Package ‘svars’

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Description Implements data-driven identification methods for structural vector autoregressive (SVAR) models. Based on an existing VAR model object (provided by e.g. VAR() from the 'vars' package), the structural impact matrix is obtained via data-driven identification techniques (i.e. changes in volatility (Rigobon, R. (2003) <doi:10.1162/003465303772815727>), least dependent innovations (Herwartz, H., Ploedt, M., (2016) <doi:10.1016/j.jimonfin.2015.11.001>) or non-Gaussian maximum likelihood (Lanne, M., Meitz, M., Saikkonen, P. (2017) <doi:10.1016/j.jeconom.2016.06.002>).

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`svars-package` *Data-driven identification of structural VAR models*

Description

This package implements data-driven identification methods for structural vector autoregressive (SVAR) models. Based on an existing VAR model object, the structural impact matrix B may be obtained via changes in volatility, least dependent innovations or non-Gaussian maximum likelihood.

Details

The main functions to retrieve structural impact matrices are:

`id.cv` Identification via changes in volatility,

`id.nglm` Identification via Non-Gaussian maximum likelihood,

`id.dc` Independence-based identification of SVAR models based on distance covariances,

`id.cvm` Independence-based identification of SVAR models based on Cramer-von Mises distance.

All of these functions require an estimated var object. Currently the classes 'vars' and 'vec2var' from the `vars` package, 'nlVar', which includes both VAR and VECM, from the `tsDyn` package as well as the list from `MTS` package are supported. Besides these core functions, some additional tools to calculate confidence bands for impulse response functions using bootstrap techniques as well as the Chow-Test for structural change are implemented. The USA dataset is used to showcase the functionalties in examples throughout the package.

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chow.test *Chow Test for Structural Break*

Description

The Chow test for structural change is implemented as sample-split and break-point test (see Luetkepohl and Kraetzig, 2004, p. 135). A multivariate time series and the presupposed structural break need to be provided.

Usage

```
chow.test(Y, SB, p, nboot = 500, rademacher = "FALSE", start = NULL,
  end = NULL, frequency = NULL, format = NULL, dateVector = NULL)
```

Arguments

Y	Data of multivariate time series in matrix form
SB	Integer, vector or date character. The structural break is specified either by an integer (number of observations in the pre-break period), a vector of ts() frequencies if a ts object is used in the VAR or a date character. If a date character is provided, either a date vector containing the whole time line in the corresponding format or common time parameters need to be provided
p	Integer. Number of lags included in the presumed VAR model
nboot	Integer. Number of bootstrap iterations to calculate quantiles and p-values
rademacher	If rademacher="TRUE", the Rademacher distribution is used to generate the bootstrap samples
start	Character. Start of the time series (only if dateVector is empty)
end	Character. End of the time series (only if dateVector is empty)
frequency	Character. Frequency of the time series (only if dateVector is empty)
format	Character. Date format (only if dateVector is empty)
dateVector	Vector. Vector of time periods containing SB in corresponding format

Value

A list with elements

`lambda_bp`	Test statistic of the Chow test with break point
`testcrit_bp`	Critical value of the test statistic lambda_bp
`p.value_bp`	p-value of the test statistic lambda_bp
`lambda_sp`	Test statistic of the Chow test with sample split
`testcrit_sp`	Critical value of the test statistic lambda_sp
`p.value_sp`	p-value of the test statistic lambda_sp

References

Luetkepohl, H., 2005. New introduction to multiple time series analysis, Springer-Verlag, Berlin.
Luetkepohl, H., Kraetzig, M., 2004. Applied time series econometrics, Cambridge University Press, Cambridge.

Examples

```
# Testing for structural break in USA data
z1 = chow.test(USA, SB = 59, p = 6)
summary(z1)

#Structural brake via Dates
#given that time series vector with dates is available
dateVector = seq(as.Date("1965/1/1"), as.Date("2008/7/1"), "quarter")
z2 <- chow.test(USA, SB = "1979-07-01", p = 6, format = "%Y-%m-%d", dateVector = dateVector)
summary(z2)

# alternatively pass sequence arguments directly
z3 <- chow.test(USA, SB = "1979-07-01", p = 6, format = "%Y-%m-%d",
                start = "1965-01-01", end = "2008-07-01",
                frequency = "quarter")
summary(z3)

# or provide ts date format (For quarterly, monthly, weekly and daily frequencies only)
z4 <- chow.test(USA, SB = c(1979,3), p = 6)
summary(z4)
```

`fev` *Forecast error variance decomposition for SVAR Models*

Description

Calculation of forecast error variance decomposition for an identified SVAR object 'svars' derived by function id.cvm( ),id.cv( ),id.dc( ) or id.ngml( ).

