# Análisis de la serie de tiempo souvenir\_sales

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### Información de contacto

```
Mail: alejandro.zavala 1001@gmail.com
Facebook: https://www.facebook.com/AlejandroZavala1001
Git: https://github.com/AlejandroZavala98
## Loading required package: zoo
##
## Attaching package: 'zoo'
## The following objects are masked from 'package:base':
##
##
       as.Date, as.Date.numeric
## Loading required package: MASS
## Warning: package 'forecast' was built under R version 4.1.1
## Registered S3 method overwritten by 'quantmod':
     method
                       from
     as.zoo.data.frame zoo
##
## Attaching package: 'forecast'
## The following object is masked from 'package:astsa':
##
##
       gas
```

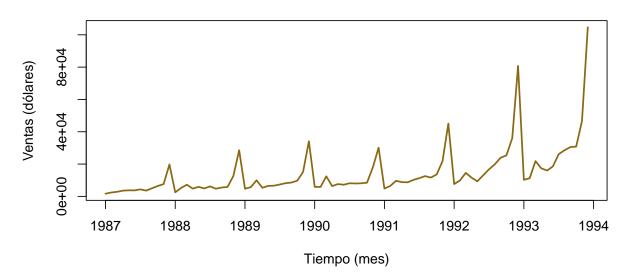
# Modelando la serie "souvenir\_sales"

### Descripción

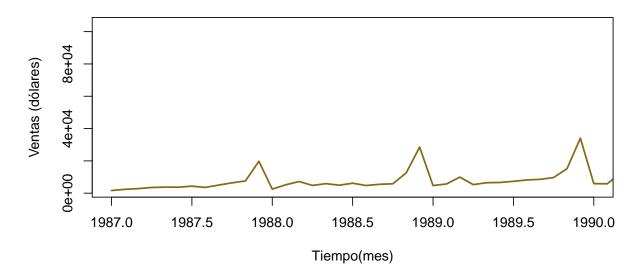
"Ventas para una tienda de recuerdos en Queensland, Australia. Enero de 1987 a diciembre de 1993. Ventas, fuente: Makridakis, Wheelwright y Hyndman (1998)"

