Package ‘rmaf’

April 15, 2015

Type Package

Title Refined Moving Average Filter

Version 3.0.1

Date 2015-04-14

Author Debin Qiu

Maintainer Debin Qiu <debinqiu@uga.edu>

Description Uses refined moving average filter based on the optimal and data-driven moving average lag q or smoothing spline to estimate trend and seasonal components, as well as irregularity (residuals) for univariate time series or data.

NeedsCompilation no

Repository CRAN

Date/Publication 2015-04-15 22:05:20

R topics documented:

`rmaf-package` *Refined Moving Average Filter Package*

Description

A refined moving average filter using the optimal and data-driven moving average lag q to estimate the trend component, and then estimate seasonal component and irregularity for univariate time series or data.

Details

Package:	rmaf
Type:	Package
Version:	3.0.1
Date:	2015-04-14
License:	GPL (>= 2)

This package contains a function to determine the optimal and data-driven moving average lag q, and two functions to estimate the trend, seasonal component and irregularity for univariate time series. A dataset of the first differences of annual global surface air temperatures in Celsius from 1880 through 1985 is also included in the package for illustrating the trend estimation.

For a complete list of functions and dataset, use `library(help = rmaf)`.

Author(s)

Debin Qiu

Maintainer: Debin Qiu <<debinqiu@uga.edu>>

References

D. Qiu, Q. Shao, and L. Yang (2013), Efficient inference for autoregressive coeficient in the presence of trend. *Journal of Multivariate Analysis* 114, 40-53.

J. Fan and Q. Yao, Nonlinear Time Series: Nonparametric and Parametric Methods, first ed., Springer, New York, 2003.

P.J. Brockwell, R.A. Davis, Time Series: Theory and Methods, second ed., Springer, New York, 1991.

See Also

`ma.filter`, `ss.filter`, `qn`

Examples

```
## The first difference of annual global surface air temperatures from 1880 to 1985 with only trend
data(globtemp)
q.n <- qn(globtemp)
fit1 <- ma.filter(globtemp)
fit2 <- ss.filter(globtemp)
```

globtemp *The First Differences of Annual Golbal Surface Air Temperatures from 1880-1985*

Description

The first differences of annual global surface air temperatures in Celsius from 1880 through 1985.

Usage

```
data(globtemp)
```

Format

A time series data with 106 observations from 1880 through 1985.

Details

The first differences of the annual global surface air temperatures in Celsius from 1880 through 1985.

Source

http://datamarket.com/data/set/22ku/annual-changes-in-global-temperature-1880-1985#!ds=22ku&display=line

See Also

qn ma.filter ss.filter

Examples

```
data(globtemp)
globtemp
```

ma.filter *Refined Moving Average Filter*

Description

uses refined moving average filter to estimate the trend component, and then obtain seasonal component if necessary.

Usage

```
ma.filter(x, q = NULL, seasonal = FALSE, period = NULL, plot = TRUE)
```

Arguments

`x`	a numeric vector or univariate time series.
`seasonal`	a logical value indicating to estimate the seasonal component. Only valid for `seasonal = TRUE`. The default is `FALSE`.
`q`	specified moving average lag q. The default is `NULL`.
`period`	seasonal period. The default is `NULL`.
`plot`	a logical value indicating to make the plots. The default is `TRUE`.

Details

For univariate time seties $x[t]$, the additive seasonal model is assumed to be

$$x[t] = m[t] + S[t] + R[t],$$

where $m[t], S[t], R[t]$ are trend, seasonal and irregular components, respectively. Once we obtain the optimal moving average lag q using `qn`, the trend can be estimated by using the refined moving average

$$mhat[t] = \sum x[t]/(2q + 1),$$

for $q + 1 \leq t \leq n - q$. If $q + 1 > n - q$, we take $q = min(n - q, q)$. If there is no seasonal component, the irregularity or residuals can be computed by $Rhat[t] = x[t] - mhat[t]$. Otherwise, the seasonal index $Shat[t]$ can be estimated by averaging the sequence $x[t] - mhat[t]$ for each of `1:period`. For example, the seasonal component in January can be estimated by the average of all of the observations made in January after removing the trend component. To ensure the identifiability of $m[t]$ and $S[t]$, we have to assume

