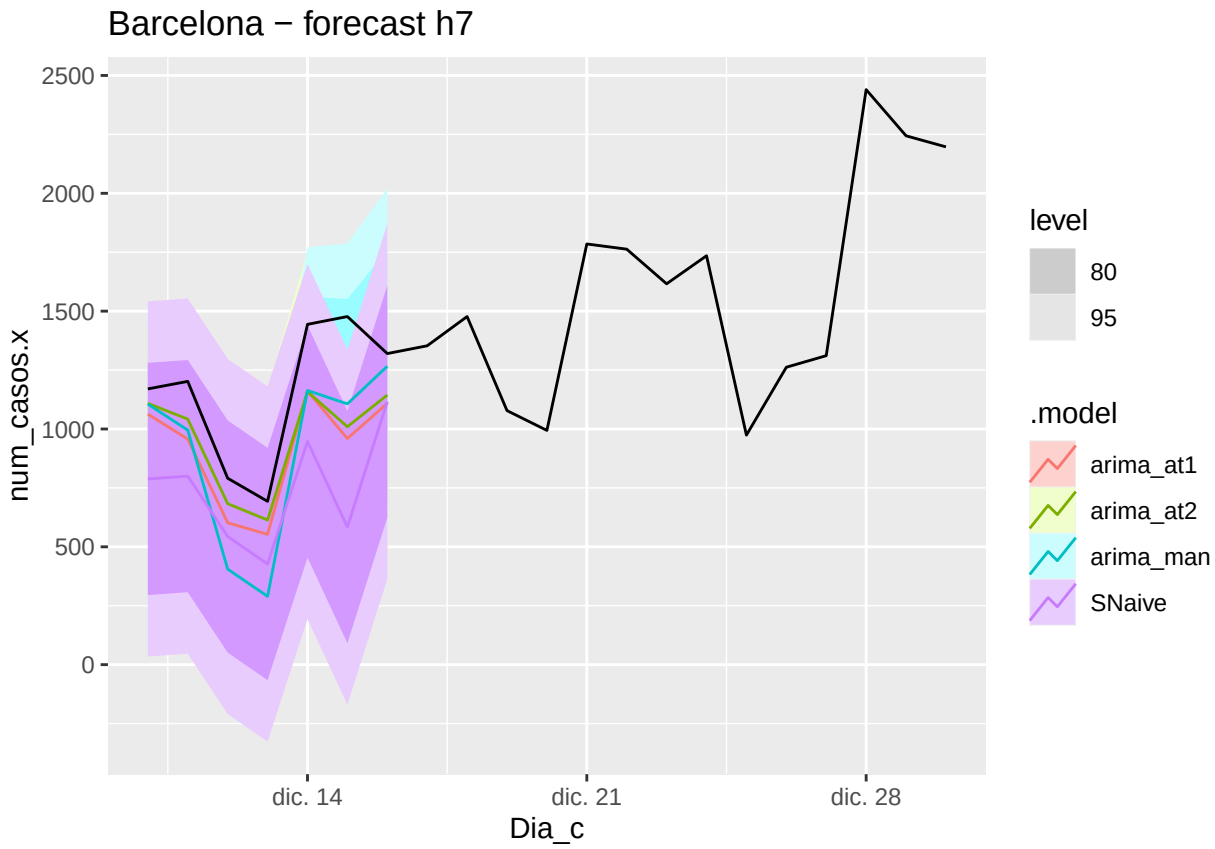
```
## # A tibble: 4 x 11
```

```
##   .model    sub_region_2 .type    ME  RMSE   MAE   MPE  MAPE  MASE RMSSE  ACF1
##   <chr>     <chr>        <chr> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
## 1 arima_at1 Barcelona    Test   391.  425.  391.  29.7  29.7  1.74 1.11  0.259
## 2 arima_at2 Barcelona    Test   313.  346.  313.  23.3  23.3  1.39 0.899 0.122
## 3 arima_man Barcelona    Test   412.  453.  412.  35.3  35.3  1.83 1.18  0.550
## 4 SNaive    Barcelona    Test   554.  612.  554.  41.8  41.8  2.46 1.59  0.189
```

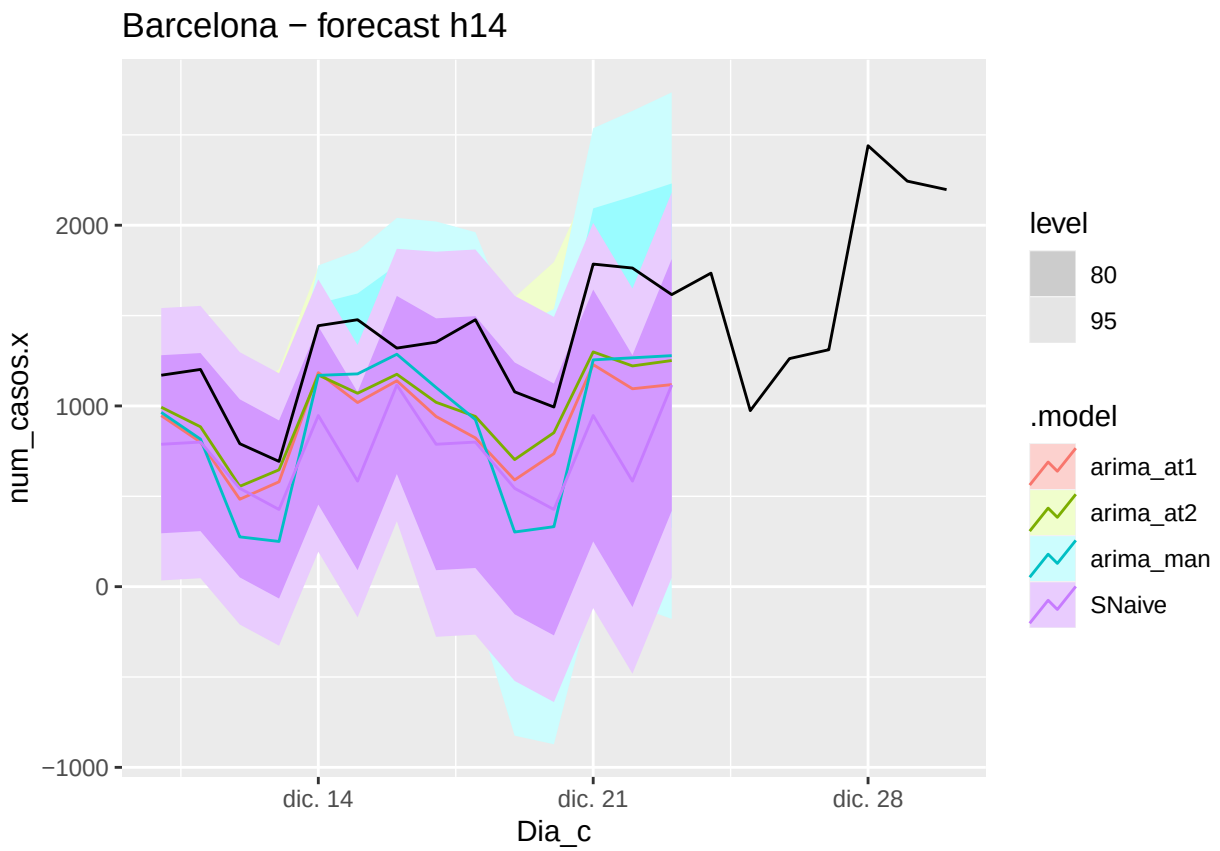
```
fabletools::accuracy(fc_fh21, Bar_N_cases)
```

```
## # A tibble: 4 x 11
##   .model    sub_region_2 .type    ME  RMSE   MAE   MPE  MAPE  MASE RMSSE  ACF1
##   <chr>     <chr>        <chr> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
## 1 arima_at1 Barcelona    Test   558.  670.  558.  36.1  36.1  2.48  1.74 0.606
## 2 arima_at2 Barcelona    Test   439.  552.  455.  27.5  29.1  2.02  1.43 0.531
## 3 arima_man Barcelona    Test   557.  663.  575.  39.4  41.2  2.55  1.72 0.524
## 4 SNaive    Barcelona    Test   700.  806.  700.  46.0  46.0  3.11  2.10 0.455
```

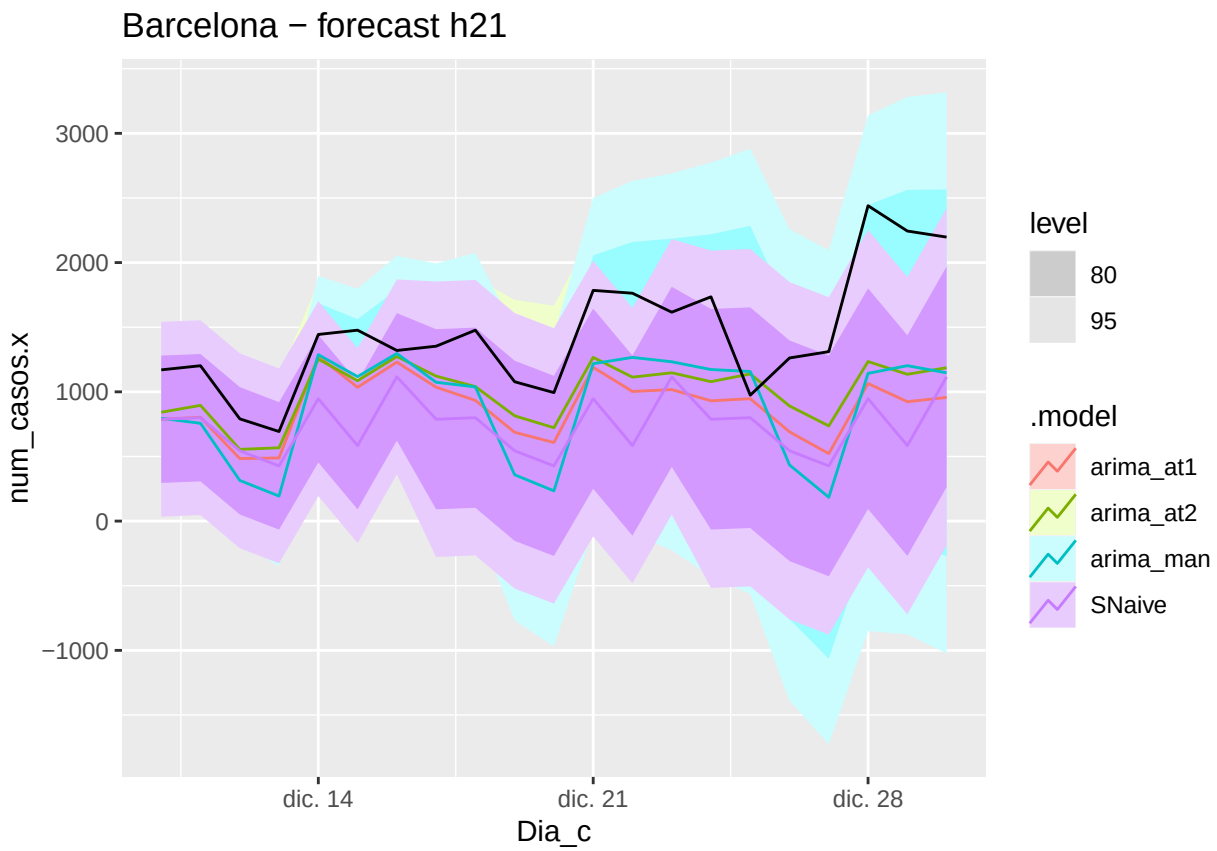
```
# Plots
fc_fh7 %>%
  #filter(.model=='arima_at1'|.model=='arima_at2'|.model=='SNaive') %>%
  autoplot(Bar_N_cases_tt) +
  labs(title="Barcelona - forecast h7")
```




```
fc_fh14 %>%
  #filter(.model=='arima_at1'|.model=='arima_at2'|.model=='SNaive') %>%
  autoplot(Bar_N_cases_tt) +
  labs(title="Barcelona - forecast h14")
```




```
fc_fh21 %>%
  #filter(.model=='arima_at1'|.model=='arima_at2'|.model=='SNaive') %>%
  autoplot(Bar_N_cases_tt) +
  labs(title="Barcelona - forecast h21")
```



3.3.3 Univariate (7, 14, 21 days) Madrid, Málaga, Córdoba and Cádiz

```
# Train and test ts
# Train
Mad_N_cases_tr <- Mad_N_cases %>%
  filter_index("2020-03-15" ~ "2020-12-9")
Mal_N_cases_tr <- Mal_N_cases %>%
  filter_index("2020-03-15" ~ "2020-12-9")
Cad_N_cases_tr <- Cad_N_cases %>%
  filter_index("2020-03-15" ~ "2020-12-9")
Sev_N_cases_tr <- Sev_N_cases %>%
  filter_index("2020-03-15" ~ "2020-12-9")

# Test
Mad_N_cases_tt <- Mad_N_cases %>%
  filter_index("2020-12-10" ~ "2020-12-31")
Mal_N_cases_tt <- Mal_N_cases %>%
  filter_index("2020-12-10" ~ "2020-12-31")
Cad_N_cases_tt <- Cad_N_cases %>%
  filter_index("2020-12-10" ~ "2020-12-31")
Sev_N_cases_tt <- Sev_N_cases %>%
  filter_index("2020-12-10" ~ "2020-12-31")
```

```
####### Madrid #######
# Model train
Mad_fit_model <- Mad_N_cases_tr %>%
```

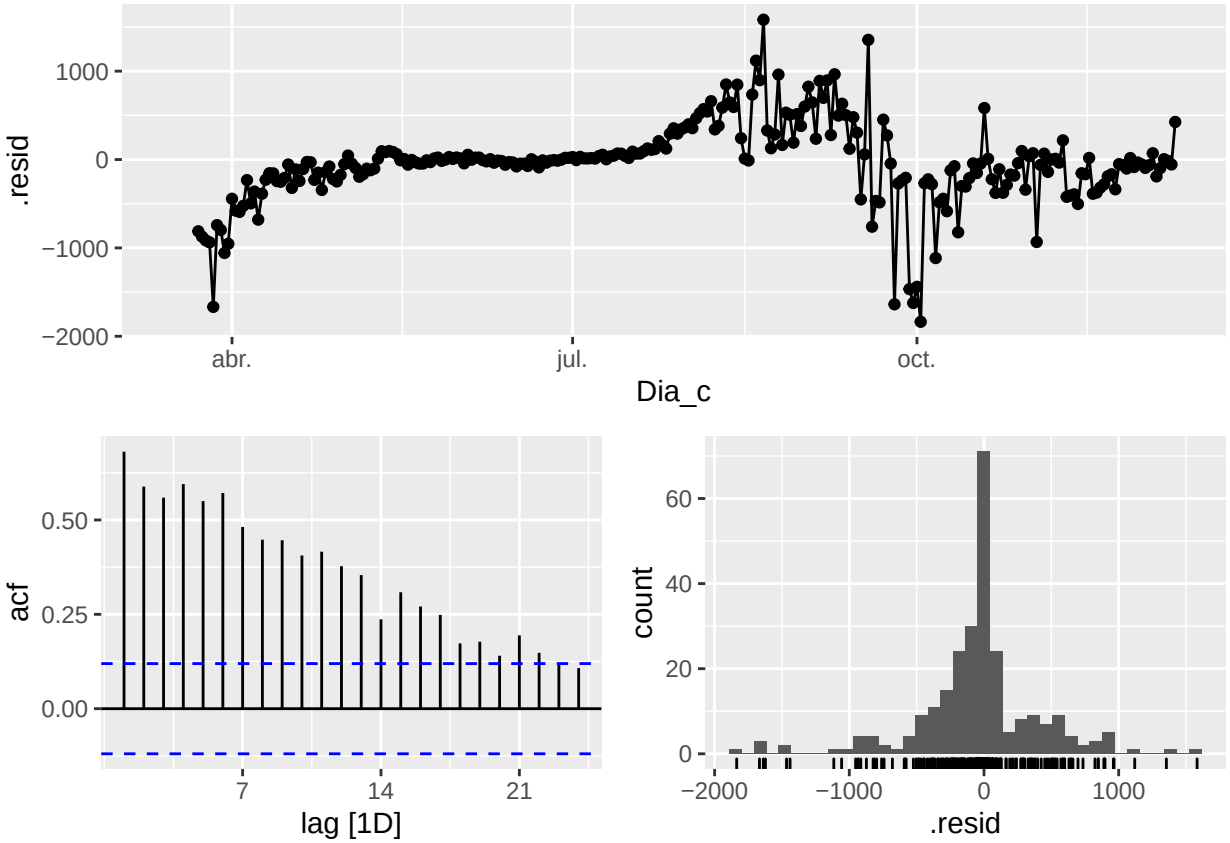
```
  model(
    SNaive = SNAIVE(num_casos.x),
    arima_man = ARIMA(num_casos.x ~ pdq(2,1,2) + PDQ(1,1,1)),
    arima_at1 = ARIMA(num_casos.x),
    arima_at2 = ARIMA(num_casos.x, stepwise = FALSE,approx = FALSE))

Mad_fit_model %>% pivot_longer(!sub_region_2,
                           names_to = "Model name",
                           values_to = "Orders")
```

```
## # A mable: 4 x 3
## # Key:     sub_region_2, Model name [4]
##   sub_region_2 `Model name`                   Orders
##   <chr>        <chr>                         <model>
## 1 Madrid       SNaive                       <SNAIVE>
## 2 Madrid       arima_man    <ARIMA(2,1,2)(1,1,1)[7]>
## 3 Madrid       arima_at1    <ARIMA(2,1,1)(1,1,2)[7]>
## 4 Madrid       arima_at2    <ARIMA(2,1,2)(2,1,0)[7]>
```

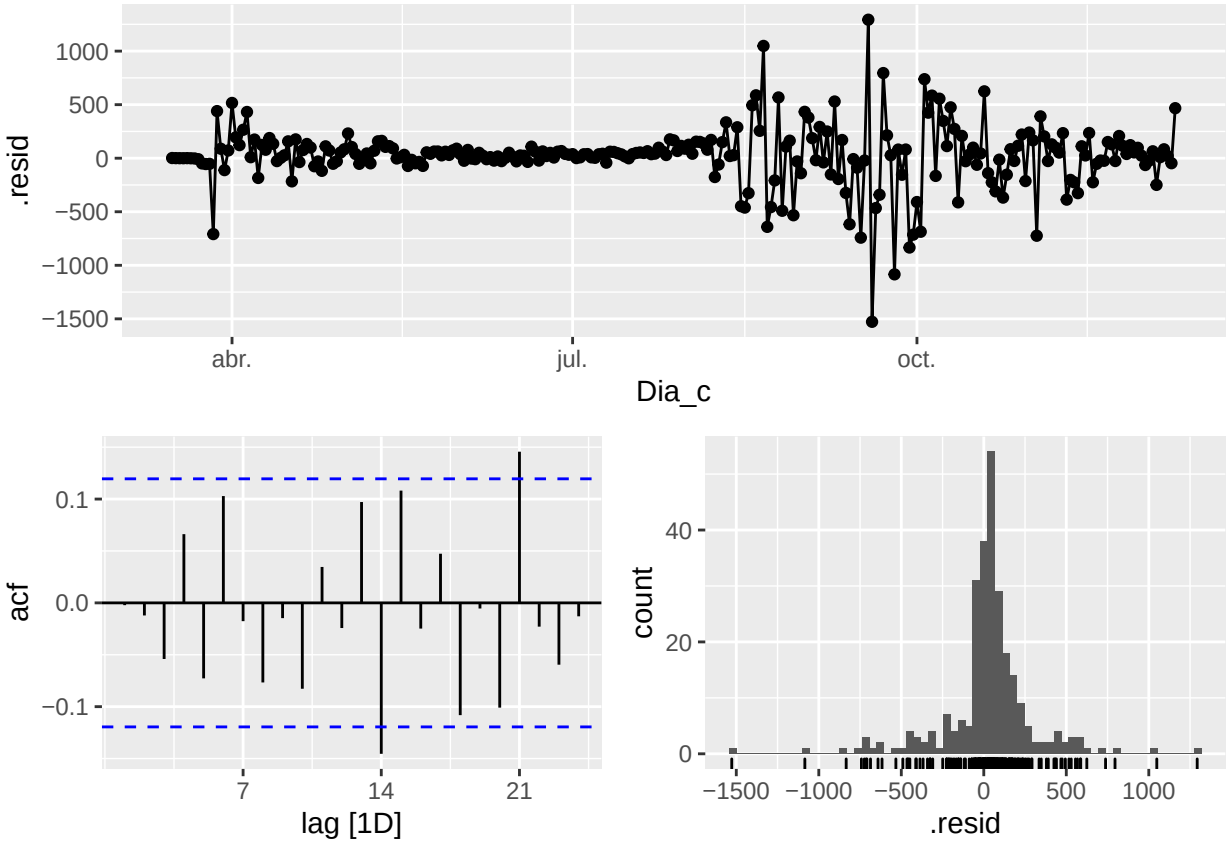
```
# Good model >> Less Sigma / More BIC or AIC
glance(Mad_fit_model) %>% arrange(AICc) %>% select(.model:BIC)
```

```
## # A tibble: 4 x 6
##   .model     sigma2 log_lik   AIC  AICc   BIC
##   <chr>       <dbl>   <dbl> <dbl> <dbl> <dbl>
## 1 arima_at2  84635.  -1849. 3712. 3712. 3737.
## 2 arima_man  82093.  -1850. 3715. 3715. 3740.
## 3 arima_at1  87043.  -1853. 3719. 3719. 3744.
## 4 SNaive    205618.     NA    NA    NA    NA
```

