Package 'SNSeg'

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Author Zifeng Zhao [aut, com], Shubo Sun [com, cre], Xiaofeng Shao [aut, ths], Feiyu Jiang [ths] Maintainer Shubo Sun <shubos2@illinois.edu> Archs i386, x64</shubos2@illinois.edu>
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 $\begin{tabular}{ll} critical_values_HD & Critical\ Values\ of\ Self-normalization\ for\ high-dimensional\ time\ series\ (SNHD) \end{tabular}$

Description

A dataset containing the critical value of each window size at each confidence level for SNHD.

Usage

```
critical_values_HD
```

Format

A data frame with 6 variables:

epsilon window size to estimate change points

- 0.9 critical value at confidence level 0.9
- 0.95 critical value at confidence level 0.95
- 0.99 critical value at confidence level 0.99
- 0.995 critical value at confidence level 0.995
- 0.999 critical value at confidence level 0.999

critical_values_multi Critical Values of Self-normalization for multi-parameters

Description

A dataset containing the critical value of each window size at each confidence level for Self-normalization change points estimate based on multi-parameters.

Usage

```
critical_values_multi
```

Format

A data frame with 7 variables:

epsilon window size to estimate change points

- p dimension of the multi-parameters
- 0.9 critical value at confidence level 0.9
- 0.95 critical value at confidence level 0.95
- 0.99 critical value at confidence level 0.99
- 0.995 critical value at confidence level 0.995
- 0.999 critical value at confidence level 0.999

critical_values_single 3

```
critical_values_single
```

Critical Values of Self-normalization for single-parameter

Description

A dataset containing the critical value of each window size at each confidence level for Self-normalization change points estimate based on one single parameter.

Usage

```
critical_values_single
```

Format

A data frame with 6 variables:

epsilon window size to estimate change points

- 0.9 critical value at confidence level 0.9
- 0.95 critical value at confidence level 0.95
- 0.99 critical value at confidence level 0.99
- 0.995 critical value at confidence level 0.995
- 0.999 critical value at confidence level 0.999

MAR

A Funtion to generate a multivariate autoregressive process (MAR) model in time series

Description

The function MAR is used for generating MAR model(s) for examples under $SNSeg_Uni_single_para$, $SNSeg_Uni_multi_para$, and $SNSeg_Multi$.

Usage

```
MAR(n, reptime, rho)
```

Arguments

n the size of time series to be generated reptime the number of time series to be generated

rho a correlation factor

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MAR_MTS_Covariance A Funtion to generate a multivariate autoregressive process (MAR)

model in time series (used for testing change points based on multi-

variate mean, covariance and bivariate correlation)

Description

The function MAR_MTS_Covariance is used for generating MAR model(s) for examples under SNSeg_Uni_single_para, SNSeg_Uni_multi_para, and SNSeg_Multi.

Usage

```
MAR_MTS_Covariance(n, reptime, rho_sets, cp_sets, sigma_cross)
```

Arguments

n the size of time series to be generated

reptime the number of time series to be generated

rho_sets correlation factors for simulation

cp_sets the critical points set to check SN prediction accuracy

sigma_cross a list to generate the covariance structure of the time series

MAR_Variance A Funtion to generate a multivariate autoregressive process (MAR)

model in time series (used for testing change points based on variance

and ACF)

Description

The function MAR_Variance is used for generating MAR model(s) for examples under SNSeg_Uni_single_para, SNSeg_Uni_multi_para, and SNSeg_Multi.

Usage

```
MAR_Variance(reptime, type = "V3")
```

Arguments

reptime the number of time series to be generated

type the type of time series for simulation, which includes V1, V2, V3, A1, A2 and

A3. The V-beginnings are for testing variance, and the A-beginnings are for

testing ACF.

max_SNsweep 5

max_SNsweep	Self-normalization test statistics segmentation plot for univariate and
	multivariate time series

Description

The function max_SNsweep is a single-parameter change point estimation framework for a multivariate time series using the self-normalized approach.