$$S[i + j * period] = S[i], \sum S[i] = 0,$$

where $i = 1, ..., period; j = floor(n/period)$. The irregularity or residuals are then computed by $Rhat[t] = x[t] - mhat[t] - Shat[t]$. For $t < q + 1$ and $t > n - q$, the corresponding estimators are based on equation (7) in D. Qiu *et al.* (2013). More details about estimating the trend component can be seen in Section 1.5 of P.J. Brockwell *et al.* (1991) or Chapter 6 of J. Fan *et al.* (2003).

For the multiplicative seasonal model

$$x[t] = m[t] * S[t] * R[t],$$

it can be transformed to an additive seasonal model by taking a logarithm on both sides if $x[t] > 0$, i.e.,

$$log(x[t]) = log(m[t]) + log(S[t]) + log(R[t]),$$

and then use the refined moving average filter for the components decomposition as the same in the additive seasonal model.

Plots of original data v.s fitted data, fitted trend, seasonal indices (if `seasonal = TRUE`) and residuals will be drawn if `plot = TRUE`.

Value

A matrix containing the following columns:

`data`	original data `x`.
`trend`	fitted trend.
`season`	seasonal indices if `seasonal = TRUE`.
`residual`	irregularity or residuals.

Author(s)

Debin Qiu

References

D. Qiu, Q. Shao, and L. Yang (2013), Efficient inference for autoregressive coeficient in the presence of trend. *Journal of Multivariate Analysis* 114, 40-53.

J. Fan and Q. Yao, Nonlinear Time Series: Nonparametric and Parametric Methods, first ed., Springer, New York, 2003.

P.J. Brockwell, R.A. Davis, Time Series: Theory and Methods, second ed., Springer, New York, 1991.

See Also

`ss.filter`

Examples

```
## decompose the trend for the first difference of annual global air temperature from 1880-1985
data(globtemp)
decomp1 <- ma.filter(globtemp)

## decompose the trend and seasonality for CO2 data with monthly and additive seasonality
decomp2 <- ma.filter(co2, seasonal = TRUE, period = 12)

## decompose the trend and seasonality for monthly airline passenger numbers from 1949-1960
decomp3 <- ma.filter(AirPassengers, seasonal = TRUE, period = 12)

## simulation data: oracally efficient estimation for AR(p) coefficients
d <- 12
n <- d*100
x <- (1:n)/n
y <- 1 + 2*x + 0.3*x^2 + sin(pi*x/6) + arima.sim(n = n,list(ar = 0.2), sd = 1)
fit <- ma.filter(y,seasonal = TRUE,period = 12,plot = FALSE)
ar(fit[,4], aic = FALSE, order.max = 1)$ar
```

qn *Optimal and Data-Driven Moving Average Lag q*

Description

Determines the optimal and data-driven moving average lag q.

Usage

```
qn(x)
```

Arguments

x	a numeric vector or univariate time series.

Details

For univariate time series $x[t]$, the moving average filter is defined as

$$mhat[t] = \sum x[t]/(2q+1)$$

for $q+1 \leq t \leq n+q$. The optimal and data-driven moving average lag q can be determined by using the rule-of-thumb estimator proposed in Section 3 of D. Qiu *et al.* (2013). It is determined by sample size n, variance $\gamma(0)$ and curvature m'' of the univariate series, where m'' is the second derivative of an unknown nonparametric trend function $m(t)$. To obtain the preliminary estimators of variance $\gamma(0)$ and curvature m'', $m(t)$ can be initially fitted by a cubic polynomial model. See L. Yang and R. Tscherning (1999) for more details. For the case when $q > n$, the optimal moving average lag q is set to be an integer part of $n^{4/5}/2$.

Value

qn	the optimal moving average lag q.

Author(s)

Debin Qiu

References

D. Qiu, Q. Shao, and L. Yang (2013), Efficient inference for autoregressive coeficient in the presence of trend. *Journal of Multivariate Analysis* 114, 40-53.

