An Overview on R Packages for Seasonal Analysis of Time Series

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Abstract: Time series analysis consists of approaches for analysing time series data so that important information and other features can be isolated from the data. Time series forecasting is the use of a model to predict perspective values on the basis of previously observed values by a model. Statisticians generally use R project or R language, a free and popular programming language and computer software environment for statistical computing and graphics, for developing statistical computer software and data analysis. Plenty of time series display cyclic variation significant as seasonality, periodic variation, or periodic fluctuations in statistics. This study introduces abundant functions in the R packages TSA, marls, depersonalize and season for analyzing seasonal processes of time series, are introduced in this study. Note that R packages marls, depersonalize and season are included in the comprehensive R archive network task view TimeSeries.

Keywords: Periodic fluctuations, periodic variation, R project, seasonality, seasonal processes

INTRODUCTION

In statistics, signal processing, econometrics and mathematical finance, a time series is a sequence of data points, measured characteristically at sequential time instants spaced at regalia time intervals (Box et al., 1976; Hamilton, 1994). Methods for analysing time series data are involved in the Time series so as to evacuate valuable statistics and other features from the data (Box et al., 1976; Hamilton, 1994). Time series forecasting uses a model to predict the prospect of values according to the past observed values. Time series are often drawn by line graphs (Box et al., 1976; Hamilton, 1994). R project or R language, which is an useful and free programming language and computer software surroundings for statistical computing and graphics, is widely applied to statisticians for improving statistical computer software and data analysis (Ripley, 2001; Gentleman et al., 2003). Base R ships, which have a lot of functionalities, are helpful for time series, especially in the stats package. Various packages on CRAN with rapidly summarized below follow this.

In statistics, cyclic variation is shown in numerous time series significant as seasonality, periodic variation, or periodic fluctuations. When examining non-seasonal tendencies, seasonal adjustment is used to shed the seasonal component of a time series. Seasonally adjusted data for unemployment rates always been reported to reveal the basic trends in labor markets (Wallis, 1974; Hillmer and Tiao, 1982). A cycle-stationary process, a signal having statistical properties that vary cyclically with time, can be regarded as multiple interspersed motionless processes (Gardner, 1986; Gardner et al., 2006). Seasonal variation is a part of a time series which is described as the regular and predictable movement around the tendency line in no more than one year (Hylleberg, 1992; Barnett and Dobson, 2010). Organizations affected by seasonal variations need to identify and measure this seasonality to help with planning for temporary increases or decreases in labor requirements, inventory, training, periodic maintenance and so on (Hylleberg, 1992; Barnett and Dobson, 2010). Beside these considerations, the organizations should know that if the variations they have experienced have been more or less expected given the regular cyclic variations (Hylleberg, 1992; Barnett and Dobson, 2010). The purpose of this study is to review R packages for seasonal analysis of time series.

R PACKAGES FOR SEASONAL ANALYSIS OF TIME SERIES

Functions in the R packages TSA, marls, depersonalize and season for analyzing seasonal processes of time series, are introduced in this section. Note that the comprehensive R archive network task view TimeSeries encloses the R packages marls, depersonalize and season (Hyndman and Zeileis, 2012).
Seasonal analysis with the R package TSA: The function acf is modified from the acf function in the stats package (Chan, 2012). The function arima is identical to the arimax function which builds on and expands the capability of the arima function in R stats viamiiting the combination of transfer functions and innovative and additive outliers (Chan, 2012). Note in the computation of Akaike’s Information Criterion (AIC), the number of parameters excludes the noise variance (Cryer and Chan, 2008; Chan, 2012). This function is deeply built on the arima function of the stats center of R (Chan, 2012). The function arima extracts the season information from an equally spaced time series and makes vector of the season information (Chan, 2012).