Usage

```
max_SNsweep(SN_sweep_result, plot_SN = TRUE)
```

Arguments

```
SN_sweep_result

a list of matrices containing the SN test statistics from SNSeg_Uni_single_para,
SNSeg_Uni_multi_para or SNSeg_Multi

plot_SN

Only if argument plot_SN is TRUE will return a SN test statistic segmentation
plot
```

```
# Please run this function before running examples:
exchange_cor_matrix <- function(d, rho){</pre>
  tmp <- matrix(rho, d, d)</pre>
  diag(tmp) <- 1</pre>
  return(tmp)
}
# univariate time series based on single parameter
set.seed(7)
n <- 2000
reptime <- 2
cp_sets <- round(n*c(0,cumsum(c(0.5,0.25)),1))
mean_shift <- c(0.4,0,0.4)
rho <- -0.7
ts <- MAR(n, reptime, rho)
no_seg <- length(cp_sets)-1</pre>
for(index in 1:no_seg){ # Mean shift
  tau1 <- cp_sets[index]+1</pre>
  tau2 <- cp_sets[index+1]</pre>
  ts[tau1:tau2,] <- ts[tau1:tau2,] + mean_shift[index]</pre>
ts <- ts[,2]
\mbox{\#} calculating SN test statistics and change points
result <- SNSeg_Uni_single_para(ts,type = "mean", confidence = 0.9,
grid_size_scale = 0.061, grid_size = NULL, plot_SN = FALSE)
# SN test statistic segmentation plot
max_SNsweep(result$SN_sweep_result, plot_SN = TRUE)
# univariate time series based on multi-parameters
set.seed(7)
```

SNSeg

```
n <- 1000
cp_sets <- c(0,333,667,1000)
no_seg <- length(cp_sets)-1</pre>
rho <- 0
# AR time series with no change-point (mean, var)=(0,1)
ts <- MAR(n, 2, rho)*sqrt(1-rho^2)
no_seg <- length(cp_sets)-1</pre>
sd_shift <- c(1,1.6,1)
for(index in 1:no_seg){ # Mean shift
  tau1 <- cp_sets[index]+1
  tau2 <- cp_sets[index+1]</pre>
  ts[tau1:tau2,] <- ts[tau1:tau2,]*sd_shift[index]</pre>
}
d < - 2
ts <- ts[,2]
# calculating SN test statistics and change points
result <- SNSeg_Uni_multi_para(ts, paras_to_test = c(0.8, 'mean', "variance", 
"acf"), confidence = 0.9, grid_size_scale = 0.05, grid_size = 83, d = 4,
plot_SN = FALSE)
# SN test statistic segmentation plot
max_SNsweep(result$SN_sweep_result, plot_SN = TRUE)
# multivariate time series (only support one single parameter!)
set.seed(10)
d <- 5
n <- 1000
cp_sets \leftarrow round(n*c(0,cumsum(c(0.075,0.3,0.05,0.1,0.05)),1))
mean_shift <- c(-3,0,3,0,-3,0)/sqrt(d)
mean_shift <- sign(mean_shift)*ceiling(abs(mean_shift)*10)/10</pre>
rho_sets <- 0.5
sigma_cross <- list(exchange_cor_matrix(d,0))</pre>
ts <- MAR_MTS_Covariance(n, 2, rho_sets, cp_sets=c(0,n), sigma_cross)</pre>
noCP <- length(cp_sets)-2</pre>
no_seg <- length(cp_sets)-1</pre>
for(rep_index in 1:2){
  for(index in 1:no_seg){ # Mean shift
    tau1 <- cp_sets[index]+1
    tau2 <- cp_sets[index+1]</pre>
    ts[[rep_index]][,tau1:tau2] <- ts[[rep_index]][,tau1:tau2] + mean_shift[index]
  }
ts <- ts[1][[1]]
# calculating SN test statistics and change points
result <- SNSeg_Multi(ts, type = "mean", confidence = 0.9,
grid_size_scale = 0.079, grid_size = NULL)
# SN test statistic segmentation plot
max_SNsweep(result$SN_sweep_result, plot_SN = TRUE)
```

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Description

The SNuni package provides three important functions: SNSeg_Uni_single_para, SNSeg_Uni_multi_para and SNSeg_Multi. Since SN-based testing approach uses test statistic to make change point estimates, two critical value tables (critical_values_single and critical_values_multi) were attached.