L. Yang, R. Tscherning (1999), Multivariate bandwidth selection for local linear regression. *Journal of the Royal Statistical Society. Series B. Statistical Methodology* 61, 793-815.

Examples

```
## load the global temperature data:
## first column is time and second column is temperature.
data(globtemp)
(q.n <- qn(globtemp))
```

`ss.filter` *Smoothing Spline Filter.*

Description

uses smoothing spline to estimate the trend, and also estimate the seasonal component if necessary.

Usage

```
ss.filter(x, seasonal = FALSE, period = NULL, plot = TRUE, ...)
```

Arguments

`x`	a numeric vector or univariate time series.
`seasonal`	a logical value indicating to estimate the seasonal component. The default is `FALSE`.
`period`	seasonal period. Only valid for `seasonal = TRUE`. The default is `FALSE`.
`plot`	a logical value indicating to make the plots. The default is `TRUE`.
`...`	optional arguments to `smooth.spline`.

Details

For univariate time seties $x[t]$, the additive seasonal model is assumed to be

$$x[t] = m[t] + S[t] + R[t],$$

where $m[t], S[t], R[t]$ are trend, seasonal and irregular components, respectively. The trend $m[t]$ is estimated by cubic (default) smoothing spline using function `smooth.spline`. The estimated trend is denoted to be $mhat[t]$. If seasonal component is present (`seasonal = TRUE`), the seasonal indices $Shat[t]$ can be estimated by averaging the sequence $x[t]-mhat[t]$ for each of `1:period`, defined as $Shat[t]$. For example, the seasonal component in January can be estimated by the average of all of the observations made in January after removing the trend component. To ensure the identifiability of $m[t]$ and $S[t]$, we have to assume

$$S[i + j * period] = S[i], \sum S[i] = 0,$$

where $i = 1, ..., period; j = floor(n/period)$. The irregularity or residuals are computed by $Rhat[t] = x[t] - mhat[t] - Shat[t]$.

For the multiplicative seasonal model

$$x[t] = m[t] * S[t] * R[t],$$

it can be transformed to an additive seasonal model by taking a logarithm on both sides if $x[t] > 0$, i.e.,

$$log(x[t]) = log(m[t]) + log(S[t]) + log(R[t]),$$

and then use the refined moving average filter for the components decomposition as the same in the additive seasonal model.

Plots of original data v.s fitted data, fitted trend, seasonal indices (if `seasonal = TRUE`) and residuals will be drawn if `plot = TRUE`.

Value

A matrix containing the following columns:

`data`	original data `x`.
`trend`	fitted trend.
`season`	seasonal indices if `seasonal = TRUE`.
`residual`	irregularity or residuals.

Author(s)

Debin Qiu

References

Green, P. J. and Silverman, B. W. (1994) Nonparametric Regression and Generalized Linear Models: A Roughness Penalty Approach. Chapman and Hall.

Hastie, T. J. and Tibshirani, R. J. (1990) Generalized Additive Models. Chapman and Hall.

J. Fan and Q. Yao, Nonlinear Time Series: Nonparametric and Parametric Methods, first ed., Springer, New York, 2003.

See Also

`ma.filter`

Examples

```
## decompose the trend for the first difference of annual global air temperature from 1880-1985
data(globtemp)
decomp1 <- ss.filter(globtemp)

## decompose the trend and seasonality for CO2 data with monthly and additive seasonality
decomp2 <- ss.filter(co2, seasonal = TRUE, period = 12)

## decompose the trend and seasonality for monthly airline passenger numbers from 1949-1960
decomp3 <- ss.filter(AirPassengers, seasonal = TRUE, period = 12)

## simulation data: oracally efficient estimation for AR(p) coefficients
d <- 12
n <- d*100
x <- (1:n)/n
```

```
y <- 1 + 2*x + 0.3*x^2 + sin(pi*x/6) + arima.sim(n = n,list(ar = 0.2), sd = 1)
fit <- ss.filter(y, seasonal = TRUE,period = 12, plot = FALSE)
ar(fit[,4], aic = FALSE, order.max = 1)$ar
```

Index