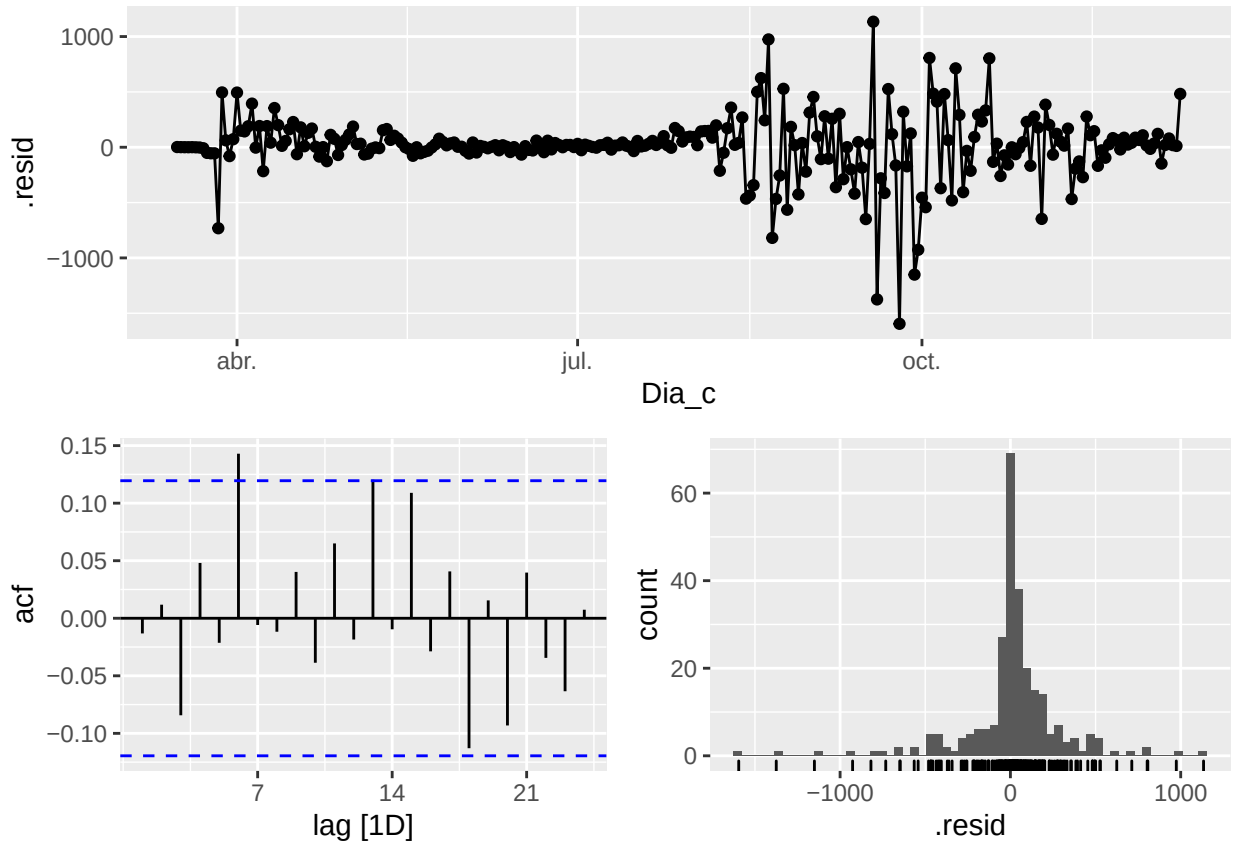
```
Mad_fit_model %>% select(SNaive) %>% gg_tsresiduals()
```



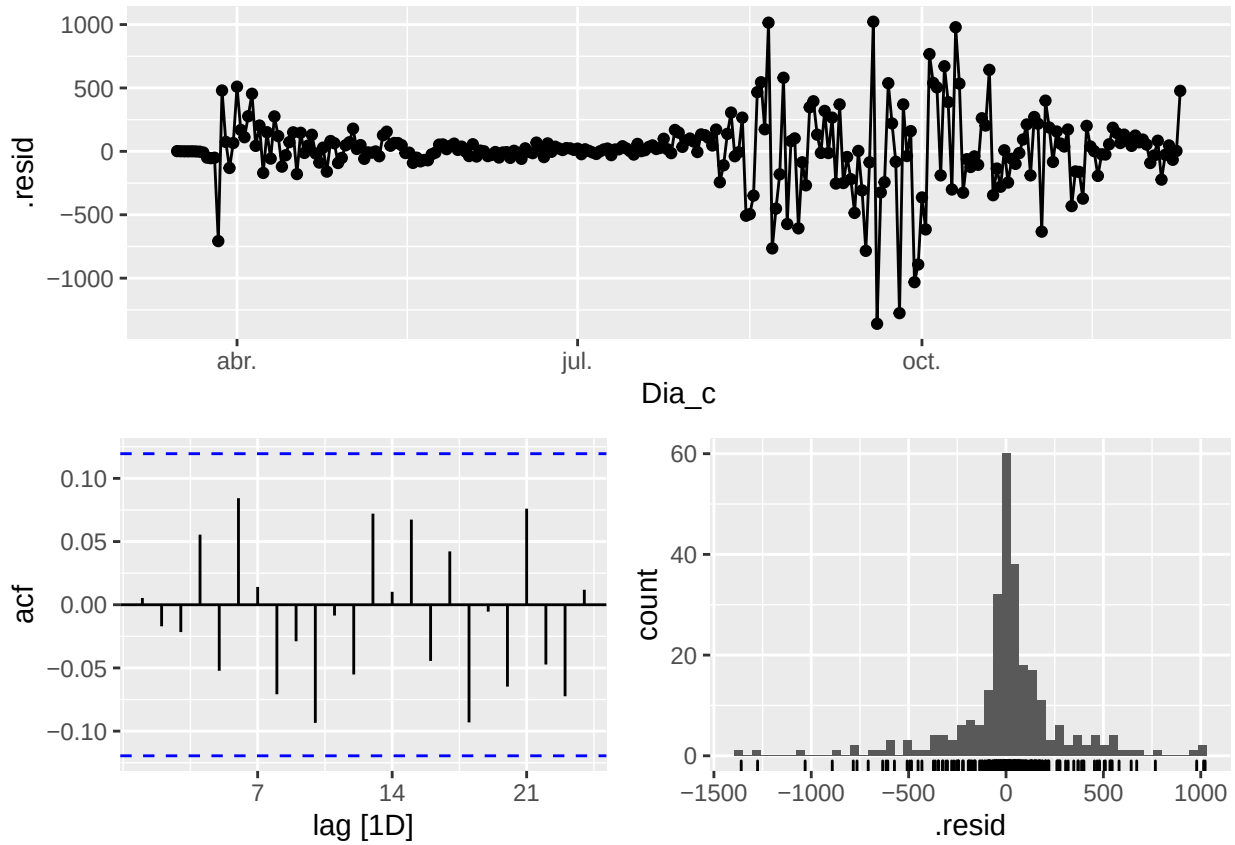

```
Mad_fit_model %>% select(arima_man) %>% gg_tsresiduals()
```




```
Mad_fit_model %>% select(arima_at1) %>% gg_tsresiduals()
```




```
Mad_fit_model %>% select(arima_at2) %>% gg_tsresiduals()
```




```
augment(Mad_fit_model) %>%
  features(.innov, ljung_box, lag=7)
```

```
## # A tibble: 4 x 4
##   sub_region_2 .model    lb_stat lb_pvalue
##   <chr>        <chr>       <dbl>     <dbl>
## 1 Madrid       arima_at1    8.47     0.293
## 2 Madrid       arima_at2    3.84     0.798
## 3 Madrid       arima_man    6.53     0.480
## 4 Madrid       SNaive     626.       0
```

```
augment(Mad_fit_model) %>%
  features(.innov, ljung_box, lag=14)
```

```
## # A tibble: 4 x 4
##   sub_region_2 .model    lb_stat lb_pvalue
##   <chr>        <chr>       <dbl>     <dbl>
## 1 Madrid       arima_at1    14.8     0.390
## 2 Madrid       arima_at2    10.3     0.738
## 3 Madrid       arima_man    19.4     0.150
## 4 Madrid       SNaive      918.      0
```

```
augment(Mad_fit_model) %>%
  features(.innov, ljung_box, lag=21)
```

```
## # A tibble: 4 x 4
##   sub_region_2 .model    lb_stat lb_pvalue
##   <chr>        <chr>       <dbl>     <dbl>
```

```
## 1 Madrid       arima_at1    25.7    0.217
## 2 Madrid       arima_at2    18.2    0.638
## 3 Madrid       arima_man    36.2    0.0208
## 4 Madrid       SNaive     1016.     0
```

```
# Forecast
Mad_fc_h7<-fabletools::forecast(Mad_fit_model, h=7)
Mad_fc_h14<-fabletools::forecast(Mad_fit_model, h=14)
Mad_fc_h21<-fabletools::forecast(Mad_fit_model, h=21)
# Accuracy
fabletools::accuracy(Mad_fc_h7, Mad_N_cases_tt)
```

```
## # A tibble: 4 x 11
##   .model    sub_region_2 .type    ME  RMSE   MAE   MPE  MAPE  MASE RMSSE   ACF1
##   <chr>     <chr>        <chr> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
## 1 arima_at1 Madrid       Test   605.  641.  605.  34.0  34.0   NaN   NaN -0.290
## 2 arima_at2 Madrid       Test   621.  653.  621.  35.0  35.0   NaN   NaN -0.299
## 3 arima_man Madrid       Test   620.  647.  620.  35.2  35.2   NaN   NaN -0.287
## 4 SNaive    Madrid       Test   684.  716.  684.  38.6  38.6   NaN   NaN -0.239
```

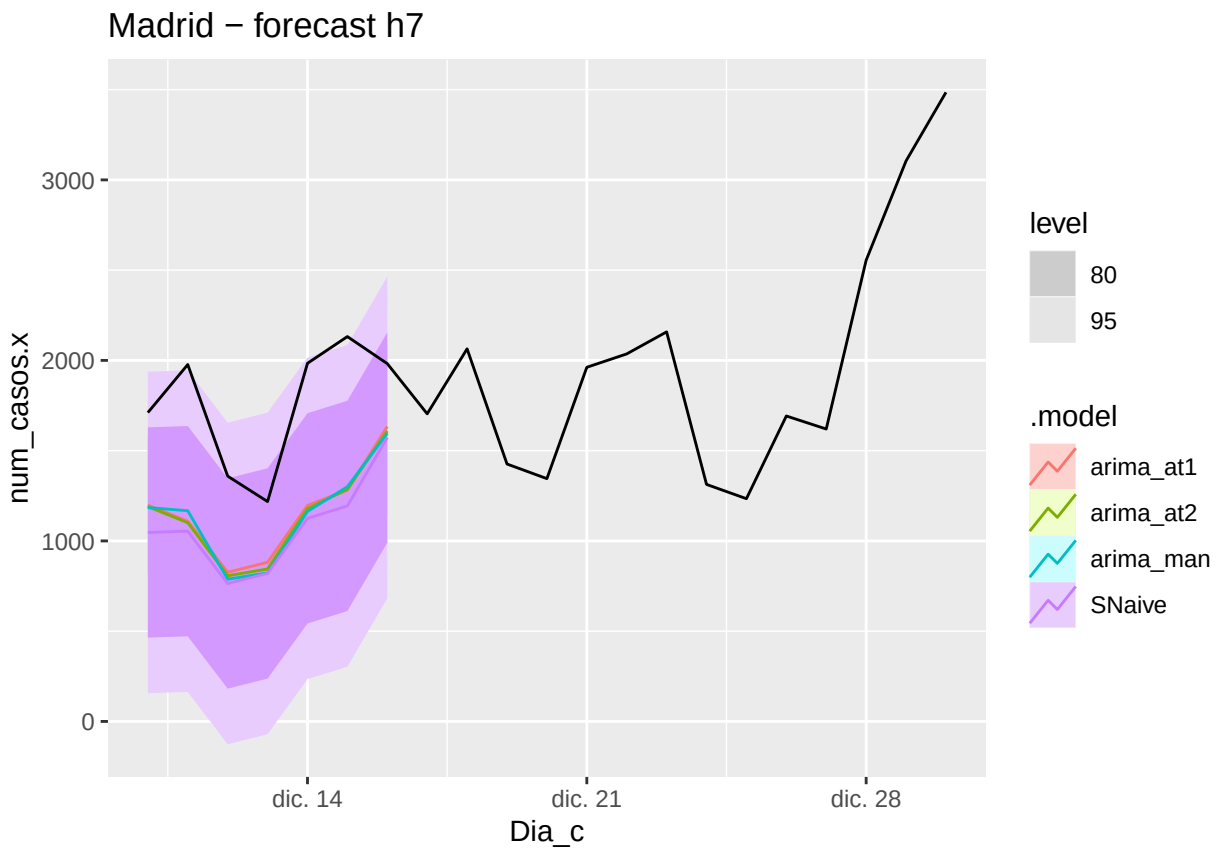
```
fabletools::accuracy(Mad_fc_h14, Mad_N_cases_tt)
```

```
## # A tibble: 4 x 11
##   .model    sub_region_2 .type    ME  RMSE   MAE   MPE  MAPE  MASE RMSSE   ACF1
##   <chr>     <chr>        <chr> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl>
## 1 arima_at1 Madrid       Test   601.  628.  601.  33.4  33.4   NaN   NaN -0.232
## 2 arima_at2 Madrid       Test   595.  619.  595.  33.2  33.2   NaN   NaN -0.208
## 3 arima_man Madrid       Test   604.  624.  604.  34.0  34.0   NaN   NaN -0.193
## 4 SNaive    Madrid       Test   707.  732.  707.  39.6  39.6   NaN   NaN -0.215
```

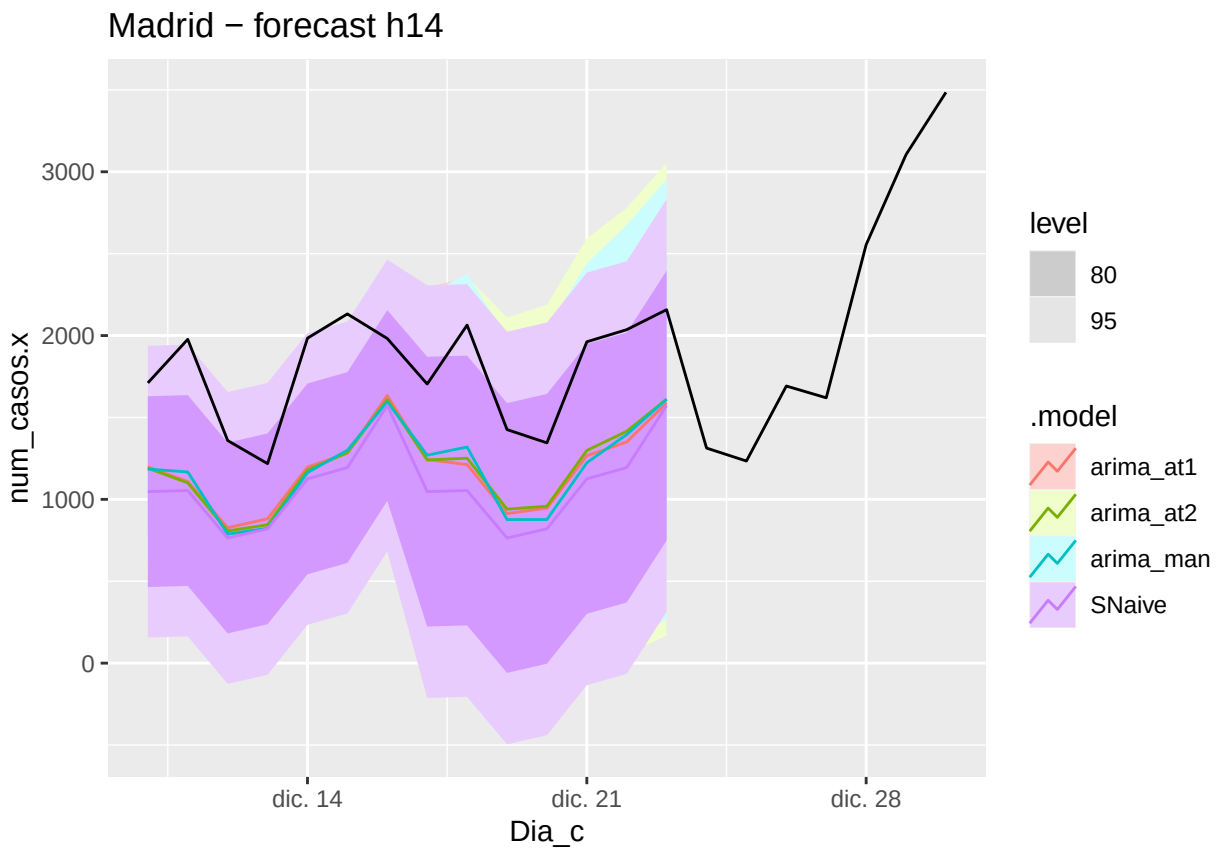
```
fabletools::accuracy(Mad_fc_h21, Mad_N_cases_tt)
```

```
## # A tibble: 4 x 11
##   .model    sub_region_2 .type    ME  RMSE   MAE   MPE  MAPE  MASE RMSSE  ACF1
##   <chr>     <chr>        <chr> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
## 1 arima_at1 Madrid       Test   696.  826.  697.  33.8  33.9   NaN   NaN 0.529
## 2 arima_at2 Madrid       Test   662.  788.  674.  32.0  33.0   NaN   NaN 0.519
## 3 arima_man Madrid       Test   695.  834.  714.  33.7  35.2   NaN   NaN 0.551
## 4 SNaive    Madrid       Test   825.  938.  825.  41.2  41.2   NaN   NaN 0.553
```

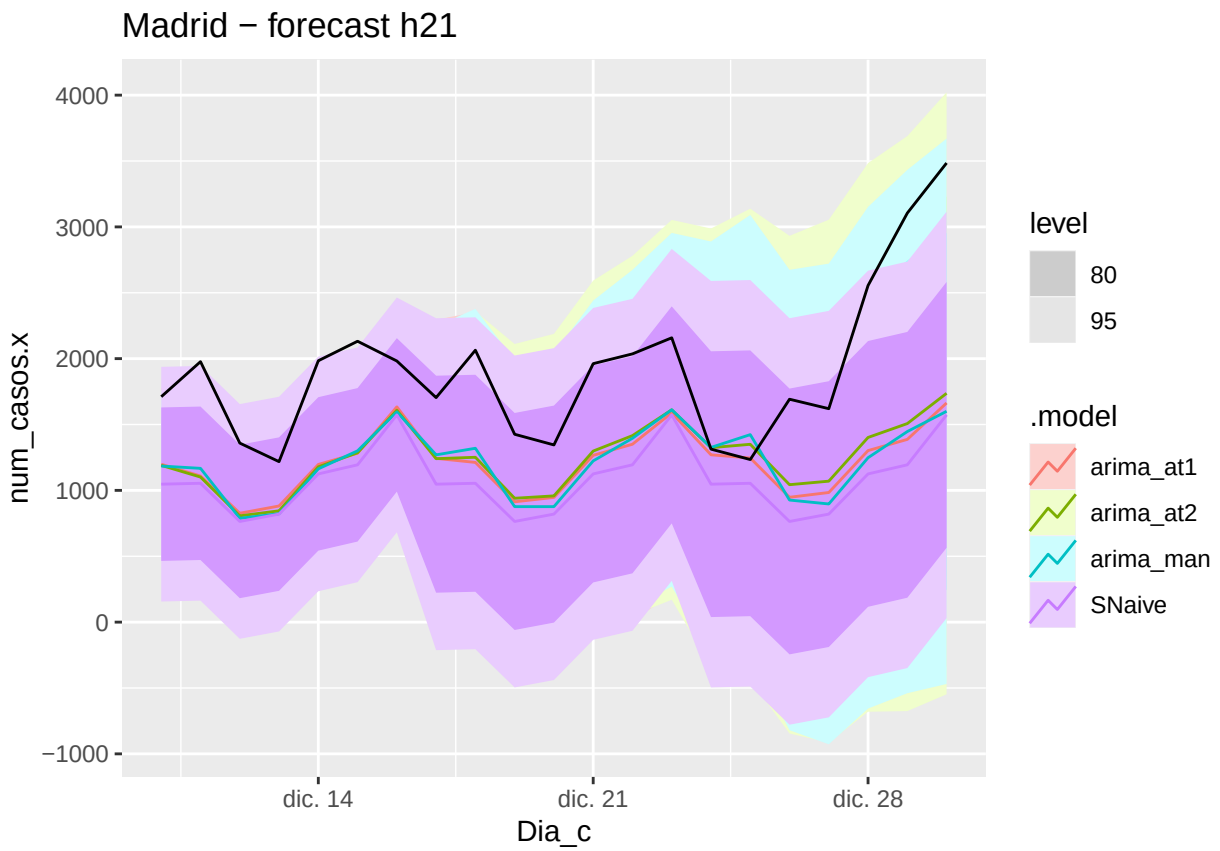
```
# Plots
Mad_fc_h7 %>%
  autoplot(Mad_N_cases_tt) +
  labs(title="Madrid - forecast h7")
```




```
Mad_fc_h14 %>%
  autoplot(Mad_N_cases_tt) +
  labs(title="Madrid - forecast h14")
```




```
Mad_fc_h21 %>%
  autoplot(Mad_N_cases_tt) +
  labs(title="Madrid - forecast h21")
```




```
####### Málaga #######
# Model train
Mal_fit_model <- Mal_N_cases_tr %>%
  model(
    SNaive = SNAIVE(num_casos.x),
    arima_man = ARIMA(num_casos.x ~ pdq(2,1,2) + PDQ(1,1,1)),
    arima_at1 = ARIMA(num_casos.x),
    arima_at2 = ARIMA(num_casos.x, stepwise = FALSE,approx = FALSE))

Mal_fit_model %>% pivot_longer(!sub_region_2,
                           names_to = "Model name",
                           values_to = "Orders")
```