SNSeg_Uni_single_para

SNSeg_Uni_single_para provides change points estimates for a univariate time series based on changes in a single parameter using self-normalized approach.

For the parameters of the user-defined time series, the function $SNSeg_Uni_single_para$ offers mean, variance, acf, bivariate correlation and quantiles as avaliale choice. To visualize the changes in time series, users can set "plot $_SN = TRUE$ " to see the SN segmentation plot. The output includes the type of the parameter, the minimal window size to contain a potential change point, and the lag(s) where the change point(s) occur.

SNSeg_Uni_multi_para

SNSeg_Uni_mul_para provides change points estimates for a univariate time series based on changes in multi-parameters using self-normalized approach.

Different from SNSeg_Uni_single_para, SNSeg_Uni_multi_para allows users to place multiple parameters as input. Users can also get the segmentation plot by setting "plot_SN = TRUE". The output is the same as those of SNSeg_Uni_single_para.

SNSeg Multi

SNSeg_Multi provides change points estimates for a multivariate time series based on changes in single-parameter using self-normalized approach.

Different from $SNSeg_Uni_single_para$ and $SNSeg_Uni_mul_para$, $SNSeg_Multi$ does not provide the segmentation plots for users. Users can plot each of the time series by "plot()" and add "abline(v = ...)", of which "..." represents the change point location from $SNSeg_Multi$'s output. The other output of $SNSeg_Multi$ is the same as the previous two functions.

critical values table

The package SNuni provides two critical values table.

Table critical_values_single records critical values of each window size at each confidence level for SN change points estimate based on one single parameter.

Table critical_values_multi records critical values of each window size at each confidence level for SN change points estimate based on multi-parameters.

SNSeg_HD	Self-normalization change points estimation for high dimensional time
	series based on changes in multi-means (SNHD).

Description

The function SNSeg_HD is a SNHD change point estimation framework.

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Usage

```
SNSeg_HD(ts, confidence = 0.9, grid_size_scale = 0.05, grid_size = NULL)
```

Arguments

ts numeric data of a univariate time series

confidence the confidence level that can be expected to produce a significant Self-normalization

test statistic. The avaliable confidence levels are 0.9, 0.95, 0.99, 0.995 and 0.999.

grid_size_scale

the window size parameter to determine the mimimum range where an estimated change point for a univariate time series can occur. The grid_size_scale can be selected from the following: 0.05, 0.06, 0.07, 0.08, 0.09, 0.1, 0.11, 0.12, 0.13,

0.14, 0.15, 0.2, 0.25, 0.3, 0.35, 0.4, 0.45 and 0.5.

grid_size the window size to cover an estimated change point, which is calculated from

grid_size_scale. The function depends on the value of grid_size instead of grid_size_scale within input, and only when grid_size is NULL will the function

use the grid_size_scale in the input.

Value

SNSeg_HD returns the minimum window size to cover a change point, and the lags of which all estimated change points take place.

grid_size the minimal window size to detect a potential change point

SN_sweep_result a list of matrices to record the test statistics, the location of the estimated change points, and the range of the window set to contain each change point

est_cp the estimated change points for the given time series

confidence the confidence level for SN tests

critical_value the critical value for SN change points estimation

```
n <- 600
p <- 100
nocp <- 5
cp_sets <- round(seq(0,nocp+1,1)/(nocp+1)*n)</pre>
num_entry <- 5</pre>
kappa <- sqrt(4/5) # Wang et al(2020)
mean_shift <- rep(c(0, kappa), 100)[1:(length(cp_sets)-1)]
set.seed(1)
ts <- matrix(rnorm(n*p,0,1),n,p)</pre>
no_seg <- length(cp_sets)-1</pre>
for(index in 1:no_seg){ # Mean shift
  tau1 <- cp_sets[index]+1
 tau2 <- cp_sets[index+1]</pre>
 ts[tau1:tau2,1:num\_entry] <- ts[tau1:tau2,1:num\_entry] + mean\_shift[index] \# sparse change
}
# grid_size undefined
SNSeg_HD(ts, confidence = 0.9, grid_size_scale = 0.05,
         grid_size = NULL)
# grid_size defined
SNSeg_HD(ts, confidence = 0.9, grid_size_scale = 0.05,
         grid_size = 52)
```

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SNSeg_Multi	Self-normalization change points estimation for multivariate time series based on single parameter changes

Description

The function SNSeg_Uni is a single-parameter change point estimation framework for a multivariate time series using the self-normalized approach.

