**Exercicio5.R**

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2023-11-09

**library**(tidyverse)

## ── Attaching core tidyverse packages ──────────────────────── tidyverse 2.0.0 ──  
## ✔ dplyr 1.1.3 ✔ readr 2.1.4  
## ✔ forcats 1.0.0 ✔ stringr 1.5.0  
## ✔ ggplot2 3.4.1 ✔ tibble 3.2.1  
## ✔ lubridate 1.9.3 ✔ tidyr 1.3.0  
## ✔ purrr 1.0.1   
## ── Conflicts ────────────────────────────────────────── tidyverse\_conflicts() ──  
## ✖ dplyr::filter() masks stats::filter()  
## ✖ dplyr::lag() masks stats::lag()  
## ℹ Use the conflicted package (<<http://conflicted.r-lib.org/>>) to force all conflicts to become errors

**library**(forecast)

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

**library**(lubridate)  
**library**(data.table)

##   
## Attaching package: 'data.table'  
##   
## The following objects are masked from 'package:lubridate':  
##   
## hour, isoweek, mday, minute, month, quarter, second, wday, week,  
## yday, year  
##   
## The following objects are masked from 'package:dplyr':  
##   
## between, first, last  
##   
## The following object is masked from 'package:purrr':  
##   
## transpose

base <- **fread**(input = **paste0**("ipca.csv"), header = T, na.strings = "NA", data.table = FALSE, dec=",")  
**plot**(base**$**IPCA,type="s")



constante <- 0.00000001 *#constante consideravelmente baixa para evitar divisões por zero*  
base**$**IPCA <- base**$**IPCA **+** constante  
  
  
***# SUAVIZACAO EXPONENCIAL SIMPLES (SES) ############################***  
alpha1 <- **ses**(base**$**IPCA, alpha = 0.1)  
alpha2 <- **ses**(base**$**IPCA, alpha = 0.5)  
alpha3 <- **ses**(base**$**IPCA, alpha = 0.9)  
  
*#calculo dos erros de cada ajuste*  
**list**(alpha1, alpha2, alpha3) **%>%** **map**(accuracy)

## [[1]]  
## ME RMSE MAE MPE MAPE MASE  
## Training set -0.03772151 0.4170827 0.2997113 -13028460 13028563 1.115368  
## ACF1  
## Training set 0.5641694  
##   
## [[2]]  
## ME RMSE MAE MPE MAPE MASE  
## Training set -0.009681632 0.3678681 0.2634438 -14448417 14448512 0.9803997  
## ACF1  
## Training set 0.2372027  
##   
## [[3]]  
## ME RMSE MAE MPE MAPE MASE  
## Training set -0.005021923 0.3656705 0.2644053 -12678688 12678780 0.9839778  
## ACF1  
## Training set -0.07210106

*#gráfico do ajuste*  
**plot**(base**$**IPCA,type="s")  
**lines**(**fitted**(alpha1), col="blue")  
**lines**(**fitted**(alpha2), col="red")  
**lines**(**fitted**(alpha3), col="green")  
**legend**("topleft",lty=1, col=**c**(1,"blue","red","green"),  
 **c**("serie original",  
 **expression**(alpha **==** 0.1),  
 **expression**(alpha **==** 0.5),  
 **expression**(alpha **==** 0.9)),  
 pch=1)



alpha\_otimo <- **ses**(base**$**IPCA)  
**summary**(alpha\_otimo)

##   
## Forecast method: Simple exponential smoothing  
##   
## Model Information:  
## Simple exponential smoothing   
##   
## Call:  
## ses(y = base$IPCA)   
##   
## Smoothing parameters:  
## alpha = 0.7307   
##   
## Initial states:  
## l = 1.8482   
##   
## sigma: 0.3639  
##   
## AIC AICc BIC   
## 1346.654 1346.724 1358.228   
##   
## Error measures:  
## ME RMSE MAE MPE MAPE MASE  
## Training set -0.006279753 0.362857 0.2606874 -13384671 13384764 0.9701419  
## ACF1  
## Training set 0.05951103  
##   
## Forecasts:  
## Point Forecast Lo 80 Hi 80 Lo 95 Hi 95  
## 351 0.2422466 -0.2241078 0.7086009 -0.4709808 0.955474  
## 352 0.2422466 -0.3353332 0.8198264 -0.6410855 1.125579  
## 353 0.2422466 -0.4283580 0.9128511 -0.7833546 1.267848  
## 354 0.2422466 -0.5099651 0.9944583 -0.9081620 1.392655  
## 355 0.2422466 -0.5835467 1.0680398 -1.0206952 1.505188  
## 356 0.2422466 -0.6510879 1.1355811 -1.1239907 1.608484  
## 357 0.2422466 -0.7138698 1.1983630 -1.2200073 1.704500  
## 358 0.2422466 -0.7727759 1.2572690 -1.3100963 1.794589  
## 359 0.2422466 -0.8284460 1.3129392 -1.3952365 1.879730  
## 360 0.2422466 -0.8813613 1.3658545 -1.4761634 1.960657