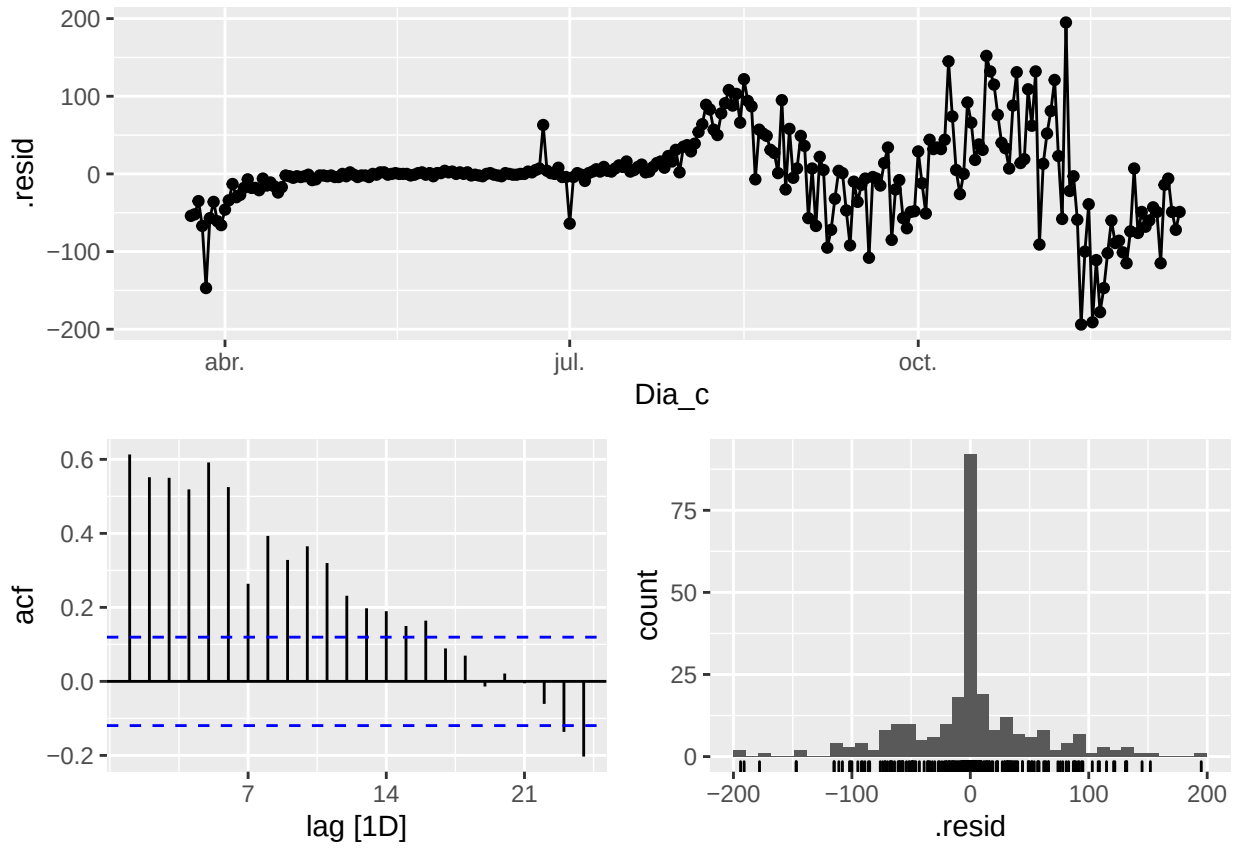
```
## # A mable: 4 x 3
## # Key:     sub_region_2, Model name [4]
##   sub_region_2 `Model name`                  Orders
##   <chr>        <chr>                        <model>
## 1 Málaga       SNaive                      <SNAIVE>
## 2 Málaga       arima_man    <ARIMA(2,1,2)(1,1,1)[7]>
## 3 Málaga       arima_at1    <ARIMA(0,1,1)(2,0,2)[7]>
## 4 Málaga       arima_at2    <ARIMA(1,1,3)(1,0,1)[7]>
```

```
# Good model >> Less Sigma / More BIC or AIC
glance(Mal_fit_model) %>% arrange(AICc) %>% select(.model:BIC)
```

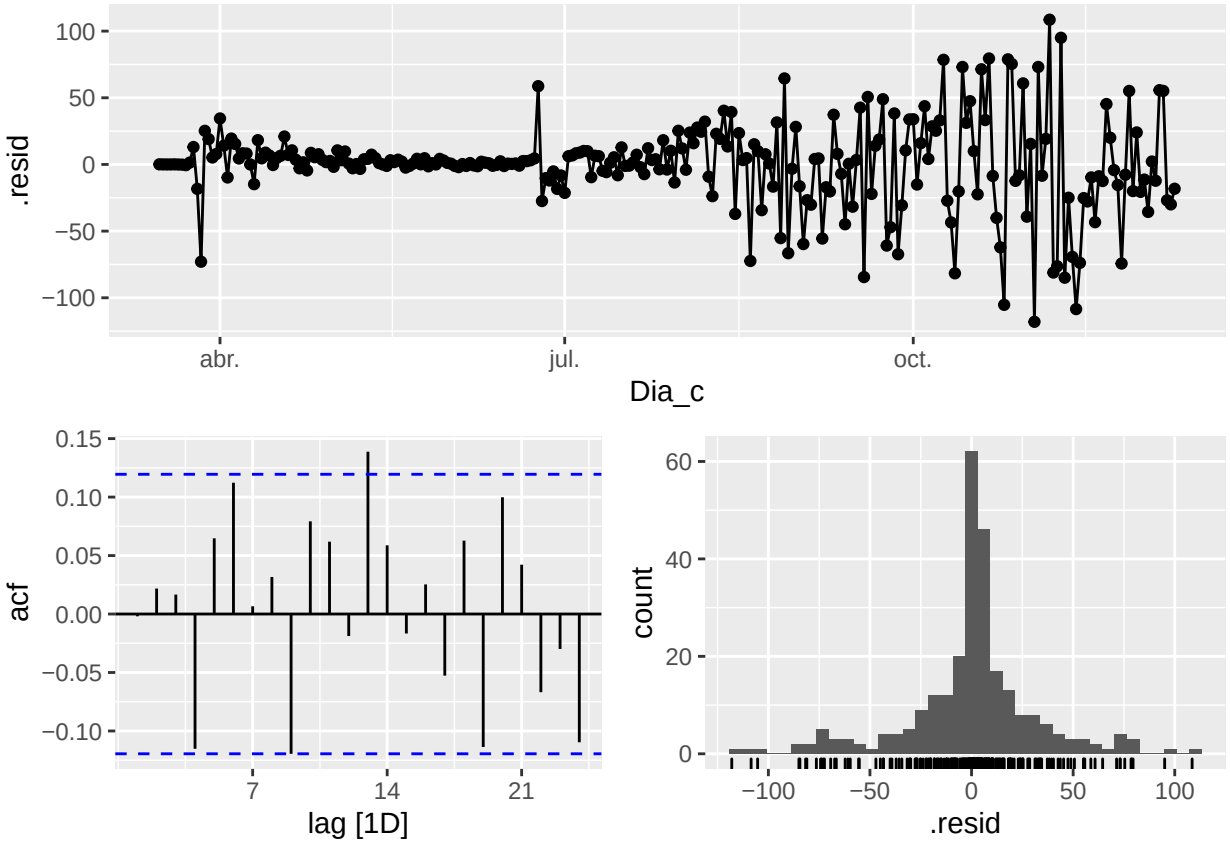
```
## # A tibble: 4 x 6
##   .model    sigma2 log_lik   AIC  AICc   BIC
```

```
##   <chr>      <dbl>   <dbl> <dbl> <dbl> <dbl>
## 1 arima_man  1096.  -1283. 2580. 2581. 2605.
## 2 arima_at2  1078.  -1316. 2645. 2646. 2670.
## 3 arima_at1  1108.  -1320. 2653. 2653. 2674.
## 4 SNaive     2991.     NA    NA    NA    NA
```

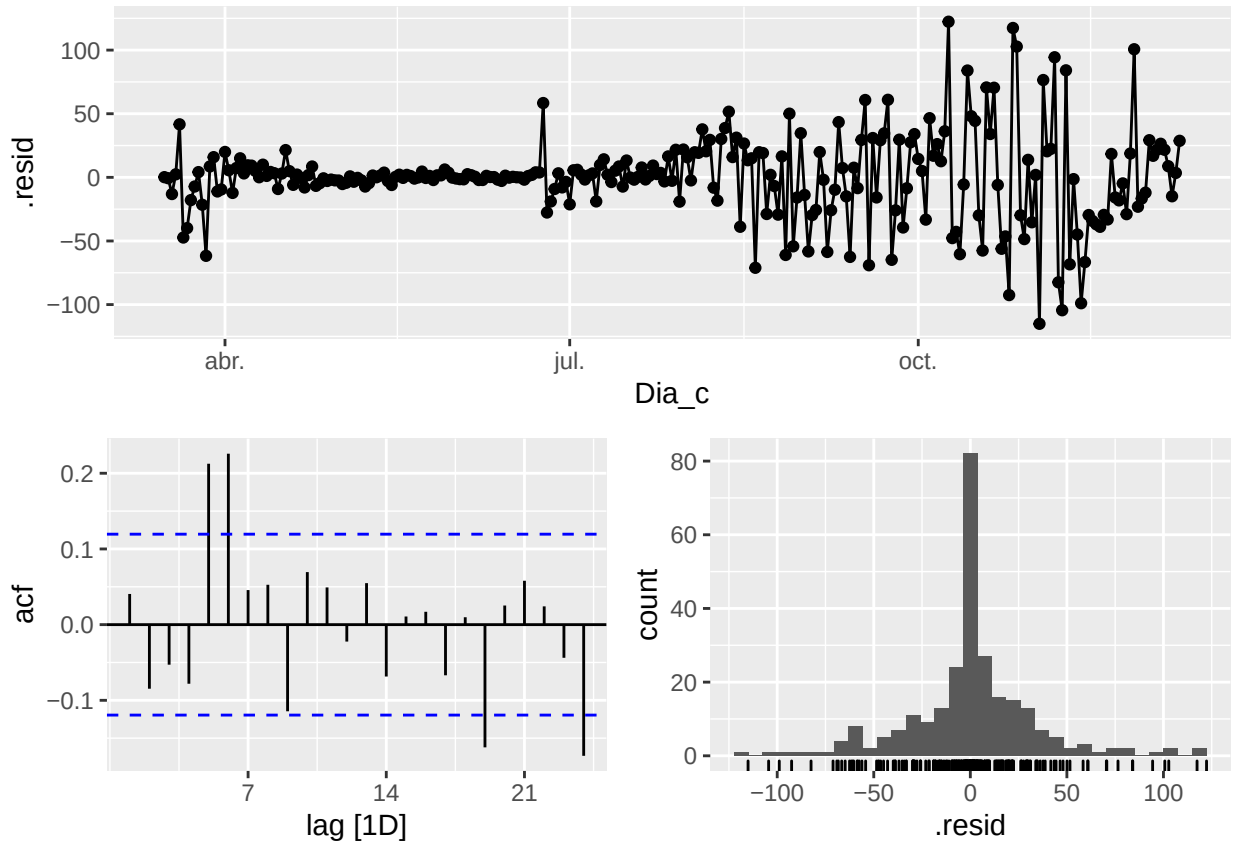
```
Mal_fit_model %>% select(SNaive) %>% gg_tsresiduals()
```



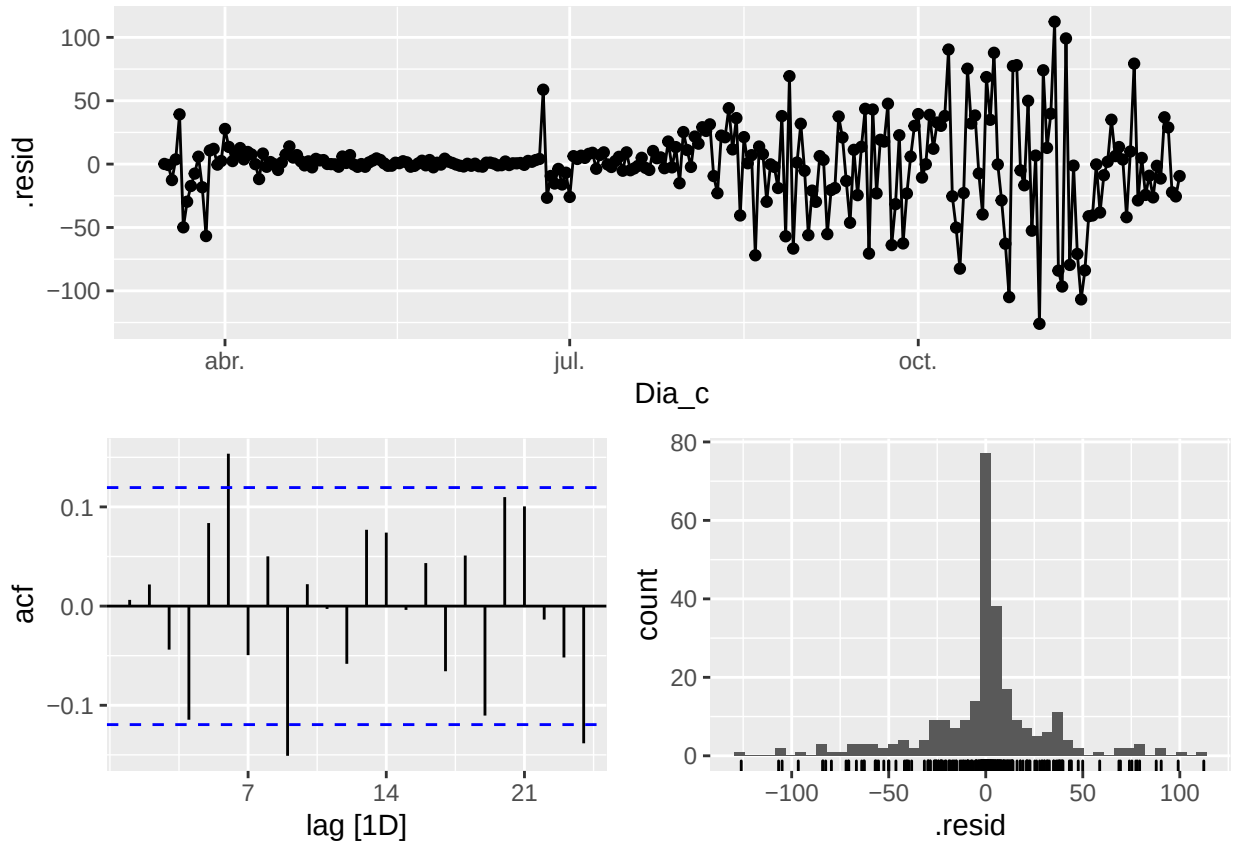

```
Mal_fit_model %>% select(arima_man) %>% gg_tsresiduals()
```




```
Mal_fit_model %>% select(arima_at1) %>% gg_tsresiduals()
```




```
Mal_fit_model %>% select(arima_at2) %>% gg_tsresiduals()
```




```
augment(Mal_fit_model) %>%
  features(.innov, ljung_box, lag=7)
```

```
## # A tibble: 4 x 4
##   sub_region_2 .model    lb_stat lb_pvalue
##   <chr>        <chr>       <dbl>     <dbl>
## 1 Málaga       arima_at1   32.0  0.0000399
## 2 Málaga       arima_at2   13.4  0.0622
## 3 Málaga       arima_man    8.52 0.289
## 4 Málaga       SNaive     521.   0
```

```
augment(Mal_fit_model) %>%
  features(.innov, ljung_box, lag=14)
```

```
## # A tibble: 4 x 4
##   sub_region_2 .model    lb_stat lb_pvalue
##   <chr>        <chr>       <dbl>     <dbl>
## 1 Málaga       arima_at1    40.9  0.000187
## 2 Málaga       arima_at2    24.9  0.0358
## 3 Málaga       arima_man    22.2  0.0740
## 4 Málaga       SNaive      693.   0
```

```
augment(Mal_fit_model) %>%
  features(.innov, ljung_box, lag=21)
```

```
## # A tibble: 4 x 4
##   sub_region_2 .model    lb_stat lb_pvalue
##   <chr>        <chr>       <dbl>     <dbl>
```

```
## 1 Málaga       arima_at1    51.2  0.000252
## 2 Málaga       arima_at2    37.5  0.0148
## 3 Málaga       arima_man    31.7  0.0635
## 4 Málaga       SNaive      711.   0
```

```
# Forecast
Mal_fc_h7<-fabletools::forecast(Mal_fit_model, h=7)
Mal_fc_h14<-fabletools::forecast(Mal_fit_model, h=14)
Mal_fc_h21<-fabletools::forecast(Mal_fit_model, h=21)
# Accuracy
fabletools::accuracy(Mal_fc_h7, Mal_N_cases_tt)
```

```
## # A tibble: 4 x 11
##   .model    sub_region_2 .type    ME  RMSE   MAE   MPE  MAPE  MASE RMSSE  ACF1
##   <chr>     <chr>        <chr> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
## 1 arima_at1 Málaga       Test   97.6 102.   97.6  56.8  56.8   NaN   NaN 0.427
## 2 arima_at2 Málaga       Test   98.0 102.   98.0  58.0  58.0   NaN   NaN 0.257
## 3 arima_man Málaga       Test   96.5 104.   96.5  57.9  57.9   NaN   NaN 0.241
## 4 SNaive    Málaga       Test   48.3  57.7  48.3  27.9  27.9   NaN   NaN 0.412
```

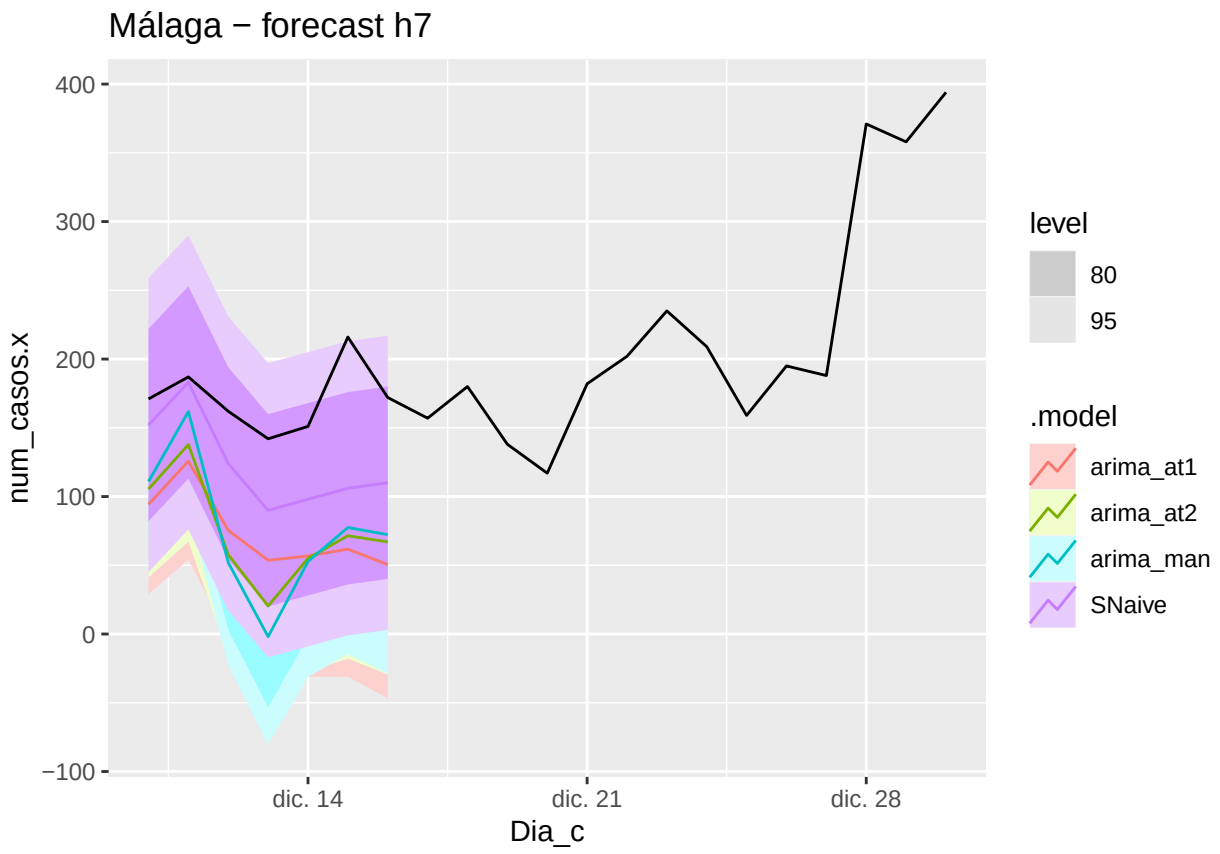
```
fabletools::accuracy(Mal_fc_h14, Mal_N_cases_tt)
```

```
## # A tibble: 4 x 11
##   .model    sub_region_2 .type    ME  RMSE   MAE   MPE  MAPE  MASE RMSSE  ACF1
##   <chr>     <chr>        <chr> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
## 1 arima_at1 Málaga       Test   109. 115.  109.   62.2  62.2   NaN   NaN 0.471
## 2 arima_at2 Málaga       Test   121. 128.  121.   71.2  71.2   NaN   NaN 0.532
## 3 arima_man Málaga       Test   124. 134.  124.   74.3  74.3   NaN   NaN 0.522
## 4 SNaive    Málaga       Test    49   63.3  49.4  26.9  27.2   NaN   NaN 0.516
```