Usage

```
SNSeg_Multi(
   ts,
   type = "mean",
   confidence = 0.9,
   grid_size = NULL,
   grid_size_scale = 0.05
)
```

Arguments

ts	numeric data of a multivariate time series	
type	the type of parameters of time series data that SN depends, which includes mean and covariance.	
confidence	the confidence level that can be expected to produce a significant Self-normalization test statistic	
grid_size	the window size to cover an estimated change point, which is calculated from grid_size_scale. The function depends on the value of grid_size instead of grid_size_scale within input, and only when grid_size is NULL will the function use the grid_size_scale in the input.	
grid_size_scale		
	the window size parameter to determine the mimimum range where an estimated change point for a time series can occur	

Value

SNSeg_Multi returns the type of the multivariate time series, the minimum window size to cover a change point, and the lags of which all estimated change points take place.

type the type of parameter being used for self-normalization

grid_size the minimal window size to detect a potential change point

SN_sweep_result a list of matrices to record the test statistics, the location of the estimated change points, and the range of the window set to contain each change point

est_cp the estimated change points for the given time series

confidence the confidence level for SN tests

critical_value the critical value for SN change points estimation

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```
# Please run this function before running examples:
exchange_cor_matrix <- function(d, rho){</pre>
  tmp <- matrix(rho, d, d)</pre>
  diag(tmp) <- 1
  return(tmp)
}
# SN Segmentation for Multivariate Mean
library(mvtnorm)
set.seed(10)
d <- 5
n <- 1000
cp_sets \leftarrow round(n*c(0, cumsum(c(0.075, 0.3, 0.05, 0.1, 0.05)), 1))
mean_shift <- c(-3,0,3,0,-3,0)/sqrt(d)
mean_shift <- sign(mean_shift)*ceiling(abs(mean_shift)*10)/10</pre>
rho_sets <- 0.5
sigma_cross <- list(exchange_cor_matrix(d,0))</pre>
ts <- MAR_MTS_Covariance(n, 2, rho_sets, cp_sets=c(0,n), sigma_cross)
noCP <- length(cp_sets)-2</pre>
no_seg <- length(cp_sets)-1</pre>
for(rep_index in 1:2){
  for(index in 1:no_seg){ # Mean shift
    tau1 <- cp_sets[index]+1</pre>
    tau2 <- cp_sets[index+1]</pre>
    ts[[rep\_index]][,tau1:tau2] <- ts[[rep\_index]][,tau1:tau2] + mean\_shift[index]
  }
ts <- ts[1][[1]]
# grid_size undefined
SNSeg_Multi(ts, type = "mean", confidence = 0.95, grid_size_scale = 0.079,
            grid_size = NULL)
# grid_size defined
SNSeg_Multi(ts, type = "mean", confidence = 0.99, grid_size_scale = 0.05,
            grid_size = 65)
# SN Segmentation for Multivariate Covariance
library(mvtnorm)
set.seed(10)
reptime <- 2
d <- 4
n <- 1000
sigma_cross <- list(exchange_cor_matrix(d,0.2), 2*exchange_cor_matrix(d,0.5),</pre>
                     4*exchange_cor_matrix(d,0.5))
rho_sets <- c(0.3, 0.3, 0.3)
mean_shift <- c(0,0,0) # with mean change
cp_sets <- round(c(0,n/3,2*n/3,n))
# 2-dimensional AR time series with change-point in bivariate correlation
ts <- MAR_MTS_Covariance(n, reptime, rho_sets, cp_sets, sigma_cross)</pre>
noCP <- length(cp_sets)-2</pre>
no_seg <- length(cp_sets)-1</pre>
for(rep_index in 1:reptime){
  for(index in 1:no_seg){ # Mean shift
    tau1 <- cp_sets[index]+1</pre>
    tau2 <- cp_sets[index+1]</pre>
```

SNSeg_Uni_multi_para Self-normalization change point estimates for univariate time series based on multi-parameters' changes

Description

The function SNSeg_Uni_multi_para is a multi-parameter change point estimation framework for a univariate time series using the self-normalized approach.

Usage