*#alpha = 0.7307*   
  
***# SUAVIZACAO EXPONENCIAL DE HOLT #################################***  
beta1 <- **holt**(base**$**IPCA, alpha = 0.6, beta = 0.4)  
**summary**(beta1)

##   
## Forecast method: Holt's method  
##   
## Model Information:  
## Holt's method   
##   
## Call:  
## holt(y = base$IPCA, alpha = 0.6, beta = 0.4)   
##   
## Smoothing parameters:  
## alpha = 0.6   
## beta = 0.4   
##   
## Initial states:  
## l = 1.6735   
## b = 0.2446   
##   
## sigma: 0.4522  
##   
## AIC AICc BIC   
## 1496.766 1496.836 1508.340   
##   
## Error measures:  
## ME RMSE MAE MPE MAPE MASE  
## Training set -0.00107864 0.4496435 0.3341213 -10689205 10689331 1.243424  
## ACF1  
## Training set 0.1352302  
##   
## Forecasts:  
## Point Forecast Lo 80 Hi 80 Lo 95 Hi 95  
## 351 0.2800603 -0.2995023 0.859623 -0.6063042 1.166425  
## 352 0.3736312 -0.4459941 1.193256 -0.8798776 1.627140  
## 353 0.4672020 -0.6861131 1.620517 -1.2966412 2.231045  
## 354 0.5607728 -0.9943569 2.115902 -1.8175928 2.939138  
## 355 0.6543436 -1.3566635 2.665351 -2.4212264 3.729914  
## 356 0.7479144 -1.7650092 3.260838 -3.0952706 4.591099  
## 357 0.8414852 -2.2142995 3.897270 -3.8319343 5.514905  
## 358 0.9350560 -2.7009777 4.571090 -4.6257777 6.495890  
## 359 1.0286268 -3.2223770 5.279631 -5.4727225 7.529976  
## 360 1.1221976 -3.7763923 6.020788 -6.3695491 8.613944

beta2 <- **holt**(base**$**IPCA)  
**summary**(beta2)

##   
## Forecast method: Holt's method  
##   
## Model Information:  
## Holt's method   
##   
## Call:  
## holt(y = base$IPCA)   
##   
## Smoothing parameters:  
## alpha = 0.7274   
## beta = 1e-04   
##   
## Initial states:  
## l = 1.8382   
## b = -0.0046   
##   
## sigma: 0.3649  
##   
## AIC AICc BIC   
## 1350.600 1350.774 1369.890   
##   
## Error measures:  
## ME RMSE MAE MPE MAPE MASE  
## Training set 0.000125196 0.362829 0.2608868 -13216513 13216607 0.9708839  
## ACF1  
## Training set 0.06208697  
##   
## Forecasts:  
## Point Forecast Lo 80 Hi 80 Lo 95 Hi 95  
## 351 0.2356096 -0.2320545 0.7032736 -0.4796210 0.9508401  
## 352 0.2310184 -0.3473061 0.8093429 -0.6534526 1.1154894  
## 353 0.2264272 -0.4445725 0.8974269 -0.7997783 1.2526327  
## 354 0.2218360 -0.5305294 0.9742015 -0.9288076 1.3724797  
## 355 0.2172449 -0.6085268 1.0430165 -1.0456638 1.4801536  
## 356 0.2126537 -0.6805292 1.1058365 -1.1533516 1.5786590  
## 357 0.2080625 -0.7478058 1.1639309 -1.2538120 1.6699370  
## 358 0.2034713 -0.8112330 1.2181756 -1.3483850 1.7553277  
## 359 0.1988802 -0.8714456 1.2692059 -1.4380418 1.8358022  
## 360 0.1942890 -0.9289214 1.3174993 -1.5235130 1.9120910