Usage

```
fev(x, horizon = 10)
```

Arguments

x	SVAR object of class "svars"
horizon	Time horizon for forecast error variance decomposition

References

Kilian, L., Luetkepohl, H., 2017. Structural Vector Autoregressive Analysis, Cambridge University Press.

See Also

id.cvm, id.dc, id.ngml or id.cv

Examples

```
v1 <- vars::VAR(USA, lag.max = 10, ic = "AIC" )
x1 <- id.dc(v1)
x2 <- fev(x1, horizon = 30)
plot(x2)
```

---

hd *Historical decomposition for SVAR Models*

Description

Calculation of historical decomposition for an identified SVAR object 'svars' derived by function id.cvm( ),id.cv( ),id.dc( ) or id.ngml( ).

Usage

```
hd(x, series = 1)
```

Arguments

x	SVAR object of class "svars"
series	Integer, indicating the series that should be decomposed.

References

Kilian, L., Luetkepohl, H., 2017. Structural Vector Autoregressive Analysis, Cambridge University Press.

See Also

id.cvm, id.dc, id.ngml or id.cv

Examples

```
v1 <- vars::VAR(USA, lag.max = 10, ic = "AIC" )
x1 <- id.dc(v1)
x2 <- hd(x1, series = 2)
plot(x2)
```

---

id.cv *Changes in volatility identification of SVAR models*

Description

Given an estimated VAR model, this function applies changes in volatility to identify the structural impact matrix B of the corresponding SVAR model

$$y_t = c_t + A_1 y_{t-1} + ... + A_p y_{t-p} + u_t = c_t + A_1 y_{t-1} + ... + A_p y_{t-p} + B\epsilon_t.$$

Matrix B corresponds to the decomposition of the pre-break covariance matrix $\Sigma_1 = BB'$. The post-break covariance corresponds to $\Sigma_2 = B\Lambda B'$ where Λ is the estimated unconditional heteroskedasticity matrix.

Usage

```
id.cv(x, SB, start = NULL, end = NULL, frequency = NULL, format = NULL,
  dateVector = NULL, max.iter = 50, crit = 0.001,
  restriction_matrix = NULL)
```

Arguments

x	An object of class 'vars', 'vec2var', 'nlVar'. Estimated VAR object
SB	Integer, vector or date character. The structural break is specified either by an integer (number of observations in the pre-break period), a vector of ts() frequencies if a ts object is used in the VAR or a date character. If a date character is provided, either a date vector containing the whole time line in the corresponding format (see examples) or common time parameters need to be provided
start	Character. Start of the time series (only if dateVector is empty)
end	Character. End of the time series (only if dateVector is empty)
frequency	Character. Frequency of the time series (only if dateVector is empty)
format	Character. Date format (only if dateVector is empty)
dateVector	Vector. Vector of time periods containing SB in corresponding format

max.iter	Integer. Number of maximum GLS iterations
crit	Integer. Critical value for the precision of the GLS estimation
restriction_matrix	Matrix. A matrix containing presupposed entries for matrix B, NA if no restriction is imposed (entries to be estimated)

Value

A list of class "svars" with elements

Lambda	Estimated unconditional heteroscedasticity matrix Λ
Lambda_SE	Matrix of standard errors of Lambda
B	Estimated structural impact matrix B, i.e. unique decomposition of the covariance matrix of reduced form residuals
B_SE	Standard errors of matrix B
n	Number of observations
Fish	Observed Fisher information matrix
Lik	Function value of likelihood
wald_statistic	Results of pairwise Wald tests
iteration	Number of GLS estimations
method	Method applied for identification
SB	Structural break (number of observations)
SBcharacter	Structural break (date; if provided in function arguments)

References

Rigobon, R., 2003. Identification through Heteroskedasticity. The Review of Economics and Statistics, 85, 777-792.
Herwartz, H. & Ploedt, M., 2016. Simulation Evidence on Theory-based and Statistical Identification under Volatility Breaks Oxford Bulletin of Economics and Statistics, 78, 94-112.