#### Visualización

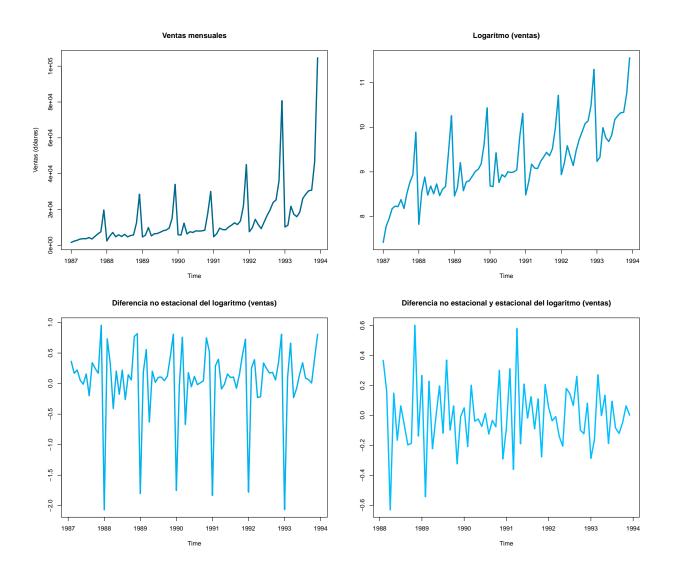
#### Ventas mensuales de recuerdos



### Ventas mensuales de recuerdos (Primeros 3 años)

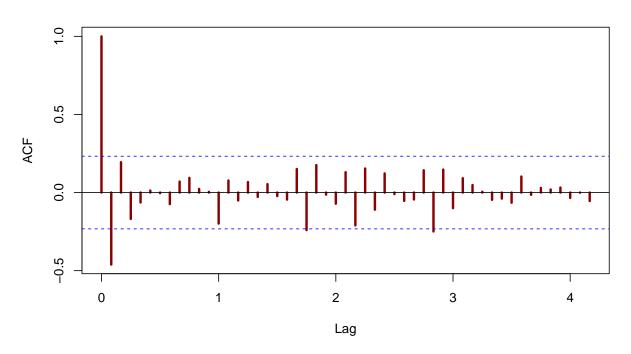


# Algunas transformaciones importantes

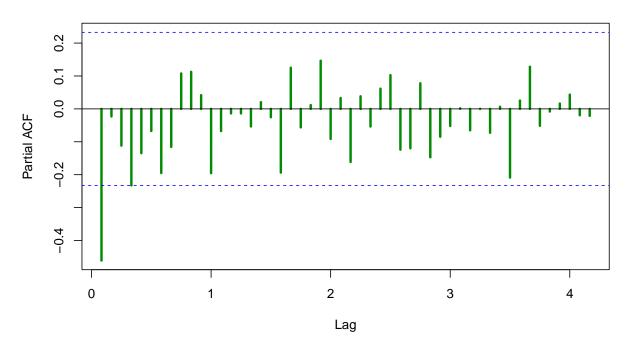


# ACF y PACF

ACF – Ventas (con transformación)



PACF – Ventas (con transformación)

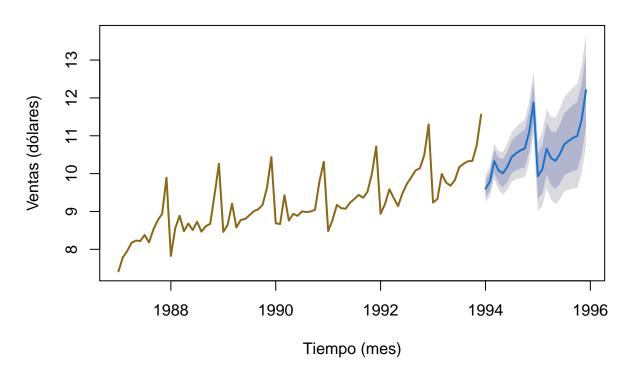


#### Ajustando diferentes modelos

```
## Modelo ( 0 1 0 0 1 0 12 ) AIC= -11.60664 SSE= 3.432906 p-VALUE= 0.0001365566
## Modelo ( 0 1 0 0 1 1 12 ) AIC= -16.09179 SSE= 2.97756 p-VALUE= 3.149952e-05
## Modelo ( 0 1 0 0 1 3 12 ) AIC= -16.41016 SSE= 2.35266 p-VALUE= 0.0003392283
## Modelo ( 0 1 0 1 1 0 12 ) AIC= -13.43083 SSE= 3.214065 p-VALUE= 4.083839e-05
## Modelo ( 0 1 0 1 1 1 12 ) AIC= -17.76362 SSE= 2.399746 p-VALUE= 0.0001916565
## Modelo ( 0 1 0 1 1 2 12 ) AIC= -15.99095 SSE= 2.349897 p-VALUE= 0.0002477782
## Modelo ( 0 1 0 1 1 3 12 ) AIC= -14.74777 SSE= 2.302026 p-VALUE= 0.0004504601
## Modelo ( 0 1 1 0 1 0 12 ) AIC= -27.78538 SSE= 2.643277 p-VALUE= 0.1742478
## Modelo ( 0 1 1 0 1 1 12 ) AIC= -34.54538 SSE= 2.233424 p-VALUE= 0.2730783
## Modelo ( 0 1 1 1 1 0 12 ) AIC= -32.33192 SSE= 2.360507 p-VALUE= 0.2584529
## Modelo ( 0 1 1 1 1 1 1 2 ) AIC= -34.0881 SSE= 1.842013 p-VALUE= 0.2843225
## Modelo ( 1 1 0 0 1 1 12 ) AIC= -34.98918 SSE= 2.209442 p-VALUE= 0.4633806
## Modelo ( 1 1 0 0 1 2 12 ) AIC= -33.38623 SSE= 2.159411 p-VALUE= 0.4515394
## Modelo ( 1 1 0 1 1 0 12 ) AIC= -32.64858 SSE= 2.340077 p-VALUE= 0.4022223
## Modelo ( 1 1 0 1 1 1 12 ) AIC= -33.48894 SSE= 2.125766 p-VALUE= 0.4442669
## Modelo ( 1 1 0 1 1 2 12 ) AIC= -31.52137 SSE= 2.093124 p-VALUE= 0.4463098
## Modelo ( 1 1 1 0 1 0 12 ) AIC= -26.17089 SSE= 2.624281 p-VALUE= 0.2507443
## Modelo ( 1 1 1 0 1 1 12 ) AIC= -33.30647 SSE= 2.201798 p-VALUE= 0.411014
## Modelo ( 1 1 1 0 1 2 12 ) AIC= -31.68924 SSE= 2.151774 p-VALUE= 0.3820814
## Modelo ( 1 1 1 1 1 0 12 ) AIC= -31.10127 SSE= 2.323818 p-VALUE= 0.3492746
## Modelo ( 1 1 1 1 1 1 1 2 ) AIC= -32.69913 SSE= 1.824041 p-VALUE= 0.3092406
```