*#alpha = 0.7274*   
*#beta = 1e-04*  
  
*#calculo dos erros de cada ajuste*  
**list**(beta1, beta2) **%>%** **map**(accuracy)

## [[1]]  
## ME RMSE MAE MPE MAPE MASE  
## Training set -0.00107864 0.4496435 0.3341213 -10689205 10689331 1.243424  
## ACF1  
## Training set 0.1352302  
##   
## [[2]]  
## ME RMSE MAE MPE MAPE MASE  
## Training set 0.000125196 0.362829 0.2608868 -13216513 13216607 0.9708839  
## ACF1  
## Training set 0.06208697

*#gráfico do ajuste*  
**plot**(base**$**IPCA,type="s")  
**lines**(**fitted**(beta1), col = "blue")  
**lines**(**fitted**(beta2), col = "red")



***# SUAVIZACAO EXPONENCIAL DE HOLT-WINTER###########################***  
base\_ts <- **ts**(base**$**IPCA, frequency=12, start=**c**(1980,1))  
base\_ts

## Jan Feb Mar Apr May Jun  
## 1980 1.86000001 1.53000001 2.62000001 2.81000001 1.71000001 1.70000001  
## 1981 0.99000001 0.99000001 1.41000001 1.47000001 1.56000001 1.34000001  
## 1982 0.44000001 0.15000001 0.30000001 0.32000001 0.47000001 1.18000001  
## 1983 -0.01999999 0.06000001 0.23000001 0.17000001 0.43000001 0.71000001  
## 1984 -0.50999999 -0.21999999 0.02000001 -0.11999999 0.33000001 0.70000001  
## 1985 0.56000001 0.31000001 1.19000001 0.95000001 0.60000001 0.62000001  
## 1986 1.31000001 0.23000001 0.14000001 0.32000001 0.59000001 0.57000001  
## 1987 0.70000001 0.28000001 0.83000001 0.71000001 0.65000001 0.52000001  
## 1988 0.65000001 0.72000001 1.31000001 3.02000001 2.10000001 2.25000001  
## 1989 0.34000001 0.78000001 0.29000001 0.34000001 0.52000001 0.76000001  
## 1990 0.69000001 0.33000001 0.44000001 0.69000001 0.86000001 0.58000001  
## 1991 0.17000001 0.35000001 0.75000001 0.55000001 0.36000001 0.59000001  
## 1992 0.05000001 0.21000001 0.33000001 0.31000001 0.48000001 0.44000001  
## 1993 0.47000001 0.18000001 0.30000001 0.38000001 0.74000001 0.54000001  
## 1994 0.28000001 0.26000001 0.45000001 0.36000001 0.28000001 0.48000001  
## 1995 0.15000001 0.24000001 0.28000001 0.41000001 0.37000001 0.75000001  
## 1996 0.04000001 0.45000001 0.75000001 0.83000001 0.63000001 0.83000001  
## 1997 0.37000001 0.53000001 0.43000001 0.52000001 0.50000001 0.56000001  
## 1998 0.41000001 0.57000001 0.59000001 0.60000001 0.79000001 0.86000001  
## 1999 0.24000001 0.35000001 0.57000001 0.54000001 0.92000001 0.55000001  
## 2000 0.25000001 0.57000001 0.42000001 0.51000001 0.78000001 1.24000001  
## 2001 0.22000001 0.54000001 0.82000001 1.01000001 0.96000001 1.27000001  
## 2002 0.44000001 0.08000001 0.26000001 0.18000001 0.30000001 0.38000001  
## 2003 0.19000001 0.16000001 0.42000001 0.28000001 0.44000001 0.29000001  
## 2004 -0.08999999 0.48000001 