See Also

For alternative identification approaches see id.cvm, id.dc or id.ngml

Examples

```
# data contains quartlery observations from 1965Q1 to 2008Q2
# assumed structural break in 1979Q3
# x = output gap
# pi = inflation
# i = interest rates
set.seed(23211)
v1 <- vars::VAR(USA, lag.max = 10, ic = "AIC" )
x1 <- id.cv(v1, SB = 59)
summary(x1)
```

```
# switching columns according to sign patter
x1$B <- x1$B[,c(3,2,1)]
x1$B[,3] <- x1$B[,3]*(-1)

# Impulse response analysis
i1 <- imrf(x1, horizon = 30)
plot(i1, scales = 'free_y')

# Restrictions
# Assuming that the interest rate doesn't influence the output gap on impact
restMat <- matrix(rep(NA, 9), ncol = 3)
restMat[1,3] <- 0
x2 <- id.cv(v1, SB = 59, restriction_matrix = restMat)
summary(x2)

#Structural brake via Dates
# given that time series vector with dates is available
dateVector = seq(as.Date("1965/1/1"), as.Date("2008/7/1"), "quarter")
x3 <- id.cv(v1, SB = "1979-07-01", format = "%Y-%m-%d", dateVector = dateVector)
summary(x3)

# or pass sequence arguments directly
x4 <- id.cv(v1, SB = "1979-07-01", format = "%Y-%m-%d", start = "1965-01-01", end = "2008-07-01",
frequency = "quarter")
summary(x4)

# or provide ts date format (For quarterly, monthly, weekly and daily frequencies only)
x5 <- id.cv(v1, SB = c(1979, 3))
summary(x5)
```

`id.cvm` *Independence-based identification of SVAR models based on Cramer-von Mises distance*

Description

Given an estimated VAR model, this function applies independence-based identification for the structural impact matrix B of the corresponding SVAR model

$$y_t = c_t + A_1 y_{t-1} + ... + A_p y_{t-p} + u_t = c_t + A_1 y_{t-1} + ... + A_p y_{t-p} + B\epsilon_t.$$

Matrix B corresponds to the unique decomposition of the least squares covariance matrix $\Sigma_u = BB'$ if the vector of structural shocks ϵ_t contains at most one Gaussian shock (Comon, 1994). A nonparametric dependence measure, the Cramer-von Mises distance (Genest and Remillard, 2004), determines least dependent structural shocks. The minimum is optained by a two step optimization algorithm similar to the technique described in Herwartz and Ploedt (2016).

Usage

```
id.cvm(x, dd = NULL, itermax = 500, steptol = 100, iter2 = 75)
```

Arguments

`x`	An object of class 'vars', 'vec2var', 'nlVar'. Estimated VAR object
`dd`	Object of class 'indepTestDist' (generated by 'indepTest' from package 'copula'). A simulated independent sample of the same size as the data. If not supplied, it will be calculated by the function
`itermax`	Maximum number of iterations for DEoptim
`steptol`	Tolerance for steps without improvement for DEoptim
`iter2`	Number of iterations for the second optimization

Value

A list of class "svars" with elements

`B`	Estimated structural impact matrix B, i.e. unique decomposition of the covariance matrix of reduced form errors
`A_hat`	Estimated VAR parameter
`method`	Method applied for identifaction
`n`	Number of observations
`type`	Type of the VAR model, e.g. 'const'
`y`	Data
`p`	Number of included lags
`K`	Number of included time series
`rotation_angles`	Rotation angles, which lead to maximum independence
`inc`	Indicator. 1 = second optimization increased the estimation precision. 0 = second optimization did not increase the estimation precision
`test.stats`	Computed test statistics of independence test
`iter1`	Number of iterations of first optimization
`test1`	Minimum test statistic from first optimization
`test2`	Minimum test statistic from second optimization