Seasonal analysis of health data: The R package season is for seasonal analysis of health data, containing regression models, time-stratified case-crossover, plotting functions and residual checks (Barnett et al., 2012). The R package season aims to fill up a sizable gap in the R software by offering numerous tools for analyzing seasonal data (Barnett et al., 2012). The package season includes graphical methods for checking and appraising seasonal patterns (Barnett et al., 2012). The regression models can be used to normal, Poisson or binomial dependent data distributions (Barnett et al., 2012). Tools can be applied to not only time series data (equally spaced in time) but also survey data (unequally spaced in time) (Barnett et al., 2012). Sinusoidal (parametric) seasonal patterns are available incosinor, ncosinor, as well as models for monthly data in monthglm and the case-crossover method to management for seasonality in the R function nonlinear test case-crossover (Barnett et al., 2012). The R function aaf makes random linear surrogates of data of a time series with the same second-order properties (Barnett et al., 2012). The AAFT uses phase-scrambling to create a surrogate of the time series, having a similar spectrum and thenparallel second-order statistics (Barnett et al., 2012). The AAFT is valuable for checking for non-linearity in a time series and can be used by nonlinearint (Kugiumtzis, 2000; Barnett et al., 2012). The R function case cross suits a time-stratified case-crossover to regularly spaced time series data but not suitable for irregularly spaced discrete data (Barnett et al., 2012). The case-crossover method compares “case” days when events occurred (e.g., deaths) with control days to look for differences in exposure that might explain differences in the number of cases (Barnett et al., 2012). Control days are chosen to be closed to case days, meaning that only recent variations in the independent variables are related (Barnett et al., 2012). Any long-term or seasonal variation in the dependent and independent variables can be eliminated by simply comparing recent values, (Barnett et al., 2012). The definition of nearby and the seasonal and long-term models in the independent variables determine this elimination (Barnett et al., 2012). Control and case days can be contrasted only when they are in the same stratum (Barnett et al., 2012). The strata length, the default value is 28 days, rules the stratum, hence that cases and controls are compared in four week sections (Barnett et al., 2012). Smaller stratum lengths provide a closer control for season, but then decrease the functional number of controls (Barnett et al., 2012). Control days, closing to the case day, may have comparable levels of the independent variables (Barnett et al., 2012). It is likely to put an exclusion around the case reduce this correlation (Barnett et al., 2012). It is possible to additionally match by day of the week (matchday) to delete any confounding by day of the week, regardless of the fact that this often reduces the number of available controls (Barnett et al., 2012). The method utilizes conditional logistic regression (see coxph and so the parameter estimates are odds ratios (Barnett et al., 2012). The code presumes that the data frame includes a date variable (in Date format) called date (Janes et al., 2005; Barnett and Dobson, 2010; Barnett et al., 2012). The function ciPhase computes the mean and confidence interval for the phase based on aseries of MCMC samples (Barnett et al., 2012). The evaluation of the phase are rotated to have a centre of n, the point on the circumference of a unit radius circle that is furthest from zero (Barnett et al., 2012). The mean and confidence interval are computed on the rotated values and then the estimates are rotated backward. Fisher (1996), Barnett and Dobson (2010) and Barnett et al. (2012). The function nonlintest realizes a bootstrap test of non-linearity in a time series, which uses the third-order moment (Barnett et al., 2012). The aaft is used to make linear surrogates with the same second-order properties, but no (third-order) non-linearity (Barnett et al., 2012). The third-order moments (third) of these linear surrogates and the actual series are then compared from lags 0 up to n.lag (excluding the skew at the co-ordinates (0, 0)) (Barnett et al., 2012). The bootstrap test applies on the whole area outside the limits and provides an indication of the overall non-linearity (Barnett et al., 2012). The plot using region reveals those co-ordinates of the third order moment that beyond the null hypothesis limits and can be a valuable clue for guessing the type of non-linearity (Barnett et al., 2012). A non-stationary seasonal pattern changes over time; so this model offers potentially extremely elastic seasonal assessments (Barnett et al., 2012). The cycle controls the frequency of the seasonal estimates and ought to be specified in units of time (Barnett et al., 2012). The estimates are made
using a forward and backward sweep of the Kalman filter (Barnett et al., 2012). Repeated estimates are made using Markov Chain Monte Carlo (MCMC) (Barnett et al., 2012). For this reason the model can take a long time to run (we will perfect this in the next version) (Barnett et al., 2012). A reasonably long-term model should be applied (niter) and the probably inadequate initial estimates should be abandoned (burn in) to give stable estimates. (Barnett and Dobson, 2004, 2010; Barnett et al., 2012). The function phasecal computes the phase given the estimated sine and cosine values from a cosinor model (Barnett et al., 2012) and returns the phase in radians, in the range (0, 2) (Barnett et al., 2012). The phase is at the top of the sinusoid (Fisher, 1996; Barnett et al., 2012). The function plotCircular applies a circular plot helpful for visualising monthly or weekly data (Barnett et al., 2012). The length of the variable area 1 is determined by the number of segments (Barnett et al., 2012). The plots are also called rose diagrams, with the segments then called 'petals' (Fisher, 1996; Barnett et al., 2012). The function plot Month plots results by month (Barnett and Dobson, 2010; Barnett et al., 2012). For modelling seasonal data, sinusoidal curves are highly prized (Barnett et al., 2012). The function sinusoid plots a sinusoid from 0 to 2 (Barnett et al., 2012). West for a seasonal pattern in Binomial data, a test of whether monthly data has a sinusoidal seasonal pattern, has little influence compared with the cosinor test. Walter and Elwood (1975), Barnett and Dobson (2010) and Barnett et al. (2012). The function nscosinor will be made faster and the plots are to be improved in the next version, (Barnett et al., 2012).