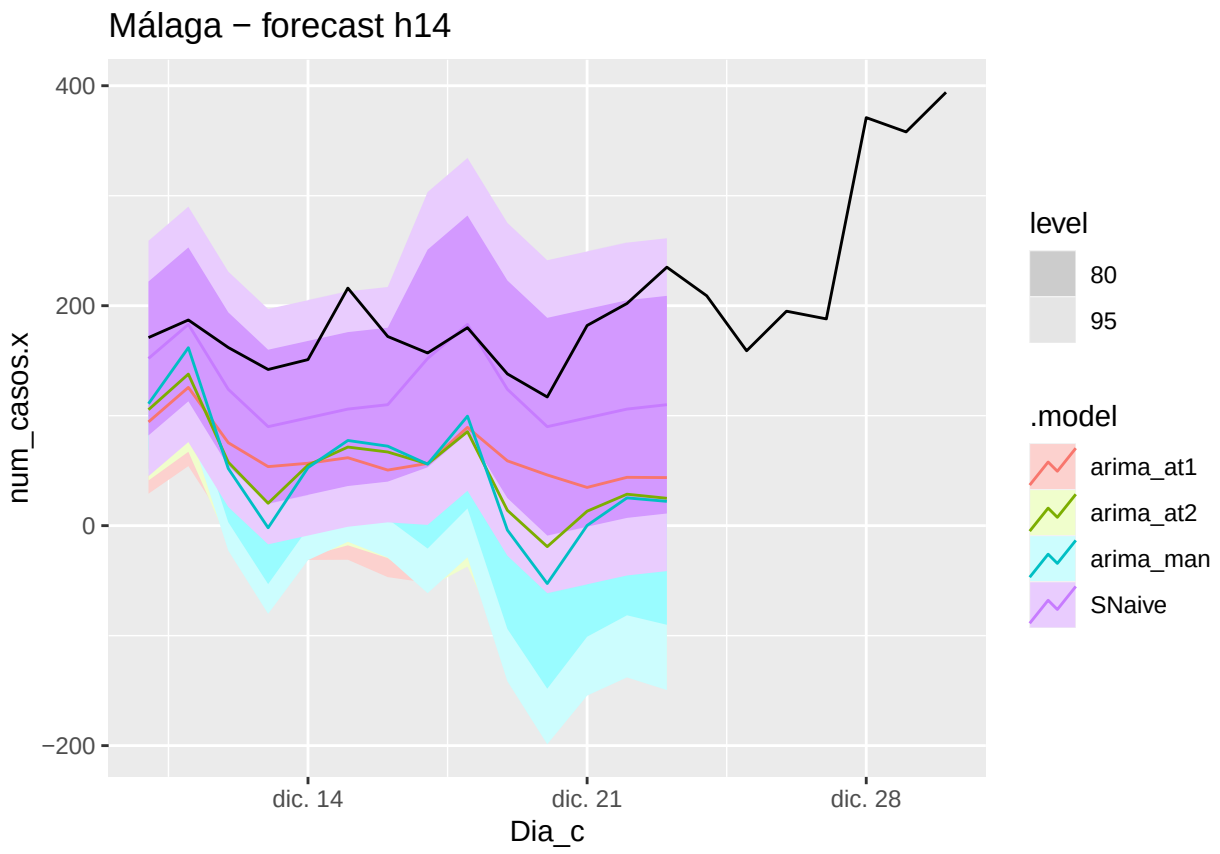
```
fabletools::accuracy(Mal_fc_h21, Mal_N_cases_tt)
```

```
## # A tibble: 4 x 11
##   .model    sub_region_2 .type    ME  RMSE   MAE   MPE  MAPE  MASE RMSSE  ACF1
##   <chr>     <chr>        <chr> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
## 1 arima_at1 Málaga       Test  143.   165. 143.   66.7  66.7   NaN   NaN 0.625
## 2 arima_at2 Málaga       Test  173.   200. 173.   81.7  81.7   NaN   NaN 0.718
## 3 arima_man Málaga       Test  181.   212. 181.   86.2  86.2   NaN   NaN 0.720
## 4 SNaive    Málaga       Test   80.8  118.  83.4  33.0  34.6   NaN   NaN 0.637
```

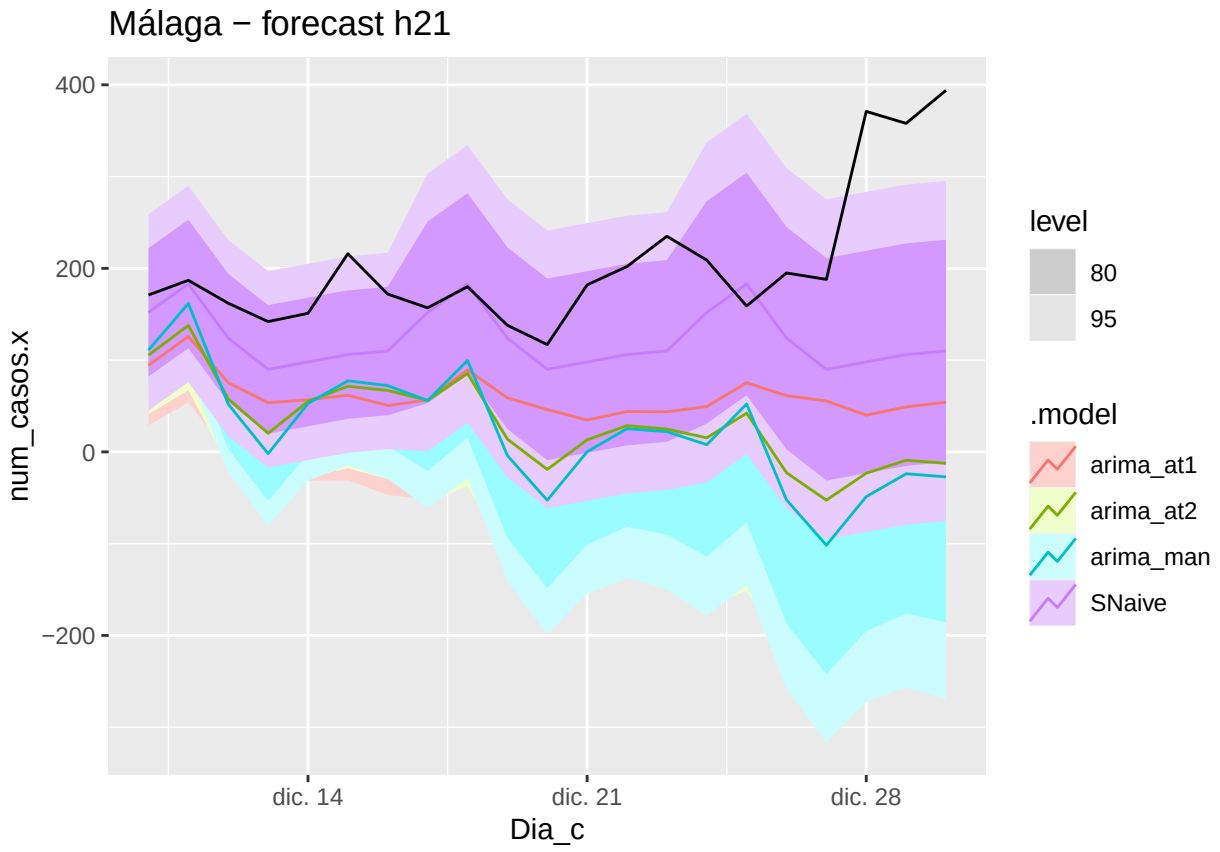
```
# Plots
Mal_fc_h7 %>%
  autoplot(Mal_N_cases_tt) +
  labs(title="Málaga - forecast h7")
```




```
Mal_fc_h14 %>%
  autoplot(Mal_N_cases_tt) +
  labs(title="Málaga - forecast h14")
```




```
Mal_fc_h21 %>%
  autoplot(Mal_N_cases_tt) +
  labs(title="Málaga - forecast h21")
```




```
####### Cádiz #######
# Model train
Cad_fit_model <- Cad_N_cases_tr %>%
  model(
    SNaive = SNAIVE(num_casos.x),
    arima_man = ARIMA(num_casos.x ~ pdq(2,1,2) + PDQ(1,1,1)),
    arima_at1 = ARIMA(num_casos.x),
    arima_at2 = ARIMA(num_casos.x, stepwise = FALSE,approx = FALSE))

Cad_fit_model %>% pivot_longer(!sub_region_2,
                           names_to = "Model name",
                           values_to = "Orders")
```

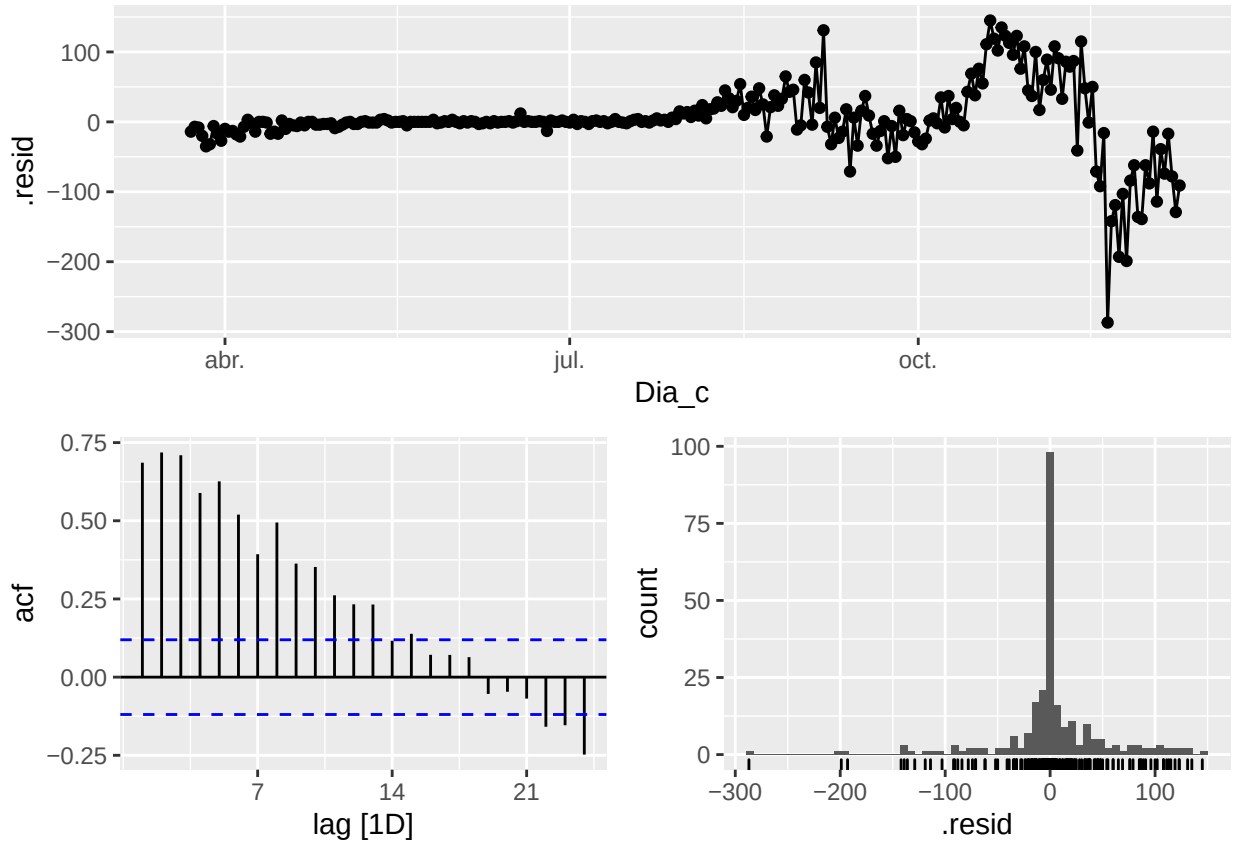
```
## # A mable: 4 x 3
## # Key:     sub_region_2, Model name [4]
##   sub_region_2 `Model name`                  Orders
##   <chr>        <chr>                        <model>
## 1 Cádiz        SNaive                      <SNAIVE>
## 2 Cádiz        arima_man    <ARIMA(2,1,2)(1,1,1)[7]>
## 3 Cádiz        arima_at1    <ARIMA(2,1,1)(2,0,0)[7]>
## 4 Cádiz        arima_at2    <ARIMA(2,1,1)(1,0,1)[7]>
```

```
# Good model >> Less Sigma / More BIC or AIC
glance(Cad_fit_model) %>% arrange(AICc) %>% select(.model:BIC)
```

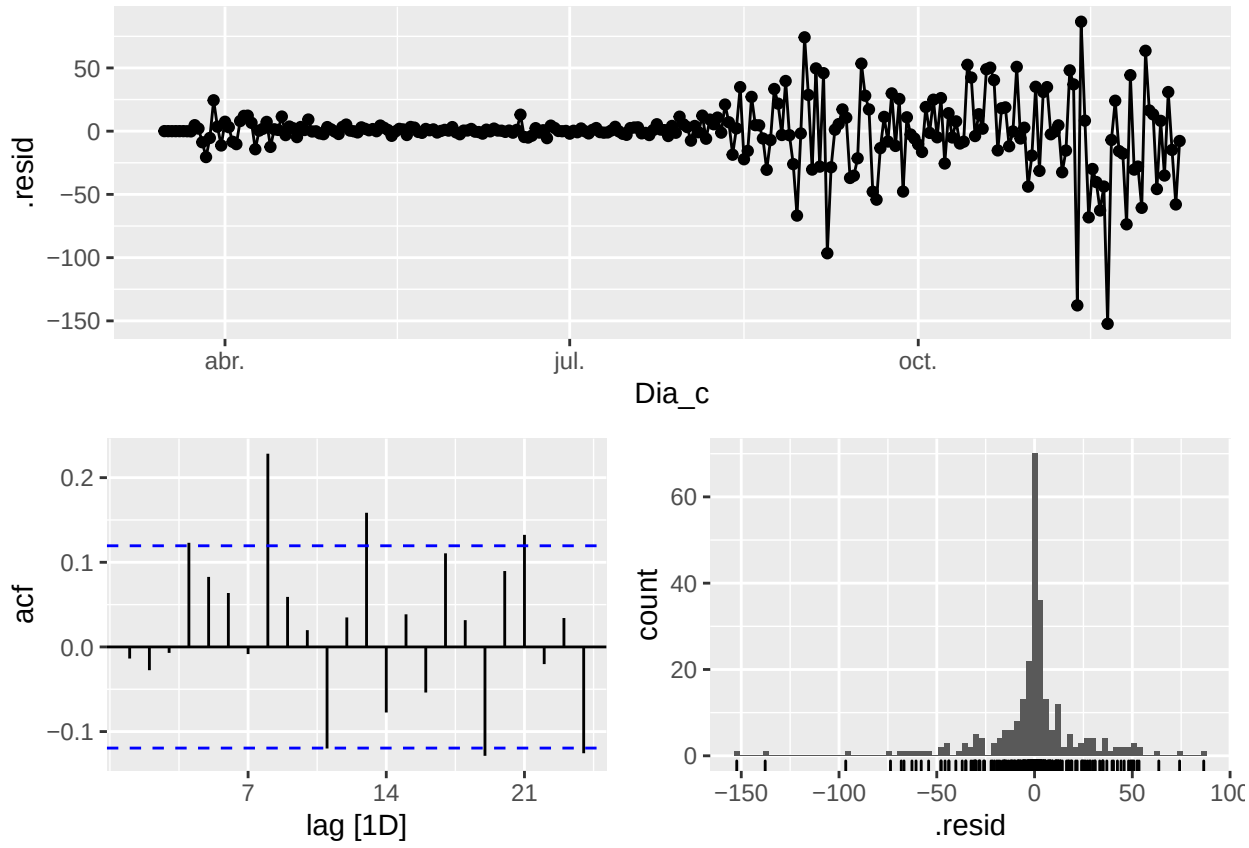
```
## # A tibble: 4 x 6
##   .model    sigma2 log_lik   AIC  AICc   BIC
```

```
##   <chr>       <dbl>   <dbl> <dbl> <dbl> <dbl>
## 1 arima_man   689.  -1223. 2459. 2459. 2484.
## 2 arima_at2   680.  -1255. 2522. 2523. 2544.
## 3 arima_at1   725.  -1263. 2538. 2538. 2560.
## 4 SNaive     2562.     NA    NA    NA    NA
```

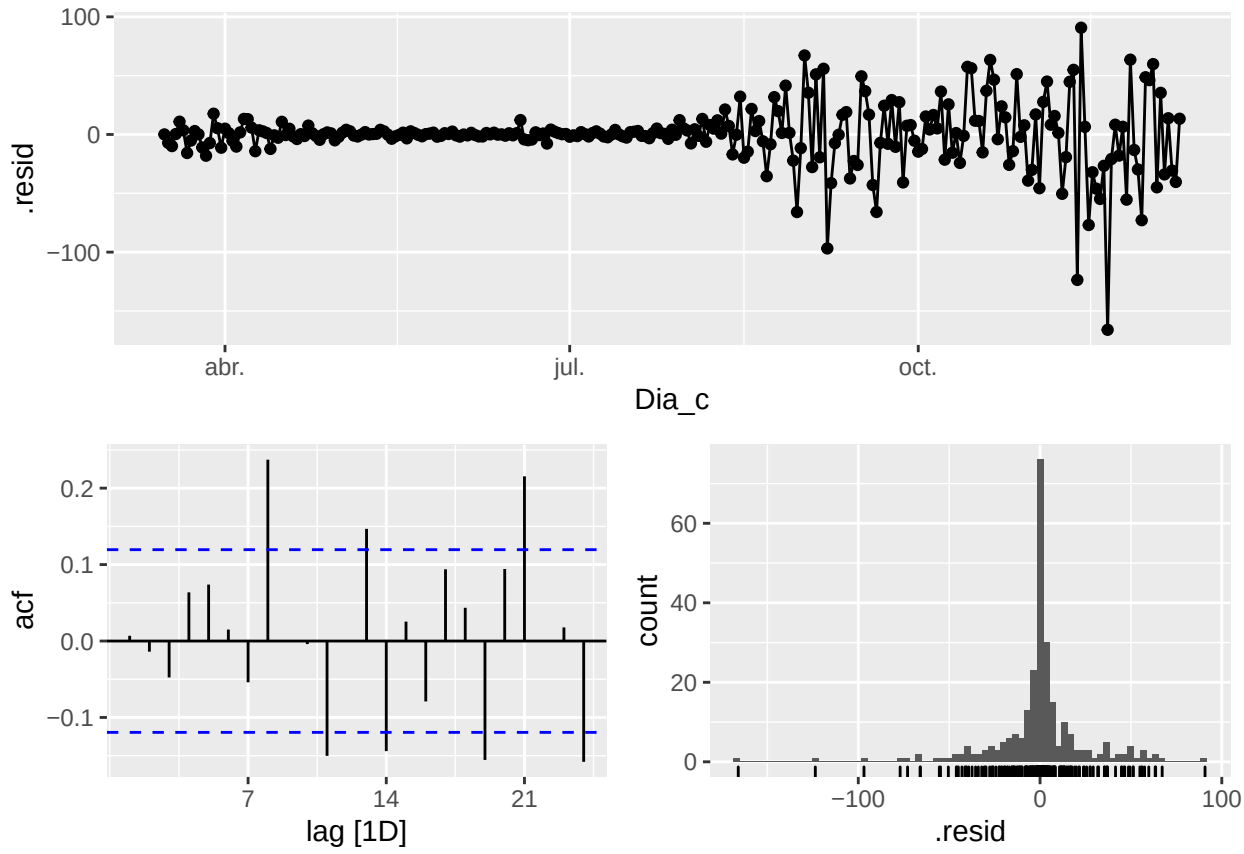
```
Cad_fit_model %>% select(SNaive) %>% gg_tsresiduals()
```