```
SNSeg_Uni_multi_para(
   ts,
   paras_to_test = c(0.9, 0.95),
   confidence = 0.9,
   grid_size_scale = 0.05,
   grid_size = NULL,
   d = 2,
   plot_SN = FALSE
)
```

Arguments

ts	numeric data of a univariate time series	
paras_to_test	the multi-parameters of ts to be measured and tested. The type(s) of input for paras_to_test includes "mean", "variance", "acf", and all numeric value of quantile(s) between 0 and 1.	
confidence	the confidence level that can be expected to produce a significant Self-normalization test statistic	
grid_size_scale		
	the window size parameter to determine the mimimum range where an estimated change point for a time series can occur	
grid_size	the window size to cover an estimated change point, which is calculated from grid_size_scale. The function depends on the value of grid_size instead of grid_size_scale within input, and only when grid_size is NULL will the function use the grid_size_scale in the input.	
d	the dimension of paras_to_test	
plot_SN	Only if argument plot_SN is TRUE will return a SN segmentation plot	

Value

SNSeg_Uni_multi_para returns the type of the multivariate time series, the minimum window size to cover a change point, and the lags where all estimated change points take place.

parameter the type of parameter being used for self-normalization

grid_size the minimal window size to detect a potential change point

SN_sweep_result a list of matrices to record the test statistics, the location of the estimated change points, and the range of the window set to contain each change point

est_cp the estimated change points for the given time series

confidence the confidence level for SN tests

critical_value the critical value for SN change points estimation

```
set.seed(7)
n <- 1000
cp_sets <- c(0,333,667,1000)
no_seg <- length(cp_sets)-1</pre>
rho <- 0
# AR time series with no change-point (mean, var)=(0,1)
ts \leftarrow MAR(n, 2, rho)*sqrt(1-rho^2)
no_seg <- length(cp_sets)-1</pre>
sd_shift <- c(1,1.6,1)
for(index in 1:no_seg){ # Mean shift
  tau1 <- cp_sets[index]+1
  tau2 <- cp_sets[index+1]</pre>
  ts[tau1:tau2,] <- ts[tau1:tau2,]*sd_shift[index]</pre>
}
d < -2
ts <- ts[,2]
# 90th and 95th quantile with grid_size undefined
SNSeg_Uni_multi_para(ts, paras_to_test = c(0.9, 0.95),
                      confidence = 0.9, grid_size_scale = 0.05, grid_size = NULL,
                      d = 2, plot_SN = FALSE)
# 90th quantile and the variance with grid_size undefined
SNSeg_Uni_multi_para(ts, paras_to_test = c(0.9, 'variance'),
                      confidence = 0.95, grid_size_scale = 0.078, grid_size = NULL,
                      d = 2, plot_SN = FALSE)
# 90th quantile, variance and acf with grid_size undefined
SNSeg_Uni_multi_para(ts, paras_to_test = c(0.9, 'variance', "acf"),
                      confidence = 0.9, grid_size_scale = 0.064, grid_size = NULL,
                      d = 3, plot_SN = TRUE)
# 60th quantile, mean, variance and acf with grid_size defined
SNSeg_Uni_multi_para(ts, paras_to_test = c(0.6, 'mean', "variance", "acf"),
                      confidence = 0.9, grid_size_scale = 0.05, grid_size = 83,
                      d = 4, plot_SN = TRUE)
```

SNSeg_Uni_single_para Self-normalization change points estimation for univariate time series based on one single parameter changes

Description

The function SNSeg_Uni_single_para is a single-parameter change point estimation framework for a univariate time series using the self-normalized approach.

Usage