References

Herwartz, H., 2015. Structural VAR modelling with independent innovations - An analysis of macroeconomic dynamics in the euro area based on a novel identification scheme
Herwartz, H. & Ploedt, M., 2016. The macroeconomic effects of oil price shocks: Evidence from a statistical identification approach, Journal of International Money and Finance, 61, 30-44
Comon, P., 1994. Independent component analysis, A new concept?, Signal Processing, 36, 287-314
Genest, C. & Remillard, B., 2004. Tests of independence and randomness based on the empirical copula process, Test, 13, 335-370

See Also

For alternative identification approaches see id.cv, id.dc or id.ngml

Examples

```
# data contains quarterly observations from 1965Q1 to 2008Q3
# x = output gap
# pi = inflation
# i = interest rates
set.seed(23211)
v1 <- vars::VAR(USA, lag.max = 10, ic = "AIC" )
cob <- copula::indepTestSim(v1$obs, v1$K, verbose=FALSE)
x1 <- id.cvm(v1, dd = cob)
summary(x1)

# switching columns according to sign pattern
x1$B <- x1$B[,c(3,2,1)]
x1$B[,3] <- x1$B[,3]*(-1)

# impulse response analysis
i1 <- imrf(x1, horizon = 30)
plot(i1, scales = 'free_y')
```

`id.dc` *Independence-based identification of SVAR models based on distance covariances*

Description

Given an estimated VAR model, this function applies independence-based identification for the structural impact matrix B of the corresponding SVAR model

$$y_t = c_t + A_1 y_{t-1} + ... + A_p y_{t-p} + u_t = c_t + A_1 y_{t-1} + ... + A_p y_{t-p} + B\epsilon_t.$$

Matrix B corresponds to the unique decomposition of the least squares covariance matrix $\Sigma_u = BB'$ if the vector of structural shocks ϵ_t contains at most one Gaussian shock (Comon, 1994). A nonparametric dependence measure, the distance covariance (Szekely et al, 2007), determines least dependent structural shocks. The algorithm described in Matteson and Tsay (2013) is applied to calculate the matrix B.

Usage

```
id.dc(x, PIT = FALSE)
```

Arguments

x	An object of class 'vars', 'vec2var', 'nlVar'. Estimated VAR object
PIT	Logical. If PIT='TRUE', the distribution and density of the independent components are estimated using gaussian kernel density estimates

Value

A list of class "svars" with elements

B	Estimated structural impact matrix B, i.e. unique decomposition of the covariance matrix of reduced form errors
A_hat	Estimated VAR parameter
method	Method applied for identifaction
n	Number of observations
type	Type of the VAR model, e.g. 'const'

References

Matteson, D. S. & Tsay, R. S., 2013. Independent Component Analysis via Distance Covariance, pre-print
Szekely, G. J.; Rizzo, M. L. & Bakirov, N. K., 2007. Measuring and testing dependence by correlation of distances Ann. Statist., 35, 2769-2794
Comon, P., 1994. Independent component analysis, A new concept?, Signal Processing, 36, 287-314

See Also

For alternative identification approaches see id.cvm, id.cv or id.ngml

Examples

```
# data contains quarterly observations from 1965Q1 to 2008Q3
# x = output gap
# pi = inflation
# i = interest rates
set.seed(23211)
v1 <- vars::VAR(USA, lag.max = 10, ic = "AIC" )
x1 <- id.dc(v1)
summary(x1)

# switching columns according to sign pattern
x1$B <- x1$B[,c(3,2,1)]
x1$B[,3] <- x1$B[,3]*(-1)

# impulse response analysis
i1 <- imrf(x1, horizon = 30)
plot(i1, scales = 'free_y')
```

`id.ngml` *Non-Gaussian maximum likelihood identification of SVAR models*

Description

Given an estimated VAR model, this function applies identification by means of a non-Gaussian likelihood for the structural impact matrix B of the corresponding SVAR model

$$y_t = c_t + A_1 y_{t-1} + ... + A_p y_{t-p} + u_t = c_t + A_1 y_{t-1} + ... + A_p y_{t-p} + B\epsilon_t.$$

Matrix B corresponds to the unique decomposition of the least squares covariance matrix $\Sigma_u = BB'$ if the vector of structural shocks ϵ_t contains at most one Gaussian shock (Comon, 94). A likelihood function of independent t-distributed structural shocks $\epsilon_t = B^{-1}u_t$ is maximized with respect to the entries of B and the degrees of freedom of the t-distribution (Lanne et al., 2017).