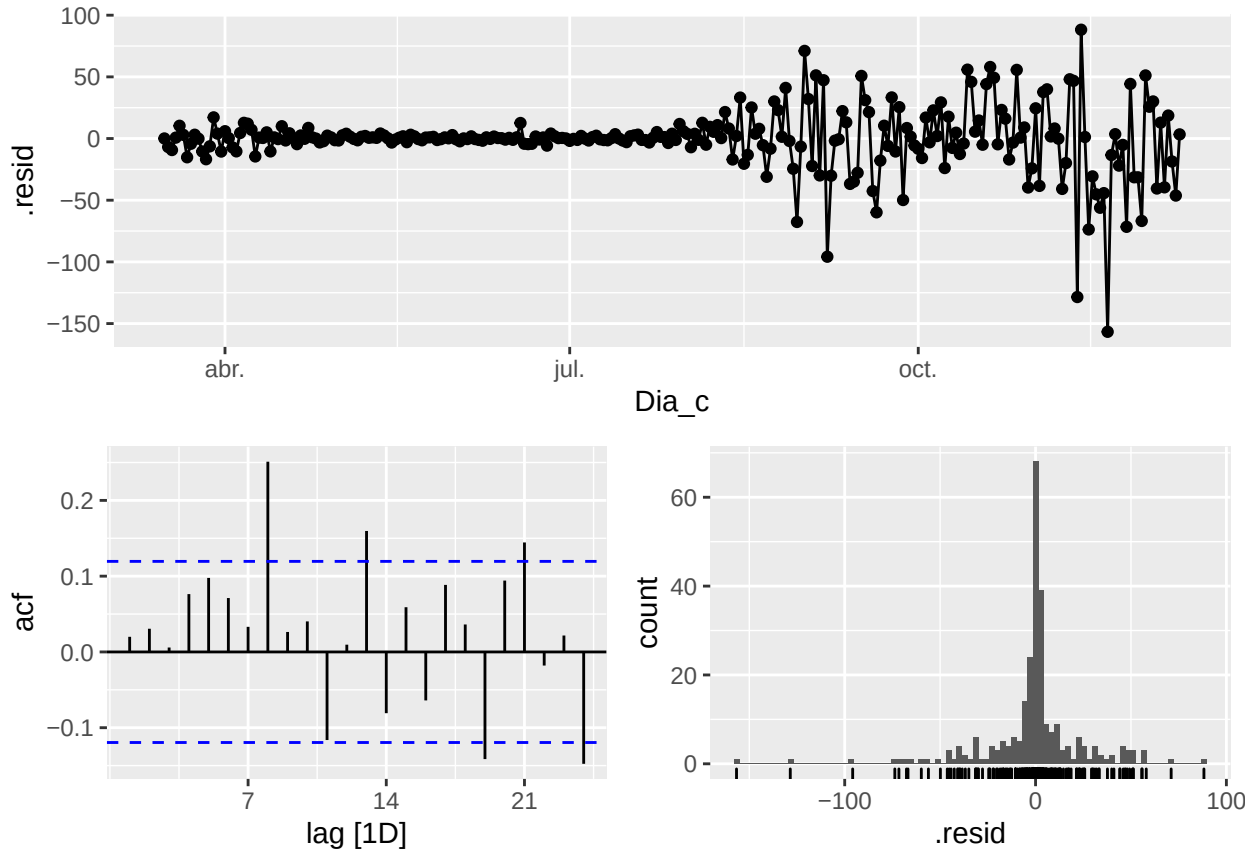

```
Cad_fit_model %>% select(arima_man) %>% gg_tsresiduals()
```




```
Cad_fit_model %>% select(arima_at1) %>% gg_tsresiduals()
```




```
Cad_fit_model %>% select(arima_at2) %>% gg_tsresiduals()
```




```
augment(Cad_fit_model) %>%
  features(.innov, ljung_box, lag=7)
```

```
## # A tibble: 4 x 4
##   sub_region_2 .model    lb_stat lb_pvalue
##   <chr>        <chr>       <dbl>     <dbl>
## 1 Cádiz        arima_at1    4.18     0.758
## 2 Cádiz        arima_at2    6.32     0.503
## 3 Cádiz        arima_man    7.47     0.382
## 4 Cádiz        SNaive     710.       0
```

```
augment(Cad_fit_model) %>%
  features(.innov, ljung_box, lag=14)
```

```
## # A tibble: 4 x 4
##   sub_region_2 .model    lb_stat lb_pvalue
##   <chr>        <chr>       <dbl>     <dbl>
## 1 Cádiz        arima_at1    38.3  0.000461
## 2 Cádiz        arima_at2    37.5  0.000611
## 3 Cádiz        arima_man    36.4  0.000910
## 4 Cádiz        SNaive      899.   0
```

```
augment(Cad_fit_model) %>%
  features(.innov, ljung_box, lag=21)
```

```
## # A tibble: 4 x 4
##   sub_region_2 .model    lb_stat  lb_pvalue
##   <chr>        <chr>       <dbl>      <dbl>
```

```
## 1 Cádiz        arima_at1    66.7 0.00000117
## 2 Cádiz        arima_at2    56.9 0.0000369
## 3 Cádiz        arima_man    53.8 0.000105
## 4 Cádiz        SNaive      911.  0
```

```
# Forecast
Cad_fc_h7<-fabletools::forecast(Cad_fit_model, h=7)
Cad_fc_h14<-fabletools::forecast(Cad_fit_model, h=14)
Cad_fc_h21<-fabletools::forecast(Cad_fit_model, h=21)
# Accuracy
fabletools::accuracy(Cad_fc_h7, Cad_N_cases_tt)
```

```
## # A tibble: 4 x 11
##   .model    sub_region_2 .type    ME  RMSE   MAE   MPE  MAPE  MASE RMSSE    ACF1
##   <chr>     <chr>        <chr> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>   <dbl>
## 1 arima_at1 Cádiz        Test  78.8   79.3  78.8 50.7   50.7   NaN   NaN -0.368
## 2 arima_at2 Cádiz        Test  82.2   82.7  82.2 53.3   53.3   NaN   NaN  0.0954
## 3 arima_man Cádiz        Test  86.6   87.6  86.6 56.6   56.6   NaN   NaN  0.165
## 4 SNaive    Cádiz        Test   3.57  20.6  17.6  2.68  10.8   NaN   NaN -0.166
```

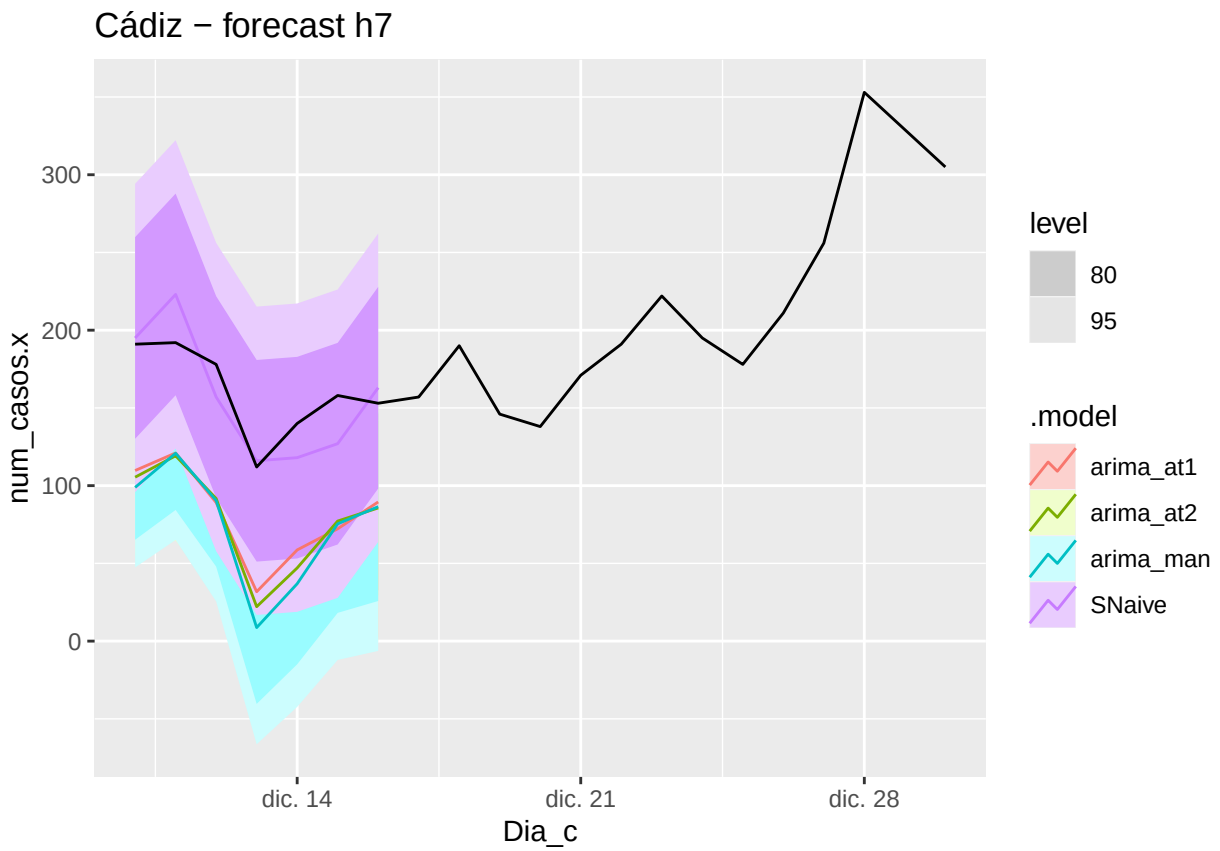
```
fabletools::accuracy(Cad_fc_h14, Cad_N_cases_tt)
```

```
## # A tibble: 4 x 11
##   .model    sub_region_2 .type    ME  RMSE   MAE   MPE  MAPE  MASE RMSSE  ACF1
##   <chr>     <chr>        <chr> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
## 1 arima_at1 Cádiz        Test  113.  119.  113.  67.6   67.6   NaN   NaN 0.730
## 2 arima_at2 Cádiz        Test  119.  126.  119.  71.8   71.8   NaN   NaN 0.731
## 3 arima_man Cádiz        Test  123.  131.  123.  75.1   75.1   NaN   NaN 0.712
## 4 SNaive    Cádiz        Test   10.1  34.3  28.8  5.48  16.5   NaN   NaN 0.583
```

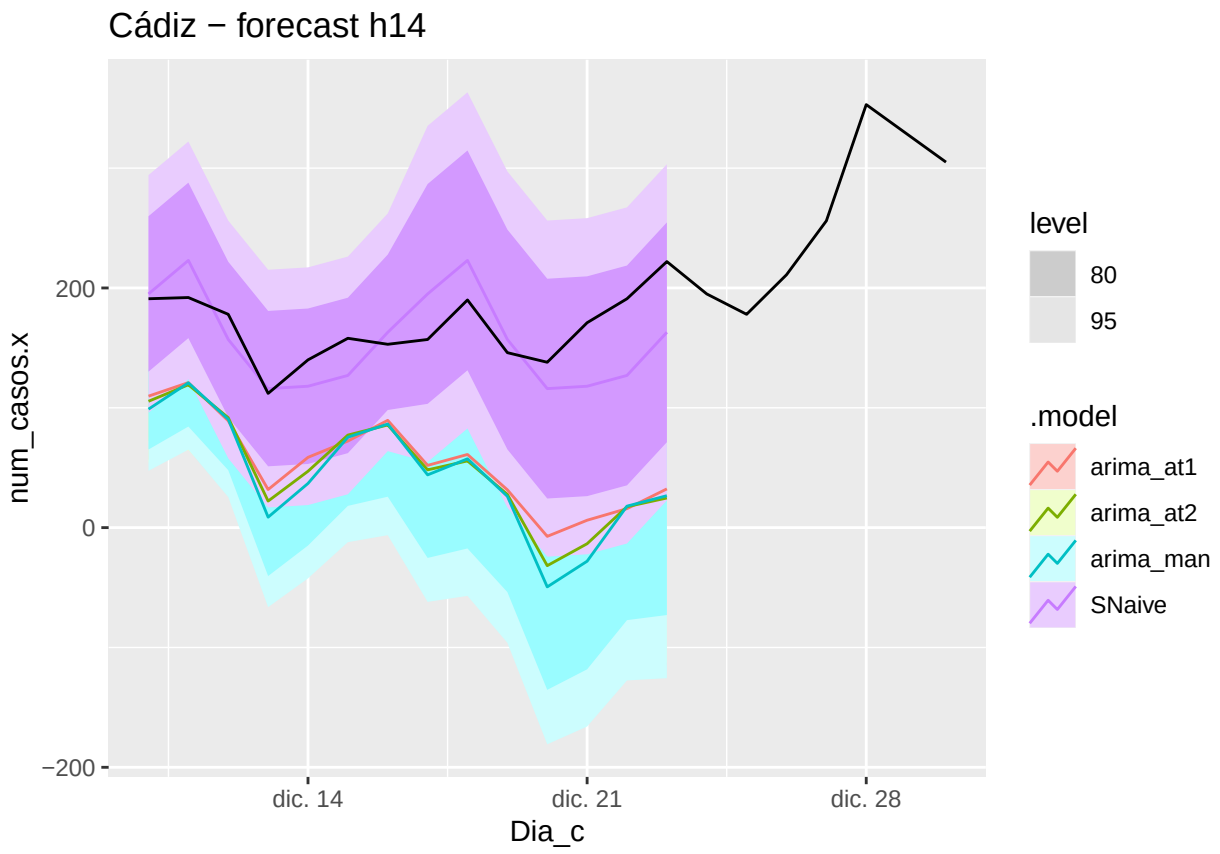
```
fabletools::accuracy(Cad_fc_h21, Cad_N_cases_tt)
```

```
## # A tibble: 4 x 11
##   .model    sub_region_2 .type    ME  RMSE   MAE   MPE  MAPE  MASE RMSSE  ACF1
##   <chr>     <chr>        <chr> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
## 1 arima_at1 Cádiz        Test  168.  193.  168.   80.4  80.4   NaN   NaN 0.859
## 2 arima_at2 Cádiz        Test  179.  207.  179.   85.7  85.7   NaN   NaN 0.857
## 3 arima_man Cádiz        Test  185.  213.  185.   88.9  88.9   NaN   NaN 0.847
## 4 SNaive    Cádiz        Test   41.4  86.5  58.1  14.6  24.4   NaN   NaN 0.758
```

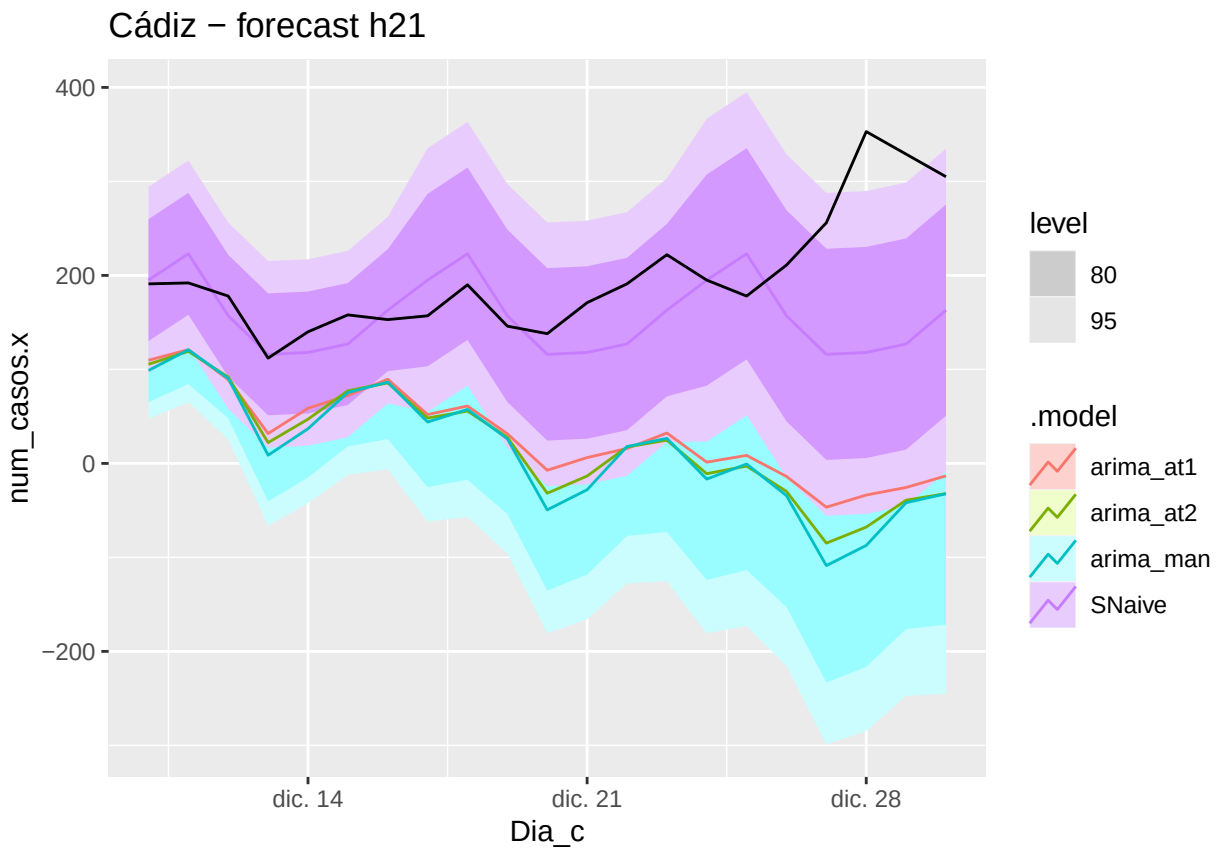
```
# Plots
Cad_fc_h7 %>%
  autoplot(Cad_N_cases_tt) +
  labs(title="Cádiz - forecast h7")
```




```
Cad_fc_h14 %>%
  autoplot(Cad_N_cases_tt) +
  labs(title="Cádiz - forecast h14")
```



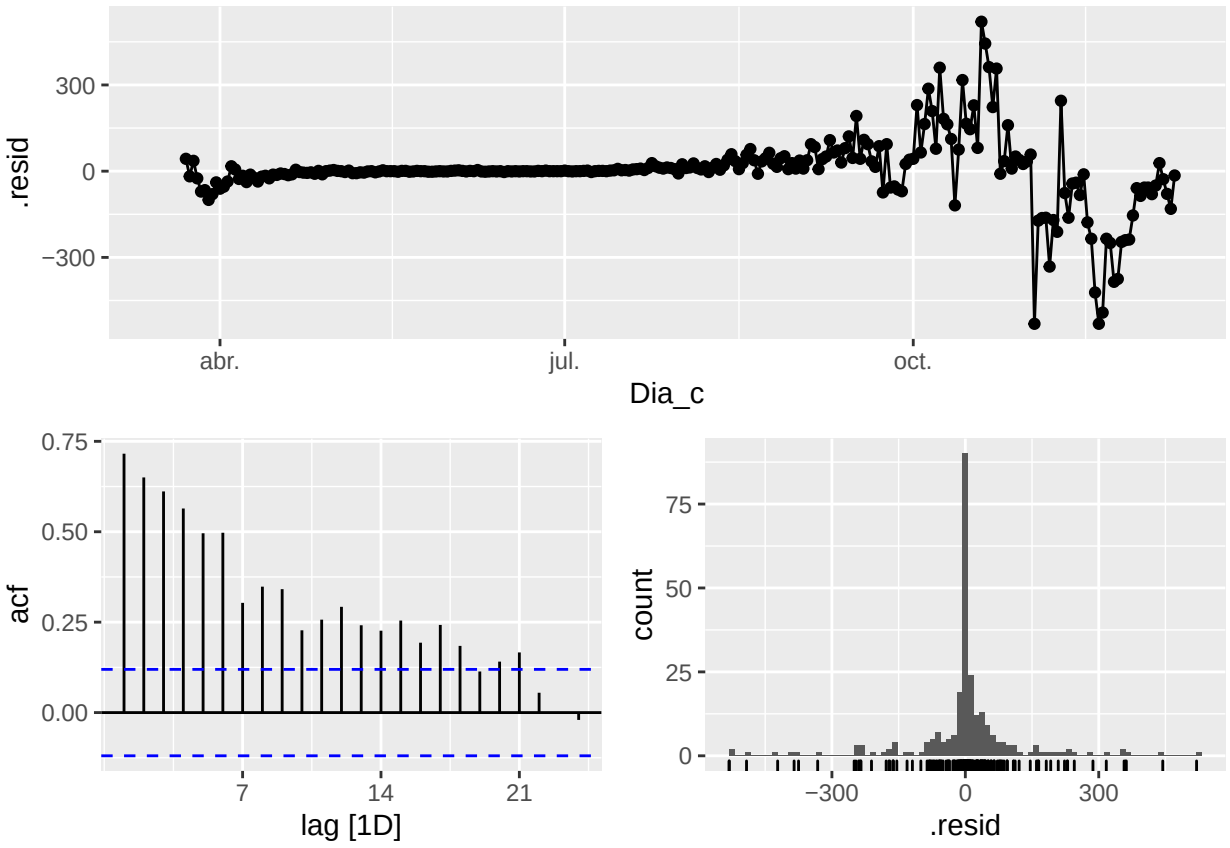

```
Cad_fc_h21 %>%
  autoplot(Cad_N_cases_tt) +
  labs(title="Cádiz - forecast h21")
```