0.45000001 -0.20999999 0.15000001 0.32000001  
## 2005 0.11000001 -0.03999999 0.10000001 0.51000001 1.15000001 0.21000001  
## 2006 0.24000001 0.64000001 0.86000001 0.89000001 1.35000001 0.25000001  
## 2007 0.87000001 1.16000001 1.25000001 0.95000001 0.73000001 0.54000001  
## 2008 -0.35999999 -0.28999999 0.59000001 0.41000001 0.62000001 0.53000001  
## 2009 0.23000001 0.26000001   
## Jul Aug Sep Oct Nov Dec  
## 1980 1.02000001 1.55000001 2.43000001 2.67000001 2.26000001 2.36000001  
## 1981 1.03000001 0.35000001 1.26000001 1.22000001 1.19000001 1.11000001  
## 1982 0.50000001 0.51000001 0.88000001 0.41000001 0.54000001 0.22000001  
## 1983 0.46000001 0.34000001 0.24000001 0.50000001 0.02000001 -0.11999999  
## 1984 1.05000001 1.10000001 0.56000001 0.30000001 0.19000001 1.09000001  
## 1985 0.13000001 0.22000001 0.42000001 0.01000001 0.23000001 1.61000001  
## 1986 0.46000001 0.38000001 0.58000001 0.41000001 0.52000001 1.33000001  
## 1987 0.36000001 0.60000001 0.80000001 0.21000001 0.42000001 1.19000001  
## 1988 1.57000001 1.23000001 0.97000001 0.61000001 -0.14999999 0.20000001  
## 1989 0.61000001 0.47000001 0.37000001 0.51000001 0.71000001 0.91000001  
## 1990 0.59000001 0.61000001 0.87000001 0.49000001 -0.01999999 0.25000001  
## 1991 0.41000001 0.43000001 0.21000001 0.10000001 -0.20999999 0.19000001  
## 1992 0.44000001 0.37000001 0.25000001 0.28000001 0.28000001 0.24000001  
## 1993 0.49000001 0.48000001 0.55000001 0.79000001 0.74000001 0.53000001  
## 1994 0.55000001 0.20000001 0.48000001 0.47000001 0.36000001 0.24000001  
## 1995 0.78000001 0.52000001 0.57000001 0.43000001 0.00000001 0.01000001  
## 1996 0.80000001 0.79000001 0.77000001 0.47000001 0.15000001 0.16000001  
## 1997 0.45000001 0.21000001 0.64000001 0.36000001 0.08000001 0.43000001  
## 1998 0.60000001 0.47000001 0.55000001 0.37000001 0.26000001 0.03000001  
## 1999 0.69000001 0.92000001 0.67000001 0.46000001 0.40000001 0.01000001  
## 2000 1.22000001 1.32000001 0.71000001 0.74000001 0.79000001 0.62000001  
## 2001 0.90000001 0.43000001 0.61000001 0.78000001 0.35000001 0.52000001  
## 2002 0.33000001 0.25000001 0.14000001 0.31000001 -0.22999999 0.24000001  
## 2003 0.32000001 0.09000001 0.22000001 0.40000001 1.26000001 0.33000001  
## 2004 0.43000001 0.75000001 0.57000001 0.13000001 0.01000001 0.19000001  
## 2005 0.25000001 0.07000001 -0.30999999 -0.37999999 0.26000001 0.36000001  
## 2006 0.86000001 0.93000001 0.31000001 0.83000001 0.53000001 0.96000001  
## 2007 1.01000001 1.62000001 1.06000001 0.47000001 0.67000001 -0.67999999  
## 2008 0.84000001 0.71000001 0.61000001 0.23000001 -0.07999999 0.12000001  
## 2009