```
SNSeg_Uni_single_para(
   ts,
   type = "mean",
   confidence = 0.9,
   quantile_level = 0.1,
   grid_size_scale = 0.05,
   grid_size = NULL,
   plot_SN = FALSE
)
```

Arguments

ts numeric data of a univariate time series

type the type of parameters of time series data that SN depends, which includes mean,

variance, acf, bivcor and quantile.

confidence the confidence level that can be expected to produce a significant Self-normalization

test statistic. The avaliable confidence levels are 0.9, 0.95, 0.99, 0.995 and 0.999.

quantile_level the quantile level of the given time series

grid_size_scale

the window size parameter to determine the mimimum range where an estimated change point for a univariate time series can occur. The grid_size_scale can be selected from the following: 0.05, 0.06, 0.07, 0.08, 0.09, 0.1, 0.11, 0.12, 0.13,

0.14, 0.15, 0.2, 0.25, 0.3, 0.35, 0.4, 0.45 and 0.5.

grid_size the window size to cover an estimated change point, which is calculated from

grid_size_scale. The function depends on the value of grid_size instead of grid_size_scale within input, and only when grid_size is NULL will the function

use the grid_size_scale in the input.

plot_SN Only if argument plot_SN is TRUE will return an SN segmentation plot

Value

SNSeg_Uni_single_para returns the type of the univariate time series, the minimum window size to cover a change point, and the lags of which all estimated change points take place.

type the type of parameter being used for self-normalization

grid_size the minimal window size to detect a potential change point

SN_sweep_result a list of matrices to record the test statistics, the location of the estimated change points, and the range of the window set to contain each change point

est_cp the estimated change points for the given time series confidence the confidence level for SN tests critical_value the critical value for SN change points estimation

```
# Please run the following function before running examples:
\label{eq:mix_GauGPD} $$ \leftarrow $ function(u,p,trunc_r,gpd_scale,gpd_shape) $$ $$
    indicator <- u<p
     rv <- rep(0, length(u))</pre>
    rv[indicator>0] <- qtruncnorm(u[indicator>0]/p,a=-Inf,b=trunc_r)
   \label{eq:continuity} $$ rv[indicator <= \emptyset] <= qgpd((u[indicator <= \emptyset] -p)/(1-p), loc=trunc_r, scale=gpd\_scale, shape=gpd\_shape) $$ $$ rv[indicator <= \emptyset] <= qgpd((u[indicator <= \emptyset] -p)/(1-p), loc=trunc_r, scale=gpd\_scale, shape=gpd\_shape) $$ $$ $$ rv[indicator <= \emptyset] <= qgpd((u[indicator <= \emptyset] -p)/(1-p), loc=trunc_r, scale=gpd\_scale, shape=gpd\_shape) $$ $$ $$ $$ rv[indicator <= \emptyset] <= qgpd((u[indicator <= \emptyset] -p)/(1-p), loc=trunc_r, scale=gpd\_scale, shape=gpd\_shape) $$ $$ $$ $$ rv[indicator <= \emptyset] <= qgpd((u[indicator <= \emptyset] -p)/(1-p), loc=trunc_r, scale=gpd\_scale, shape=gpd\_shape) $$ $$ $$ $$ rv[indicator <= \emptyset] <= qgpd((u[indicator <= \emptyset] -p)/(1-p), loc=trunc_r, scale=gpd\_scale, shape=gpd\_shape) $$ $$ $$ $$ rv[indicator <= \emptyset] <= qgpd((u[indicator <= \emptyset] -p)/(1-p), loc=trunc_r, scale=gpd\_scale, shape=gpd\_shape) $$ $$ $$ $$ $$ rv[indicator <= \emptyset] <= qgpd((u[indicator <= \emptyset] -p)/(1-p), loc=trunc_r, scale=gpd\_scale, shape=gpd\_shape) $$ $$ $$ rv[indicator <= \emptyset] <= qgpd((u[indicator <= \emptyset] -p)/(1-p), loc=trunc_r, scale=gpd\_scale, shape=gpd\_scale, shape=gpd\_
# SN Segmentation for Mean
set.seed(7)
n <- 2000
reptime <- 2
cp_sets <- round(n*c(0, cumsum(c(0.5, 0.25)), 1))
mean_shift <- c(0.4,0,0.4)
rho <- -0.7
ts <- MAR(n, reptime, rho)</pre>
no_seg <- length(cp_sets)-1</pre>
for(index in 1:no_seg){ # Mean shift
    tau1 <- cp_sets[index]+1</pre>
    tau2 <- cp_sets[index+1]</pre>
    ts[tau1:tau2,] <- ts[tau1:tau2,] + mean_shift[index]</pre>
}
ts <- ts[,2]
# grid_size undefined
SNSeg_Uni_single_para(ts,type = "mean", confidence = 0.9,
                 grid_size_scale = 0.05, grid_size = NULL, plot_SN = FALSE)
# grid_size defined
SNSeg_Uni_single_para(ts,type = "mean", confidence = 0.9,
                 grid_size_scale = 0.05, grid_size = 116, plot_SN = FALSE)
# SN Segmentation for Variance
set.seed(7)
ts <- MAR_Variance(2, "V1")</pre>
ts <- ts[,2]
# grid_size undefined
SNSeg_Uni_single_para(ts,type = "variance", confidence = 0.9,
                 grid_size_scale = 0.067, grid_size = NULL, plot_SN = FALSE)
# grid_size defined
SNSeg_Uni_single_para(ts,type = "variance", confidence = 0.9,
                 grid_size_scale = 0.05, grid_size = 67, plot_SN = FALSE)
# SN Segmentation for ACF
set.seed(7)
ts <- MAR_Variance(2, "A3")
ts <- ts[,2]
# grid_size undefined
SNSeg_Uni_single_para(ts,type = "acf", confidence = 0.9,
                 grid_size_scale = 0.05, grid_size = NULL, plot_SN = FALSE)
# grid_size defined
```