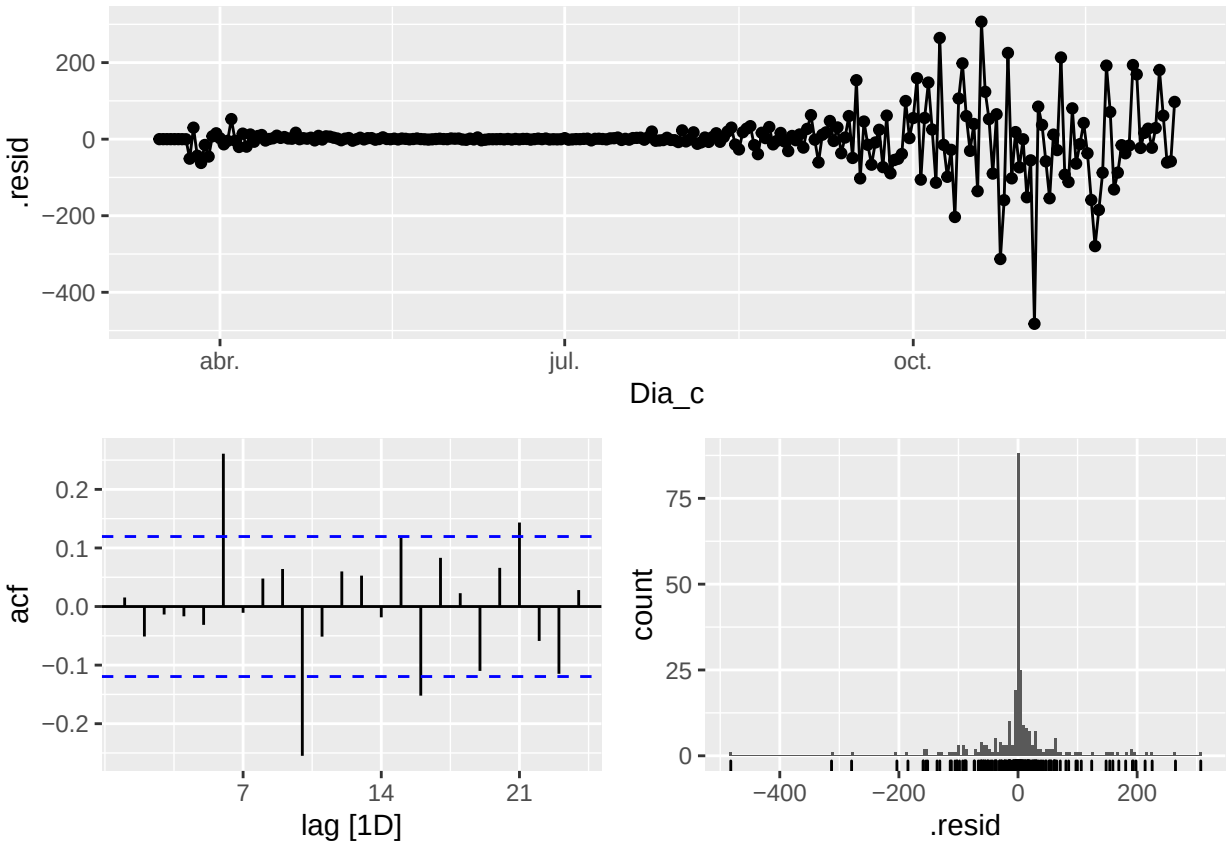

```
####### Sevilla #######
# Model train
Sev_fit_model <- Sev_N_cases_tr %>%
  model(
    SNaive = SNAIVE(num_casos.x),
    arima_man = ARIMA(num_casos.x ~ pdq(2,1,2) + PDQ(1,1,1)),
    arima_at1 = ARIMA(num_casos.x),
    arima_at2 = ARIMA(num_casos.x, stepwise = FALSE,approx = FALSE))

# Good model >> Less Sigma / More BIC or AIC
glance(Sev_fit_model) %>% arrange(AICc) %>% select(.model:BIC)
```

```
## # A tibble: 4 x 6
##   .model    sigma2 log_lik   AIC  AICc   BIC
##   <chr>      <dbl>   <dbl> <dbl> <dbl> <dbl>
## 1 arima_at2  5249.  -1493. 2998. 2998. 3019.
## 2 arima_man  5592.  -1494. 3003. 3003. 3028.
## 3 arima_at1  5485.  -1499. 3008. 3008. 3025.
## 4 SNaive    14589.     NA    NA    NA    NA
```

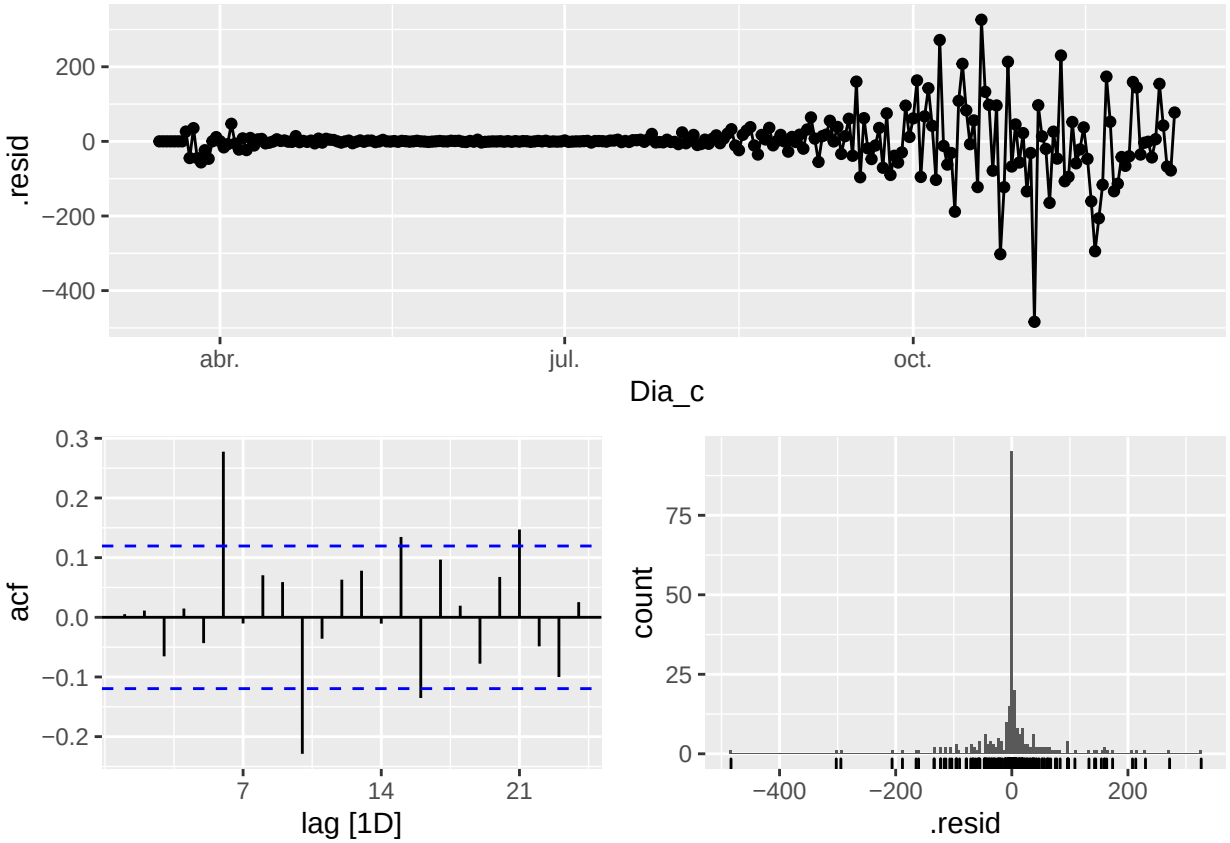
```
Sev_fit_model %>% select(SNaive) %>% gg_tsresiduals()
```



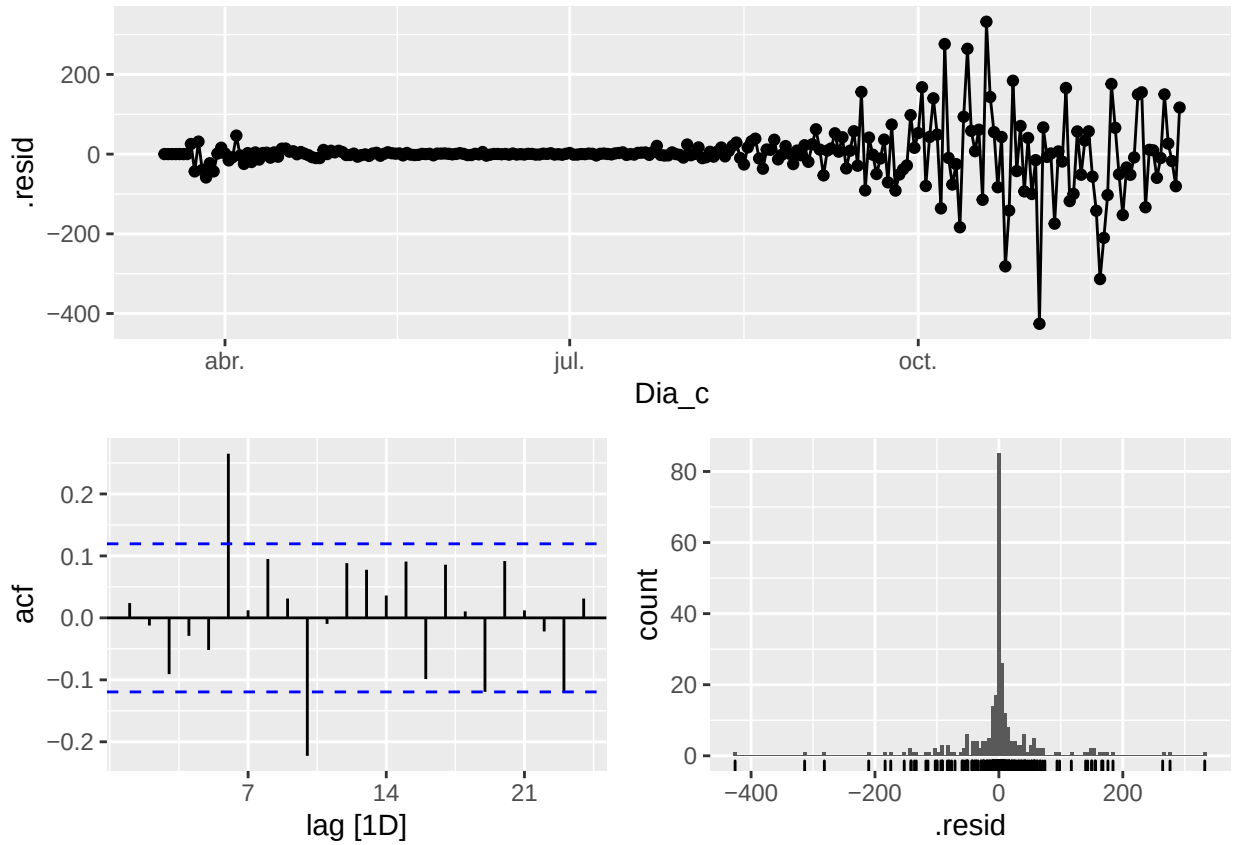

```
Sev_fit_model %>% select(arima_man) %>% gg_tsresiduals()
```




```
Sev_fit_model %>% select(arima_at1) %>% gg_tsresiduals()
```




```
Sev_fit_model %>% select(arima_at2) %>% gg_tsresiduals()
```




```
augment(Sev_fit_model) %>%
  features(.innov, ljung_box, lag=7, dof=3)
```

```
## # A tibble: 4 x 4
##   sub_region_2 .model    lb_stat lb_pvalue
##   <chr>        <chr>       <dbl>     <dbl>
## 1 Sevilla      arima_at1    23.2  0.000117
## 2 Sevilla      arima_at2    22.9  0.000131
## 3 Sevilla      arima_man    20.1  0.000482
## 4 Sevilla      SNaive      591.   0
```

```
augment(Sev_fit_model) %>%
  features(.innov, ljung_box, lag=14, dof=3)
```

```
## # A tibble: 4 x 4
##   sub_region_2 .model    lb_stat  lb_pvalue
##   <chr>        <chr>       <dbl>      <dbl>
## 1 Sevilla      arima_at1    43.5 0.00000879
## 2 Sevilla      arima_at2    44.0 0.00000730
## 3 Sevilla      arima_man    42.8 0.0000118
## 4 Sevilla      SNaive      743.  0
```

```
augment(Sev_fit_model) %>%
  features(.innov, ljung_box, lag=21, dof=3)
```

```
## # A tibble: 4 x 4
##   sub_region_2 .model    lb_stat   lb_pvalue
##   <chr>        <chr>       <dbl>       <dbl>
```

```
## 1 Sevilla      arima_at1    66.3 0.000000190
## 2 Sevilla      arima_at2    58.0 0.00000430
## 3 Sevilla      arima_man    66.4 0.000000181
## 4 Sevilla      SNaive      815.  0
```

```
# Forecast
Sev_fc_h7<-fabletools::forecast(Sev_fit_model, h=7)
Sev_fc_h14<-fabletools::forecast(Sev_fit_model, h=14)
Sev_fc_h21<-fabletools::forecast(Sev_fit_model, h=21)
# Accuracy
fabletools::accuracy(Sev_fc_h7, Sev_N_cases_tt)
```

```
## # A tibble: 4 x 11
##   .model    sub_region_2 .type    ME  RMSE   MAE   MPE  MAPE  MASE RMSSE    ACF1
##   <chr>     <chr>        <chr> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>   <dbl>
## 1 arima_at1 Sevilla      Test   88.2  93.7  88.2  61.1  61.1   NaN   NaN -0.0150
## 2 arima_at2 Sevilla      Test  101.  106.  101.   67.4  67.4   NaN   NaN -0.373
## 3 arima_man Sevilla      Test  123.  128.  123.   85.2  85.2   NaN   NaN  0.156
## 4 SNaive    Sevilla      Test   35.1  48.5  39.1  21.1  23.8   NaN   NaN -0.360
```

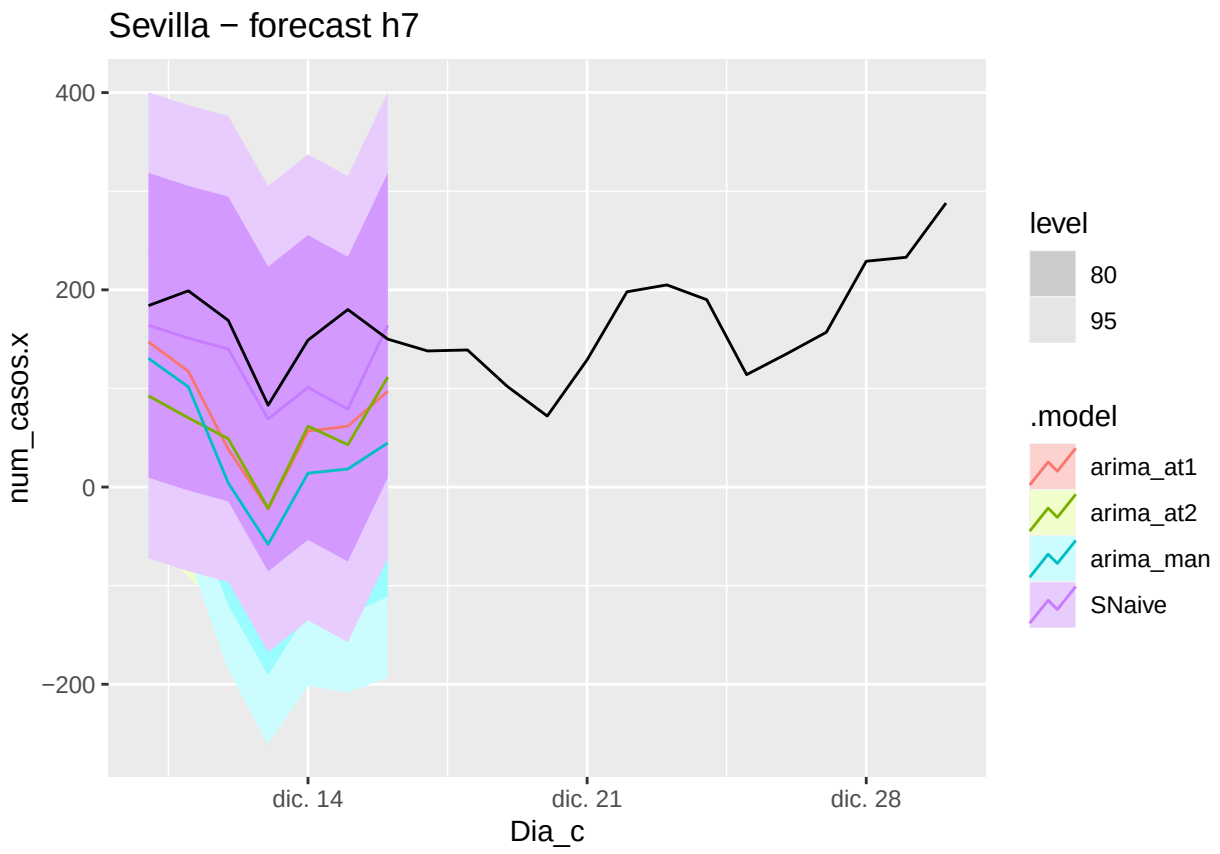
```
fabletools::accuracy(Sev_fc_h14, Sev_N_cases_tt)
```

```
## # A tibble: 4 x 11
##   .model    sub_region_2 .type    ME  RMSE   MAE   MPE  MAPE  MASE RMSSE  ACF1
##   <chr>     <chr>        <chr> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
## 1 arima_at1 Sevilla      Test  102.  110.  102.   76.5  76.5   NaN   NaN 0.436
## 2 arima_at2 Sevilla      Test   98.6 103.   98.6  70.2  70.2   NaN   NaN 0.186
## 3 arima_man Sevilla      Test  163.  175.  163.  123.  123.    NaN   NaN 0.614
## 4 SNaive    Sevilla      Test   25.8  50.2  38.6  13.5  24.1   NaN   NaN 0.299
```

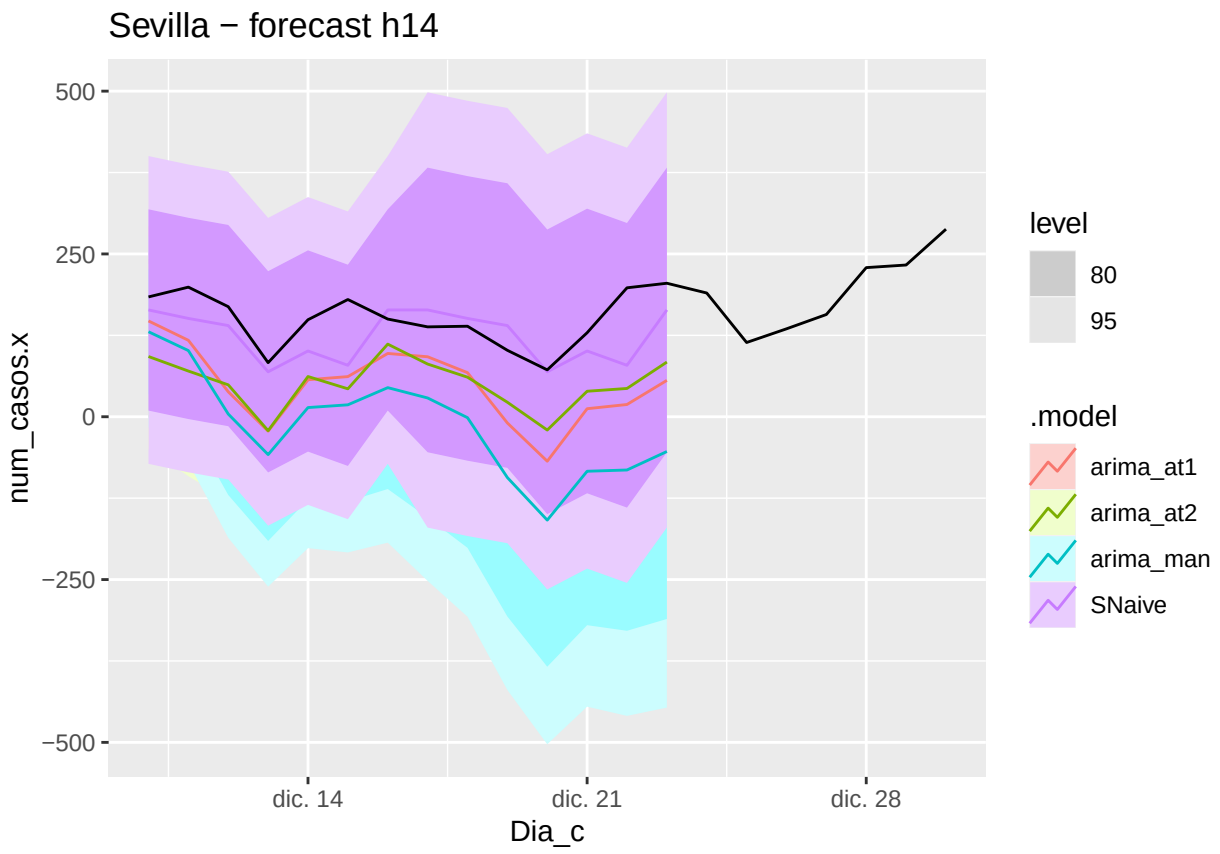
```
fabletools::accuracy(Sev_fc_h21, Sev_N_cases_tt)
```

```
## # A tibble: 4 x 11
##   .model    sub_region_2 .type    ME  RMSE   MAE   MPE  MAPE  MASE RMSSE  ACF1
##   <chr>     <chr>        <chr> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
## 1 arima_at1 Sevilla      Test  136.  153.  136.   86.9  86.9   NaN   NaN 0.682
## 2 arima_at2 Sevilla      Test  125.  136.  125.   77.8  77.8   NaN   NaN 0.639
## 3 arima_man Sevilla      Test  227.  254.  227.  146.  146.    NaN   NaN 0.779
## 4 SNaive    Sevilla      Test   40.0  69.2  52.5  18.5  29.0   NaN   NaN 0.547
```