*#A série temporal contém valores negativos, portanto consideraremos um modelo de*  
*#sazonalidade aditiva, já que o modelo com sazonalidade multiplicativa assume*  
*#que os valores da série temporal e seus componentes (tendência, sazonalidade)*  
*#são estritamente positivos*  
  
gama\_ad <- **hw**(base\_ts, seasonal = "additive")  
  
*# calculo dos erros do ajuste*  
**list**(gama\_ad) **%>%** **map**(accuracy)

## [[1]]  
## ME RMSE MAE MPE MAPE MASE  
## Training set 0.002361196 0.3458065 0.249496 -9155259 9155339 0.630502  
## ACF1  
## Training set 0.06372361

**summary**(gama\_ad)

##   
## Forecast method: Holt-Winters' additive method  
##   
## Model Information:  
## Holt-Winters' additive method   
##   
## Call:  
## hw(y = base\_ts, seasonal = "additive")   
##   
## Smoothing parameters:  
## alpha = 0.7023   
## beta = 1e-04   
## gamma = 1e-04   
##   
## Initial states:  
## l = 2.1001   
## b = -0.0064   
## s = -0.0532 -0.1536 -0.0455 0.0676 0.0727 0.0996  
## 0.1746 0.1444 0.0916 0.0387 -0.2073 -0.2295  
##   
## sigma: 0.354  
##   
## AIC AICc BIC   
## 1340.963 1342.807 1406.548   
##   
## Error measures:  
## ME RMSE MAE MPE MAPE MASE  
## Training set 0.002361196 0.3458065 0.249496 -9155259 9155339 0.630502  
## ACF1  
## Training set 0.06372361  
##   
## Forecasts:  
## Point Forecast Lo 80 Hi 80 Lo 95 Hi 95  
## Mar 2009 0.46894466 0.01528521 0.9226041 -0.2248676 1.162757  
## Apr 2009 0.51558373 -0.03881521 1.0699827 -0.3322963 1.363464  
## May 2009 0.56218759 -0.07729540 1.2016706 -0.4158172 1.540192  
## Jun 2009 0.58603375 -0.12849256 1.3005601 -0.5067399 1.678807  
## Jul 2009 0.50480294 -0.27762035 1.2872262 -0.6918102 1.701416  
## Aug 2009 0.47159234 -0.37330624 1.3164909 -0.8205685 1.763753  
## Sep 2009 0.46029895 -0.44277915 1.3633770 -0.9208398 1.841438  
## Oct 2009 0.34088445 -0.61686057 1.2986295 -1.1238602 1.805629  
## Nov 2009 0.22657536 -0.78289483 1.2360456 -1.3172761 1.770427  
## Dec 2009 0.32069808 -0.73798679 1.3793829 -1.2984207 1.939817  
## Jan 2010 0.13811388 -0.96761044 1.2438382 -1.5529455 1.829173  
## Feb 2010 0.15404873 -0.99680659 1.3049041 -1.6060326 1.914130  
## Mar 2010 0.39368549 -0.80062101 1.5879920 -1.4328487 2.220220  
## Apr 2010 0.44032456 -0.79590674 1.6765559 -1.4503281 2.330977  
## May 2010 0.48692843 -0.78986316 1.7637200 -1.4657558 2.439613  
## Jun 2010 0.51077458 -0.80533891 1.8268881 -1.5020473 2.523596  
## Jul 2010 0.42954377 -0.92476113 1.7838487 -1.6416868 2.500774  
## Aug 2010 0.39633317 -0.99512575 1.7877921 -1.7317196 2.524386  
## Sep 2010 0.38503978 -1.04261674 1.8126963 -1.7983724 2.568452  
## Oct 2010 0.26562528 -1.19734343 1.7285940 -1.9717923 2.503043  
## Nov 2010 0.15131619 -1.34614195 1.6487743 -2.1388484 2.441481  
## Dec 2010 0.24543891 -1.28574148 1.7766193 -2.0962994 2.587177  
## Jan 2011 0.06285471 -1.50133038 1.6270398 -2.3293600 2.455069  
## Feb 2011 0.07878956 -1.51772719 1.6753063 -2.3628721 2.520451

*# analise grafica do ajuste*  
**plot**(base\_ts)  
**lines**(**fitted**(gama\_ad), col = "blue")



*# COMPARACAO GERAL#############################################################*  
  
**list**(alpha\_otimo, beta2, gama\_ad) **%>%** **map**(accuracy)

## [[1]]  
## ME RMSE MAE MPE MAPE MASE  
## Training set -0.006279753 0.362857 0.2606874 -13384671 13384764 0.9701419  
## ACF1  
## Training set 0.05951103  
##   
## [[2]]  
## ME RMSE MAE MPE MAPE MASE  
## Training set 0.000125196 0.362829 0.2608868 -13216513 13216607 0.9708839  
## ACF1  
## Training set 0.06208697  
##   
## [[3]]  
## ME RMSE MAE MPE MAPE MASE  
## Training set 0.002361196 0.3458065 0.249496 -9155259 9155339 0.630502  
## ACF1  
## Training set 0.06372361

**Analisando as métricas de erro dos três modelos, Modelo Holt-Winter - sazionalidade adidiva - teve os melhores resultados (se ajustou melhor aos dados): com valores de RMSE, MAE, MPE, MAPE e MASE mais baixos que o restante, perdendo apenas no ACF1, onde todos os modelos têm valores relativamente baixos, mas o Modelo SES é ligeiramente melhor.**