```
SNSeg_Uni_single_para(ts,type = "acf", confidence = 0.9,
       grid_size_scale = 0.05, grid_size = 92, plot_SN = FALSE)
# SN Segmentation for bivariate correlation
library(mvtnorm)
set.seed(7)
n <- 1000
sigma_cross <- list(4*matrix(c(1,0.8,0.8,1), nrow=2),</pre>
      matrix(c(1,0.2,0.2,1), nrow=2), matrix(c(1,0.8,0.8,1), nrow=2))
cp_sets <- round(c(0,n/3,2*n/3,n))
noCP <- length(cp_sets)-2</pre>
rho_sets \leftarrow rep(0.5, noCP+1)
ts <- MAR_MTS_Covariance(n, 2, rho_sets, cp_sets, sigma_cross)</pre>
ts <- ts[1][[1]]
# grid_size undefined
SNSeg_Uni_single_para(ts,type = "bivcor", confidence = 0.9,
        grid_size_scale = 0.05, grid_size = NULL, plot_SN = TRUE)
# grid_size defined
SNSeg_Uni_single_para(ts,type = "bivcor", confidence = 0.9,
        grid_size_scale = 0.05, grid_size = 77, plot_SN = TRUE)
# SN Segmentation for quantile
library(truncnorm)
library(evd)
set.seed(7)
n <- 1000
cp_sets \leftarrow c(0,n/2,n)
noCP <- length(cp_sets)-2</pre>
reptime <- 2
rho <- 0.2
# AR time series with no change-point (mean, var)=(0,1)
ts <- MAR(n, reptime, rho)*sqrt(1-rho^2)
trunc_r <- 0
p <- pnorm(trunc_r)</pre>
gpd_scale <- 2</pre>
gpd_shape <- 0.125
for(ts_index in 1:reptime){
 ts[(cp_sets[2]+1):n, ts_index] <- mix_GauGPD(pnorm(ts[(cp_sets[2]+1):n, ts_index]),
                                      p,trunc_r,gpd_scale,gpd_shape)
ts <- ts[,2]
SNSeg_Uni_single_para(ts,type = "quantile", confidence = 0.9, quantile_level = 0.9,
        grid\_size\_scale = 0.066, grid\_size = NULL, plot\_SN = TRUE)
SNSeg_Uni_single_para(ts,type = "quantile", confidence = 0.9, quantile_level = 0.8,
        grid_size_scale = 0.05, grid_size = 102, plot_SN = TRUE)
```

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