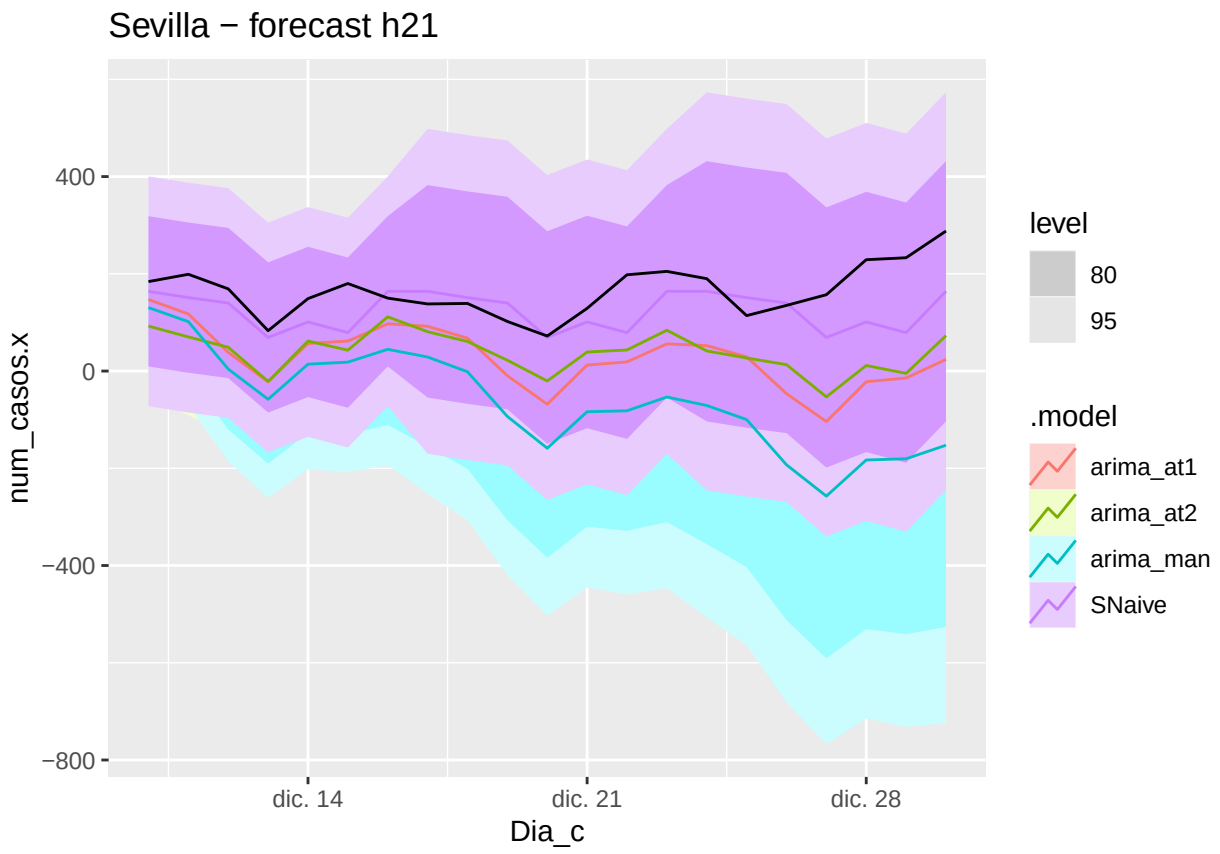
```
# Plots
Sev_fc_h7 %>%
  autoplot(Sev_N_cases_tt) +
  labs(title="Sevilla - forecast h7")
```




```
Sev_fc_h14 %>%
  autoplot(Sev_N_cases_tt) +
  labs(title="Sevilla - forecast h14")
```




```
Sev_fc_h21 %>%
  autoplot(Sev_N_cases_tt) +
  labs(title="Sevilla - forecast h21")
```



3.3.4 Multivariate (7, 14, 21 days) Málaga

```
# Model train
# We have added mobility variables to models
fit_model <- Mal_N_cases_tr %>%
  model(
    SNaive = SNAIVE(num_casos.x),
    arima_man = ARIMA(num_casos.x ~ retail_and_recreation_percent_change_from_baseline +
                        grocery_and_pharmacy_percent_change_from_baseline +
                        parks_percent_change_from_baseline +
                        transit_stations_percent_change_from_baseline +
                        workplaces_percent_change_from_baseline +
                        residential_percent_change_from_baseline + Total + pdq(2,1,2) +
                        PDQ(1,1,1)),
    arima_at1 = ARIMA(num_casos.x~ retail_and_recreation_percent_change_from_baseline +
                        grocery_and_pharmacy_percent_change_from_baseline +
                        parks_percent_change_from_baseline +
                        transit_stations_percent_change_from_baseline +
                        workplaces_percent_change_from_baseline +
                        residential_percent_change_from_baseline + Total),
    arima_at2 = ARIMA(num_casos.x~ retail_and_recreation_percent_change_from_baseline +
                        grocery_and_pharmacy_percent_change_from_baseline +
                        parks_percent_change_from_baseline +
                        transit_stations_percent_change_from_baseline +
                        workplaces_percent_change_from_baseline +
```

```
                        residential_percent_change_from_baseline + Total,
                      stepwise = FALSE,approx = FALSE))

# Show and report model
fit_model
```

```
## # A mable: 1 x 5
## # Key:     sub_region_2 [1]
##   sub_region_2   SNaive                                arima_man
##   <chr>         <model>                                  <model>
## 1 Málaga       <SNAIVE> <LM w/ ARIMA(2,1,2)(1,1,1)[7] errors>
## # ... with 2 more variables: arima_at1 <model>, arima_at2 <model>
```

```
report(fit_model)
```

```
## # A tibble: 4 x 9
##   sub_region_2 .model    sigma2 log_lik   AIC  AICc   BIC ar_roots   ma_roots
##   <chr>        <chr>      <dbl>   <dbl> <dbl> <dbl> <dbl> <list>     <list>
## 1 Málaga       SNaive     2991.      NA    NA    NA    NA  <NULL>     <NULL>
## 2 Málaga       arima_man   989.  -1266. 2560. 2562. 2610. <cpl [9]>  <cpl [9]>
## 3 Málaga       arima_at1   967.  -1298. 2620. 2621. 2663. <cpl [14]> <cpl [8]>
## 4 Málaga       arima_at2   901.  -1288. 2604. 2605. 2654. <cpl [8]>  <cpl [10]>
```

```
# Good model >> Less Sigma - More BIC or AIC
fit_model %>% pivot_longer(!sub_region_2,
                           names_to = "Model name",
                           values_to = "Orders")
```

```
## # A mable: 4 x 3
## # Key:     sub_region_2, Model name [4]
##   sub_region_2 `Model name`                                  Orders
##   <chr>        <chr>                                        <model>
## 1 Málaga       SNaive                                     <SNAIVE>
## 2 Málaga       arima_man    <LM w/ ARIMA(2,1,2)(1,1,1)[7] errors>
## 3 Málaga       arima_at1    <LM w/ ARIMA(0,1,1)(2,0,1)[7] errors>
## 4 Málaga       arima_at2    <LM w/ ARIMA(1,1,3)(1,0,1)[7] errors>
```

```
glance(fit_model) %>% arrange(AICc) %>% select(.model:BIC)
```

```
## # A tibble: 4 x 6
##   .model    sigma2 log_lik   AIC  AICc   BIC
##   <chr>      <dbl>   <dbl> <dbl> <dbl> <dbl>
## 1 arima_man   989.  -1266. 2560. 2562. 2610.
## 2 arima_at2   901.  -1288. 2604. 2605. 2654.
## 3 arima_at1   967.  -1298. 2620. 2621. 2663.
## 4 SNaive     2991.     NA    NA    NA    NA
```

```
# We use a Ljung-Box test >> large p-value, confirmins residuals are similar to white noise.
augment(fit_model) %>%
  features(.innov, ljung_box, lag=7)
```

```
## # A tibble: 4 x 4
##   sub_region_2 .model    lb_stat lb_pvalue
##   <chr>        <chr>       <dbl>     <dbl>
## 1 Málaga       arima_at1   26.8   0.000360
## 2 Málaga       arima_at2    8.77  0.269
## 3 Málaga       arima_man   22.6   0.00202
```

```
## 4 Málaga       SNaive     521.    0
```

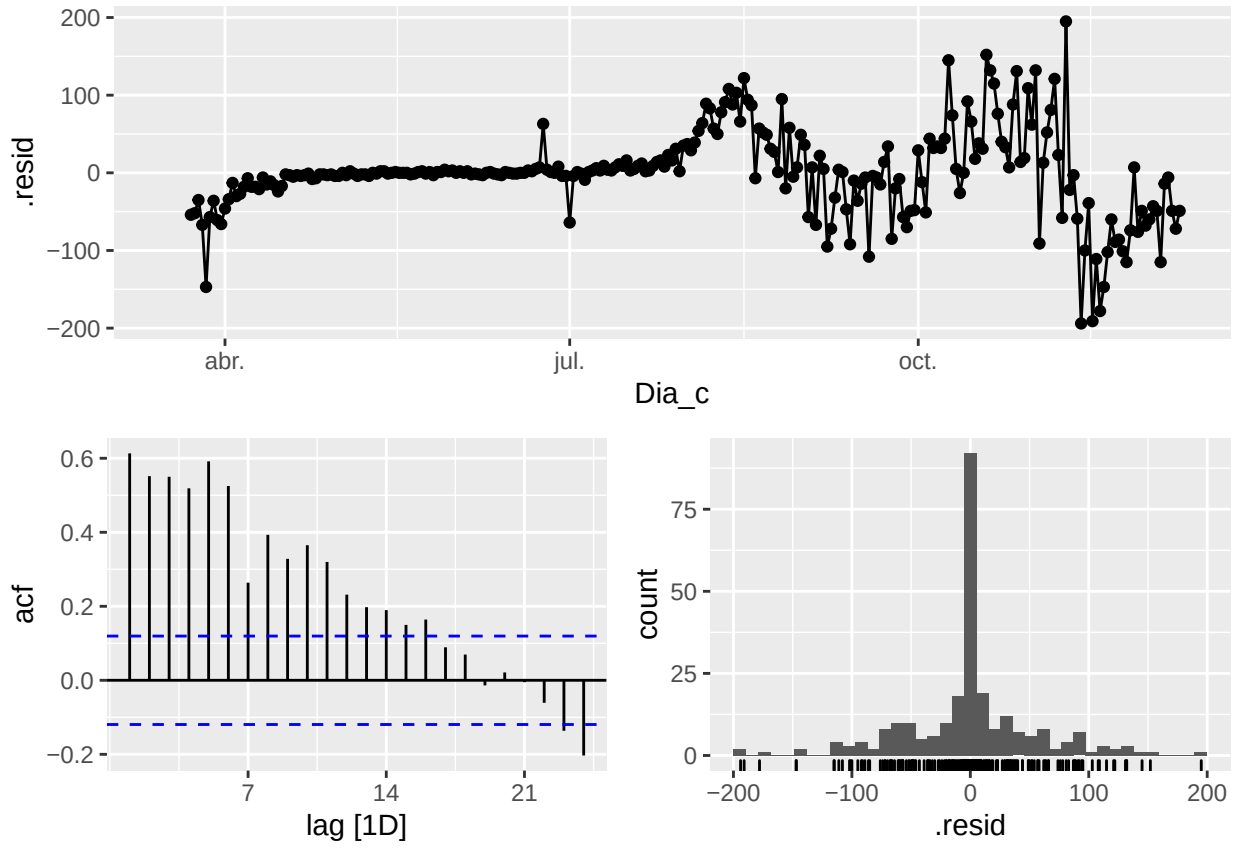
```
augment(fit_model) %>%
  features(.innov, ljung_box, lag=14)
```

```
## # A tibble: 4 x 4
##   sub_region_2 .model    lb_stat lb_pvalue
##   <chr>        <chr>       <dbl>     <dbl>
## 1 Málaga       arima_at1    34.5   0.00174
## 2 Málaga       arima_at2    16.7   0.272
## 3 Málaga       arima_man    31.1   0.00535
## 4 Málaga       SNaive      693.    0
```

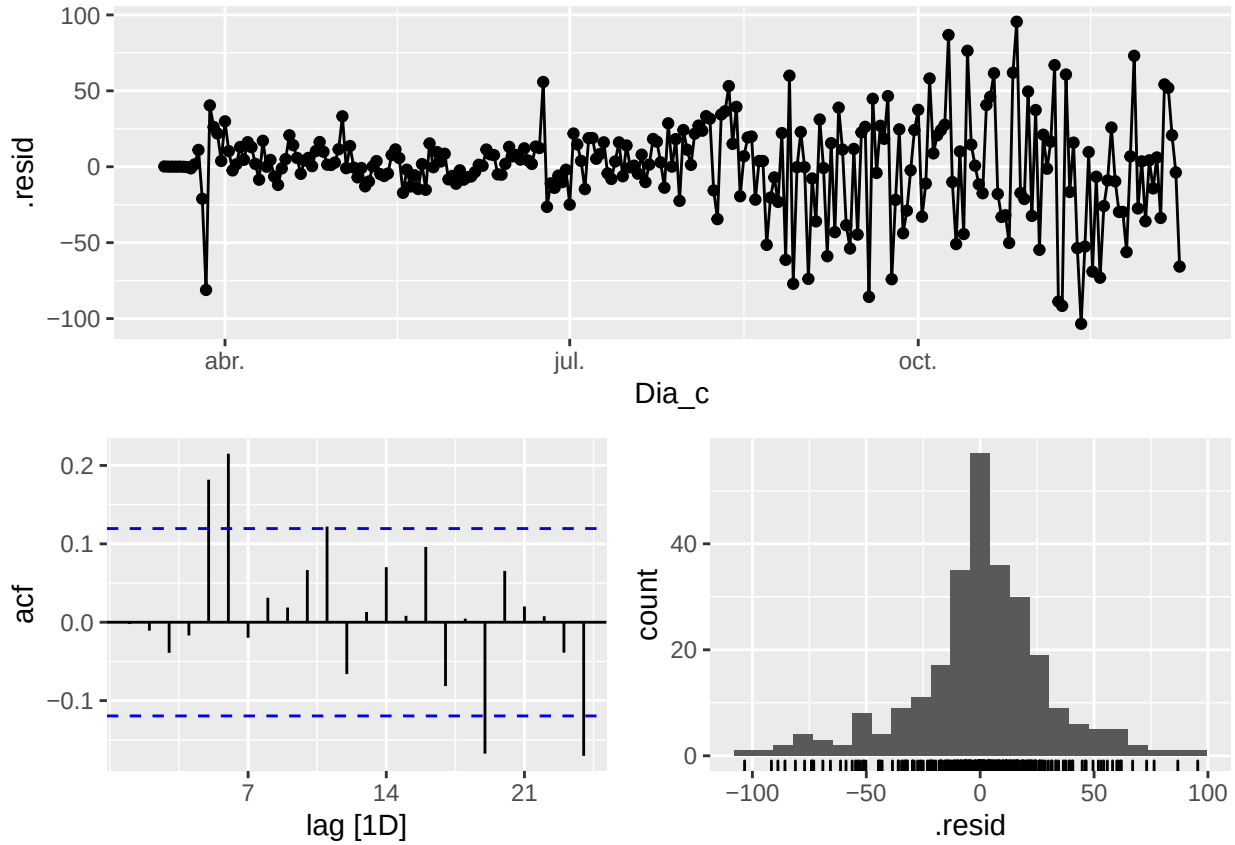
```
augment(fit_model) %>%
  features(.innov, ljung_box, lag=21)
```

```
## # A tibble: 4 x 4
##   sub_region_2 .model    lb_stat lb_pvalue
##   <chr>        <chr>       <dbl>     <dbl>
## 1 Málaga       arima_at1    48.3  0.000623
## 2 Málaga       arima_at2    31.1  0.0723
## 3 Málaga       arima_man    45.3  0.00159
## 4 Málaga       SNaive      711.   0
```

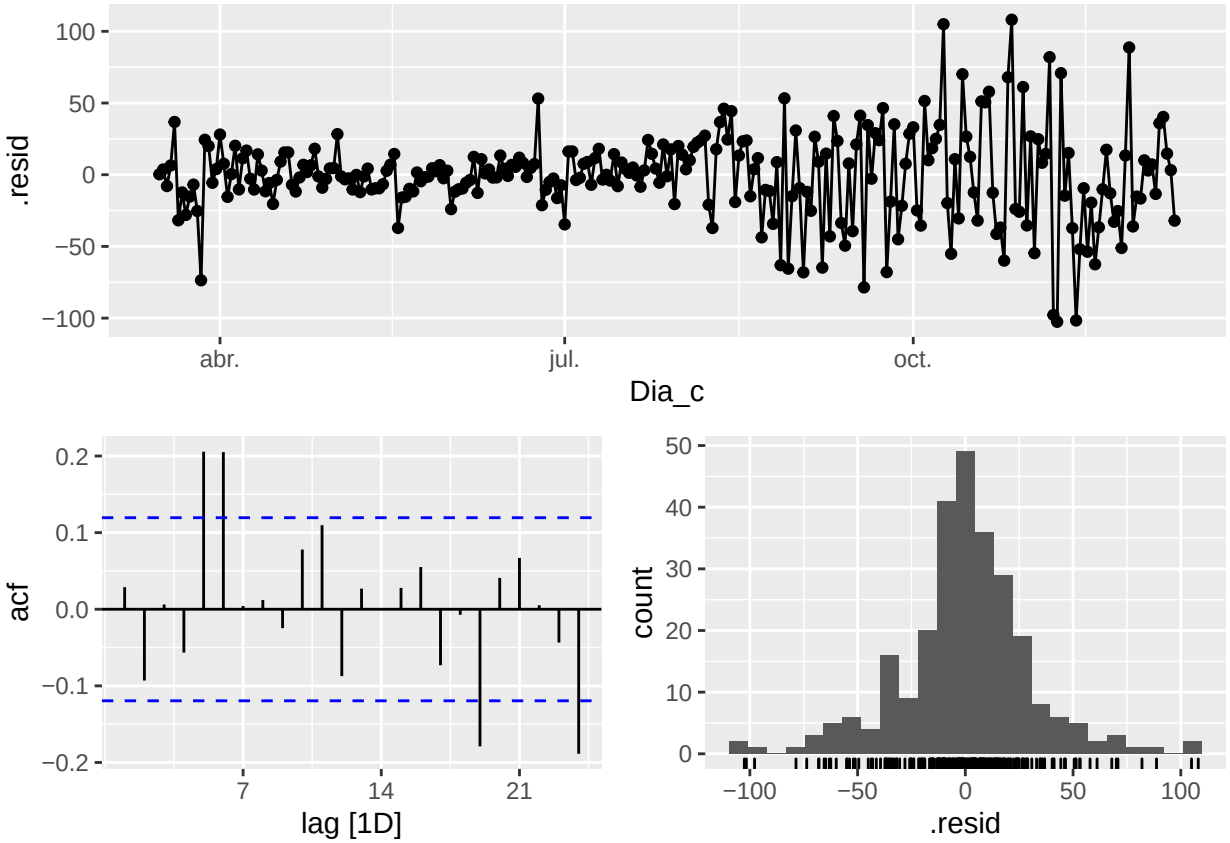
```
fit_model %>% select(SNaive) %>% gg_tsresiduals()
```