**Multiplicative AR (1) with seasonal processes:**
Multiplicative AR (1) (Yamamoto, 1982) with Seasonal processes, processes (Paramonov, 2012), is a stochastic process model built on top of AR (1) and can be abbreviated as MAR(1)S (Petruccelli and Woolford, 1984; Chan et al., 1985; Chan and Wei, 1987; Baltagi and Wu, 1999). The R package mar1s (Paramonov, 2012) picks up MAR(1)S or GARCH models (Drost and Nijman, 1993; Lamoureux and Lastrapes, 1990; Nelson and Cao, 1992; Karolyi, 1995; Baille et al., 1996; Tse, 2000; Garcia et al., 2005). The package mar1s offers the following procedures for MAR(1)S:

- Fitting
- Composition
- Decomposition
- Advanced simulation
- Prediction (Paramonov, 2012)

The function fit.mar1s fits MAR(1)S process model to time series (Paramonov, 2012). The function composes. Ar1 composes AR (1) process realization by given vectors of innovations (Paramonov, 2012). The function compose.mar1s composes MAR(1)S process realization by given vector of log-innovations (Paramonov, 2012). The function decomposes. Ar1 extracts AR (1) process residuals from time series (Paramonov, 2012). The function decompose. mar1s extracts MAR(1)S process components from time series (Paramonov, 2012). The function sim.mar1s simulates from MAR(1)S process (Paramonov, 2012). The function predict.mar1s is a wrapper around the functionsim.mar1s which estimates confidence intervals for the future values of the MAR(1)S process (Paramonov, 2012). The function seasonal.ave extracts seasonal component of time series by averaging observations on the same place in the cycle (Paramonov, 2012). The function seasonal. smooth extracts seasonal component of time series by fitting the data with a linear combination of smooth periodic functions (Paramonov, 2012).

**Optimal depersonalization for geophysical time series using AR fitting:** A harmonic regression is fit to the data to estimate the seasonal means and standard deviations (Young et al., 1999; McLeod, 2012). The number of terms in the harmonic regression may be determined using the Bayesian Information Criterion (BIC) or generalized Akaike’s Information Criterion (generalized AIC) (Young et al., 1999; McLeod, 2012; Sakai, 1990; Haughton et al., 1990; Albert and Hansberger, 2005; Tominaga, 2010). The R package deseasonalize that is an optimal depersonalization for geophysical time series using AR fitting, depersonalize daily or monthly time series (McLeod, 2012; Hipel and McLeod, 1994; McLeod and Zhang, 2008). In R package deseasonalize the main function ds is a depersonalization process for monthly and annual (McLeod, 2012; Hipel and McLeod, 1994; McLeod and Zhang, 2008). Most users would employ the ds, but not the utility function gets in R package deseasonalize (McLeod, 2012). The function print.deseasonalize can give a terse summary (McLeod, 2012). The function summary. Deseasonalize provides summary for deseasonalize objects (McLeod, 2012; Hipel and McLeod, 1994; McLeod and Zhang, 2008).

**CONCLUSION**

Time series analysis includes methods for analysing time series data so as to deracinate meaningful statistics and other characteristics from the data. Plenty of functions in the R packages TSA, mar1s, depersonalize and season for analyzing seasonal processes of time series, are introduced in this study.

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