# Pronóstico

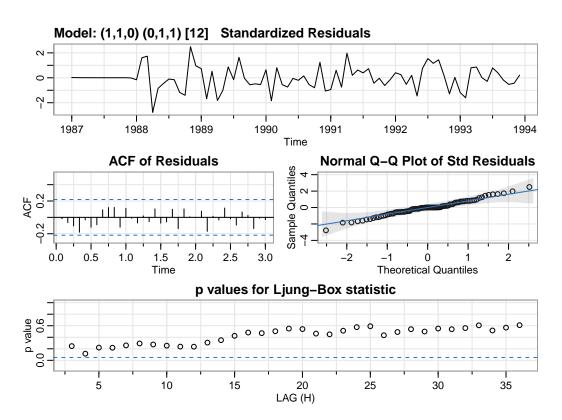
# Ventas mensuales de recuerdos



	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
Jan 1994	9.600020	9.373967	9.826071	9.254303	9.945736
Feb 1994	9.786505	9.533944	10.039066	9.400246	10.172764
Mar 1994	10.329605	10.025423	10.633786	9.864399	10.794810
Apr 1994	10.081973	9.746705	10.417240	9.569225	10.594720
May 1994	10.008096	9.638604	10.377587	9.443007	10.573184
Jun 1994	10.181170	9.783094	10.579245	9.572365	10.789974
Jul 1994	10.439372	10.013362	10.865383	9.787845	11.090900
Aug 1994	10.534857	10.083237	10.986477	9.844164	11.225551
Sep 1994	10.613025	10.136886	11.089165	9.884833	11.341218
Oct 1994	10.664526	10.165207	11.163846	9.900883	11.428170
Nov 1994	11.096784	10.575248	11.618321	10.299163	11.894406
Dec 1994	11.877167	11.334355	12.419979	11.047007	12.707327

#### Modelo final

```
## initial value -1.527727
          2 value -1.675635
## iter
          3 value -1.682326
## iter
          4 value -1.682437
          5 value -1.682439
## iter
          5 value -1.682439
## iter
          5 value -1.682439
## iter
## final value -1.682439
## converged
## initial value -1.692103
          2 value -1.704334
## iter
          3 value -1.707567
## iter
## iter
          4 value -1.707595
## iter
          5 value -1.707595
          5 value -1.707595
## iter
          5 value -1.707595
## iter
## final value -1.707595
## converged
```



```
## $fit
##
## Call:
## arima(x = xdata, order = c(p, d, q), seasonal = list(order = c(P, D, Q), period = S),
## include.mean = !no.constant, transform.pars = trans, fixed = fixed, optim.control = list(trace =
## REPORT = 1, reltol = tol))
##
```

```
## Coefficients:
##
             ar1
                     sma1
         -0.5017
##
                  -0.5107
## s.e.
         0.1013
                   0.1543
##
## sigma^2 estimated as 0.03111: log likelihood = 20.49, aic = -34.99
## $degrees_of_freedom
## [1] 69
##
## $ttable
##
       Estimate
                    SE t.value p.value
## ar1
        -0.5017 0.1013 -4.9531 0.0000
## sma1 -0.5107 0.1543 -3.3098 0.0015
##
## $AIC
## [1] -0.4266974
##
## $AICc
## [1] -0.4248449
##
## $BIC
## [1] -0.3439164
```

De tal modo se propone el siguiente modelo:

```
Y_t = 0.4983Y_{t-1} + 0.5017Y_{t-2} + Y_{t-12} - 0.4983Y_{t-13} - 0.5017Y_{t-14} + Z_t - 0.5107Z_{t-12} Z_t \sim N(0, 0.03111) Y_t = \log(x_t)
```