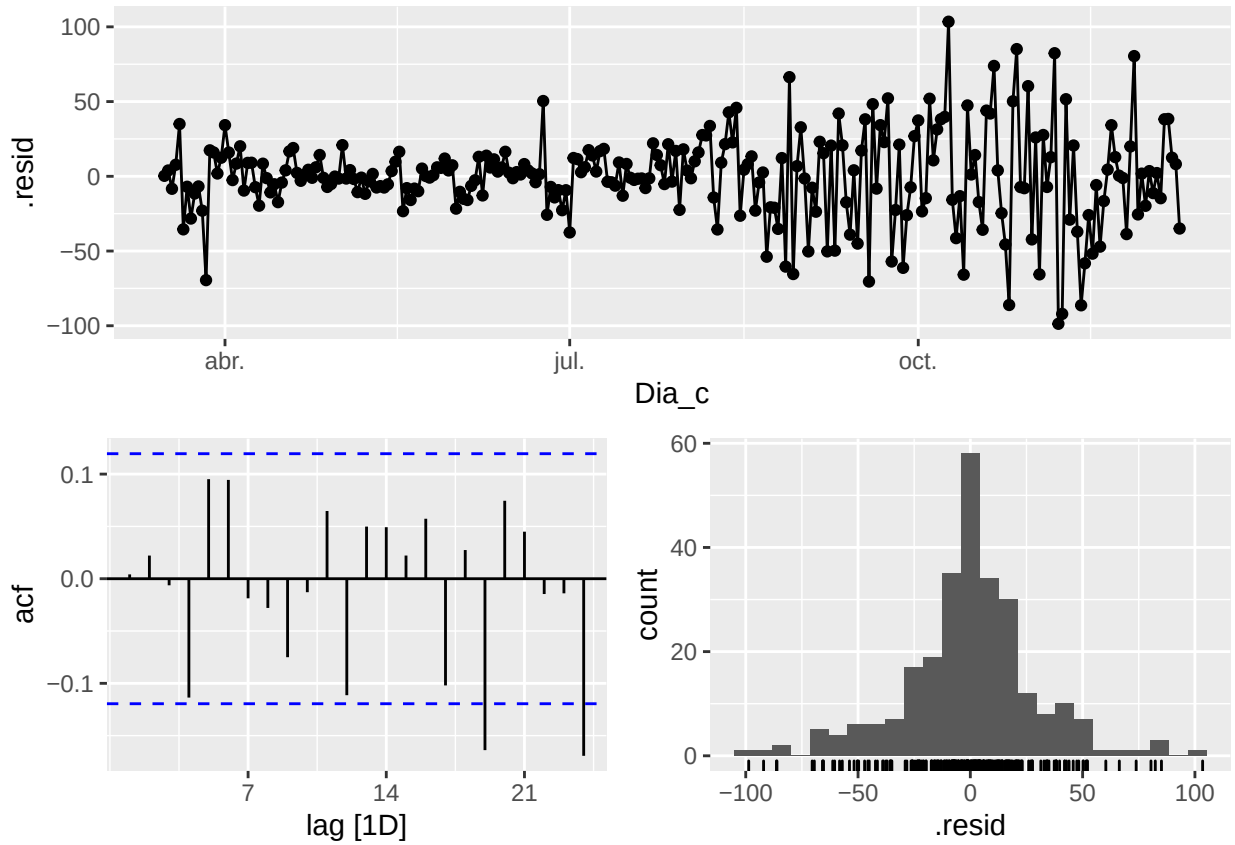

```
fit_model %>% select(arima_man) %>% gg_tsresiduals()
```




```
fit_model %>% select(arima_at1) %>% gg_tsresiduals()
```




```
fit_model %>% select(arima_at2) %>% gg_tsresiduals()
```




```
# Significant spikes out of 30 is still consistent with white noise.
# To be sure, use a Ljung-Box test, which has a large p-value, confirming that the
# residuals are similar to white noise.
# Note that the alternative models also pass this test.

# New data (dynamic regression)
# Here it is needed generate future values for the exogenous variables
# Foir simplicity we select a rand number included into the 2nd and 3rd quantile for
# the variable
# h7
Mal_N_cases_fr7 <- new_data(Mal_N_cases_tr, 7) %>%
  mutate(retail_and_recreation_percent_change_from_baseline =
           runif(7,quantile(Mal_N_cases_tt$retail_and_recreation_percent_change_from_baseline,
                            0.25),
                 quantile(Mal_N_cases_tt$retail_and_recreation_percent_change_from_baseline,
                          0.75)),
         grocery_and_pharmacy_percent_change_from_baseline =
           runif(7,quantile(Mal_N_cases_tt$grocery_and_pharmacy_percent_change_from_baseline,
                            0.25),
                 quantile(Mal_N_cases_tt$grocery_and_pharmacy_percent_change_from_baseline,
                          0.75)),
         parks_percent_change_from_baseline =
           runif(7,quantile(Mal_N_cases_tr$parks_percent_change_from_baseline,
                            0.25),
                 quantile(Mal_N_cases_tt$parks_percent_change_from_baseline,
                          0.75)),
```

```
          transit_stations_percent_change_from_baseline =
            runif(7,quantile(Mal_N_cases_tt$transit_stations_percent_change_from_baseline,
                             0.25),
                  quantile(Mal_N_cases_tt$transit_stations_percent_change_from_baseline,
                           0.75)),
          workplaces_percent_change_from_baseline =
            runif(7,quantile(Mal_N_cases_tt$workplaces_percent_change_from_baseline,
                             0.25),
                  quantile(Mal_N_cases_tt$workplaces_percent_change_from_baseline,
                           0.75)),
          residential_percent_change_from_baseline =
            runif(7,quantile(Mal_N_cases_tt$residential_percent_change_from_baseline,
                             0.25),
                  quantile(Mal_N_cases_tt$residential_percent_change_from_baseline,
                           0.75)),
          Total = runif(7,quantile(Mal_N_cases_tt$Total,0.25),
                        quantile(Mal_N_cases_tt$Total,0.75)))

# h14
Mal_N_cases_fr14 <- new_data(Mal_N_cases_tr, 14) %>%
  mutate(retail_and_recreation_percent_change_from_baseline =
            runif(14,quantile(Mal_N_cases_tt$retail_and_recreation_percent_change_from_baseline,
                              0.25),
                  quantile(Mal_N_cases_tt$retail_and_recreation_percent_change_from_baseline,
                           0.75)),
          grocery_and_pharmacy_percent_change_from_baseline =
            runif(14,quantile(Mal_N_cases_tt$grocery_and_pharmacy_percent_change_from_baseline,
                              0.25),
                  quantile(Mal_N_cases_tt$grocery_and_pharmacy_percent_change_from_baseline,
                           0.75)),
          parks_percent_change_from_baseline =
            runif(14,quantile(Mal_N_cases_tt$parks_percent_change_from_baseline,
                              0.25),
                  quantile(Mal_N_cases_tt$parks_percent_change_from_baseline,
                           0.75)),
          transit_stations_percent_change_from_baseline =
            runif(14,quantile(Mal_N_cases_tt$transit_stations_percent_change_from_baseline,
                              0.25),
                  quantile(Mal_N_cases_tt$transit_stations_percent_change_from_baseline,
                           0.75)),
          workplaces_percent_change_from_baseline =
            runif(14,quantile(Mal_N_cases_tt$workplaces_percent_change_from_baseline,
                              0.25),
                  quantile(Mal_N_cases_tt$workplaces_percent_change_from_baseline,
                           0.75)),
          residential_percent_change_from_baseline =
            runif(14,quantile(Mal_N_cases_tt$residential_percent_change_from_baseline,
                              0.25),
                  quantile(Mal_N_cases_tt$residential_percent_change_from_baseline,
                           0.75)),
          Total = runif(14,quantile(Mal_N_cases_tt$Total,0.25),
                        quantile(Mal_N_cases_tt$Total,0.75)))
```

```
# h21
Mal_N_cases_fr21 <- new_data(Mal_N_cases_tr, 21) %>%
  mutate(retail_and_recreation_percent_change_from_baseline =
           runif(21,quantile(Mal_N_cases_tt$retail_and_recreation_percent_change_from_baseline,
                             0.25),
                 quantile(Mal_N_cases_tt$retail_and_recreation_percent_change_from_baseline,
                          0.75)),
         grocery_and_pharmacy_percent_change_from_baseline =
           runif(21,quantile(Mal_N_cases_tt$grocery_and_pharmacy_percent_change_from_baseline,
                             0.25),
                 quantile(Mal_N_cases_tt$grocery_and_pharmacy_percent_change_from_baseline,
                          0.75)),
         parks_percent_change_from_baseline =
           runif(21,quantile(Mal_N_cases_tt$parks_percent_change_from_baseline,
                             0.25),
                 quantile(Mal_N_cases_tt$parks_percent_change_from_baseline,
                          0.75)),
         transit_stations_percent_change_from_baseline =
           runif(21,quantile(Mal_N_cases_tt$transit_stations_percent_change_from_baseline,
                             0.25),
                 quantile(Mal_N_cases_tt$transit_stations_percent_change_from_baseline,
                          0.75)),
         workplaces_percent_change_from_baseline =
           runif(21,quantile(Mal_N_cases_tt$workplaces_percent_change_from_baseline,
                             0.25),
                 quantile(Mal_N_cases_tt$workplaces_percent_change_from_baseline,
                          0.75)),
         residential_percent_change_from_baseline =
           runif(21,quantile(Mal_N_cases_tt$residential_percent_change_from_baseline,
                             0.25),
                 quantile(Mal_N_cases_tt$residential_percent_change_from_baseline,
                          0.75)),
         Total = runif(21,quantile(Mal_N_cases_tt$Total,0.25),
                       quantile(Mal_N_cases_tt$Total,0.75)))

# Forecast
fc_fh7<-fabletools::forecast(fit_model, new_data = Mal_N_cases_fr7)
fc_fh14<-fabletools::forecast(fit_model, new_data = Mal_N_cases_fr14)
fc_fh21<-fabletools::forecast(fit_model, new_data = Mal_N_cases_fr21)

# Accuracy
fabletools::accuracy(fc_fh7, Mal_N_cases)
```

```
## # A tibble: 4 x 11
##   .model    sub_region_2 .type    ME  RMSE   MAE   MPE  MAPE  MASE RMSSE    ACF1
##   <chr>     <chr>        <chr> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>   <dbl>
## 1 arima_at1 Málaga       Test   47.6  53.6  47.6  26.8  26.8  1.35 0.981  0.0240
## 2 arima_at2 Málaga       Test   37.7  43.8  37.7  21.1  21.1  1.07 0.802 -0.0677
## 3 arima_man Málaga       Test   57.7  63.1  57.7  34.4  34.4  1.64 1.16   -0.157
## 4 SNaive    Málaga       Test   48.3  57.7  48.3  27.9  27.9  1.37 1.06    0.412
```

```
fabletools::accuracy(fc_fh14, Mal_N_cases)
```

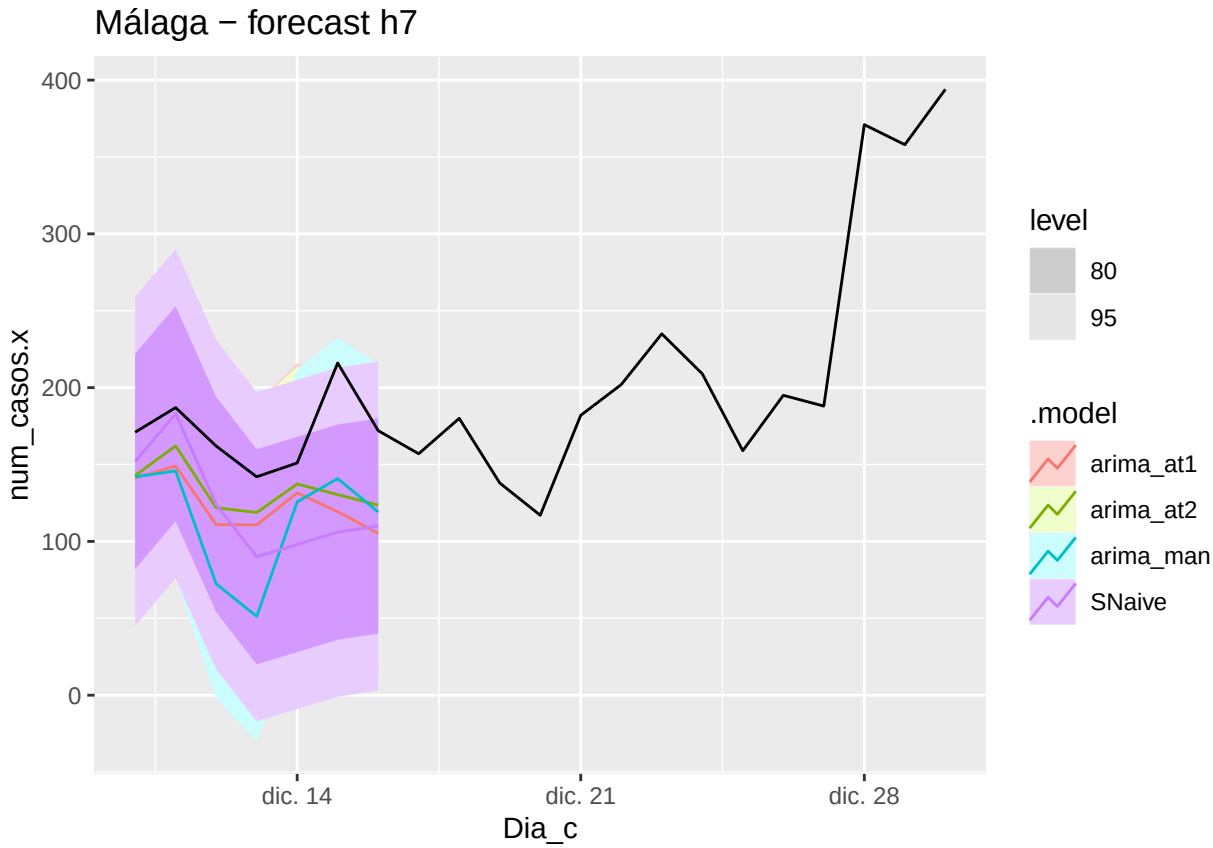
```
## # A tibble: 4 x 11
```

```
##   .model    sub_region_2 .type    ME  RMSE   MAE   MPE  MAPE  MASE RMSSE  ACF1
##   <chr>     <chr>        <chr> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
## 1 arima_at1 Málaga       Test   70.9  83.7  73.2  39.6  40.8  2.08  1.53 0.221
## 2 arima_at2 Málaga       Test   59.1  70.1  61.1  33.0  34.1  1.74  1.28 0.196
## 3 arima_man Málaga       Test   80.6  91.0  82.7  47.8  49.0  2.35  1.67 0.136
## 4 SNaive    Málaga       Test   49    63.3  49.4  26.9  27.2  1.40  1.16 0.516
```

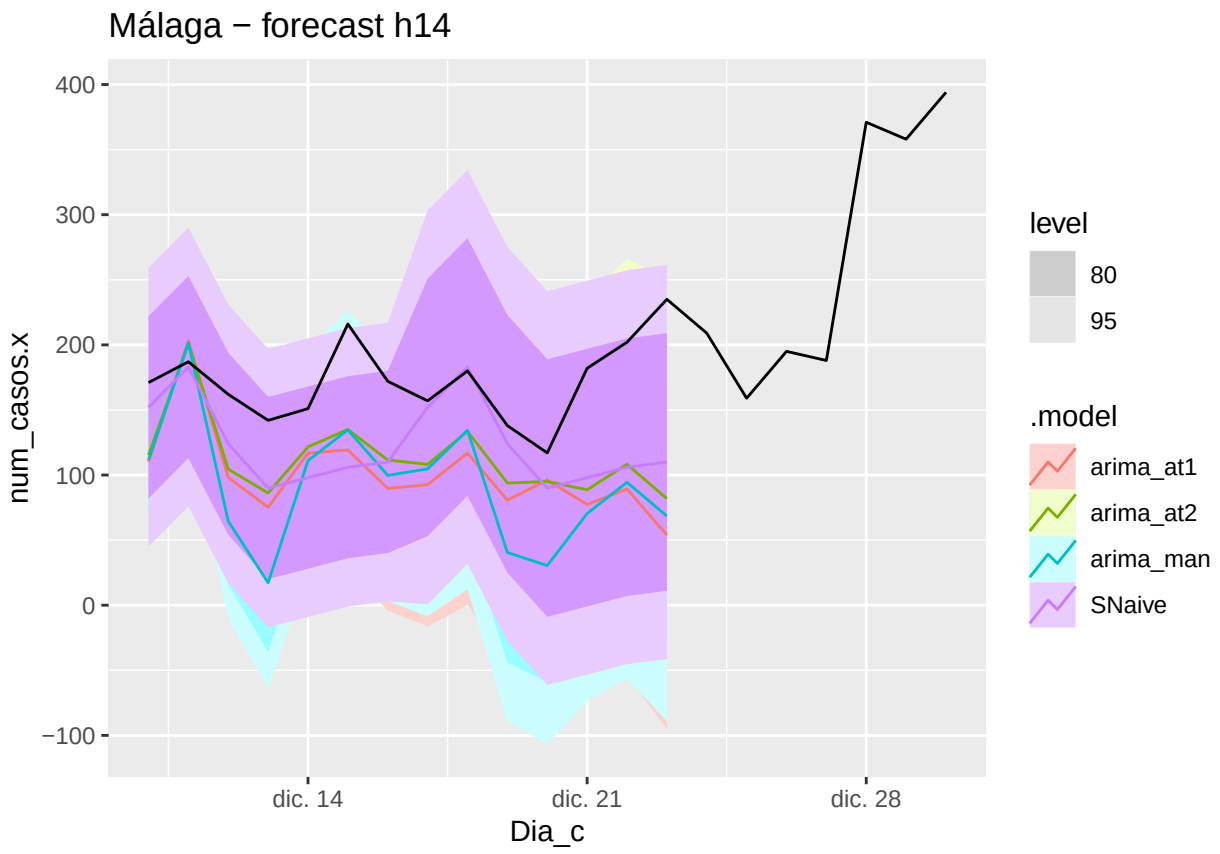
```
fabletools::accuracy(fc_fh21, Mal_N_cases)
```

```
## # A tibble: 4 x 11
##   .model    sub_region_2 .type    ME  RMSE   MAE   MPE  MAPE  MASE RMSSE  ACF1
##   <chr>     <chr>        <chr> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
## 1 arima_at1 Málaga       Test  110.   142. 111.   48.7  49.1  3.16  2.60 0.625
## 2 arima_at2 Málaga       Test   97.7  130.  98.7  42.2  42.8  2.81  2.39 0.638
## 3 arima_man Málaga       Test  124.   153. 125.   57.6  58.2  3.55  2.81 0.636
## 4 SNaive    Málaga       Test   80.8  118.  83.4  33.0  34.6  2.37  2.16 0.637
```

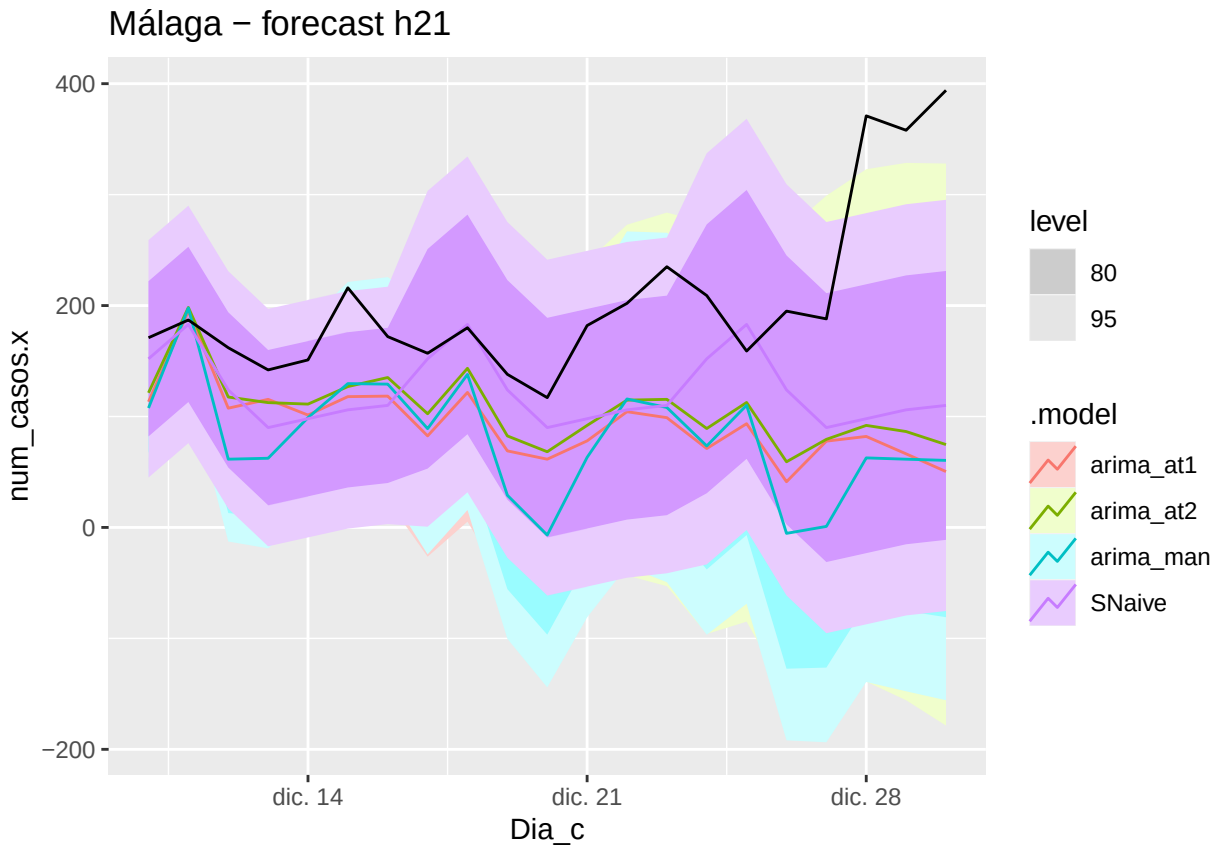
```
# Plots
fc_fh7 %>%
  #filter(.model=='arima_at1'|.model=='arima_at2'|.model=='SNaive') %>%
  autoplot(Mal_N_cases_tt) +
  labs(title="Málaga - forecast h7")
```




```
fc_fh14 %>%
  #filter(.model=='arima_at1'|.model=='arima_at2'|.model=='SNaive') %>%
  autoplot(Mal_N_cases_tt) +
  labs(title="Málaga - forecast h14")
```




```
fc_fh21 %>%
  #filter(.model=='arima_at1'|.model=='arima_at2'|.model=='SNaive') %>%
  autoplot(Mal_N_cases_tt) +
  labs(title="Málaga - forecast h21")
```



3.4 Till here 16-Apr-2021

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