Usage

```
id.ngml(x, stage3 = FALSE)
```

Arguments

`x`	An object of class 'vars', 'vec2var', 'nlVar'. Estimated VAR object
`stage3`	Logical. If stage3="TRUE", the VAR parameters are estimated via non-gaussian maximum likelihood (computationally demanding)

Value

A list of class "svars" with elements

`B`	Estimated structural impact matrix B, i.e. unique decomposition of the covariance matrix of reduced form errors
`sigma`	Estimated scale of the standardized matrix B_stand, i.e. $B = B_stand * diag(\sigma_1, ..., \sigma_K)$
`sigma_SE`	Standard errors of the scale
`df`	Estimated degrees of freedom
`df_SE`	Standard errors of the degrees of freedom
`Fish`	Observed Fisher information matrix
`A_hat`	Estimated VAR parameter
`B_stand`	Estimated standardized structural impact matrix
`B_stand_SE`	Standard errors of standardized matrix B_stand
`Lik`	Function value of likelihood
`method`	Method applied for identifaction
`n`	Number of observations
`type`	Type of the VAR model, e.g. 'const'

References

Lanne, M., Meitz, M., Saikkonen, P., 2017. Identification and estimation of non-Gaussian structural vector autoregressions. J. Econometrics 196 (2), 288-304.
Comon, P., 1994. Independent component analysis, A new concept?, Signal Processing, 36, 287-314

See Also

For alternative identification approaches see id.cvm, id.dc or id.cv

Examples

```
# data contains quarterly observations from 1965Q1 to 2008Q3
# x = output gap
# pi = inflation
# i = interest rates
set.seed(23211)
v1 <- vars::VAR(USA, lag.max = 10, ic = "AIC" )
x1 <- id.ngml(v1)
summary(x1)

# switching columns according to sign pattern
x1$B <- x1$B[,c(3,2,1)]
x1$B[,3] <- x1$B[,3]*(-1)

# impulse response analysis
i1 <- imrf(x1, horizon = 30)
plot(i1, scales = 'free_y')
```

---

imrf *Impulse Response Functions for SVAR Models*

Description

Calculation of impulse response functions for an identified SVAR object 'svars' derived by function id.cvm( ),id.cv( ),id.dc( ) or id.ngml( ).

Usage

```
imrf(x, horizon = 20)
```

Arguments

x	SVAR object of class "svars"
horizon	Time horizon for the impulse responses

See Also

id.cvm, id.dc, id.ngml or id.cv

Examples

```
v1 <- vars::VAR(USA, lag.max = 10, ic = "AIC" )
x1 <- id.ngml(v1)
x2 <- imrf(x1, horizon = 20)
plot(x2)
```

---

js.test *Chi-square test for joint hypotheses*

Description

Based on an existing bootstrap object, the test statistic allows to test joint hypotheses for selected entries of the structural matrix B. The test statistic reads as

$$(Rvec(\widehat{B}) - r)'R(\widehat{\text{Cov}}[vec(B^*)])^{-1}R'(Rvec(\widehat{b} - r)) \sim \chi^2_J,$$

where $\widehat{\text{Cov}}[vec(B^*)]$ is the estimated covariance of vectorized bootstrap estimates of structural parameters. The composite null hypothesis is $H_0 : Rvec(B) = r$.

Usage

```
js.test(x, R, r = NULL)
```

Arguments

x	Object of class 'sboot'
R	A J*K^2 selection matrix, where J is the number of hypotheses and K the number of time series.
r	A J*1 vector of restrictions

Value

A list with elements

test_statistic	Test statistic
p_value	P-value

References

Herwartz, H., 2017. Hodges Lehmann detection of structural shocks - An analysis of macroeconomic dynamics in the Euro Area, Oxford Bulletin of Economics and Statistics

Examples

```
# data contains quarterly observations from 1965Q1 to 2008Q3
# x = output gap
# pi = inflation
# i = interest rates
v1 <- vars::VAR(USA, lag.max = 10, ic = "AIC" )
x1 <- id.dc(v1)

# Bootstrapping of SVAR
bb <- wild.boot(x1, nboot = 1000, horizon = 30)

# Testing the hypothesis of a lower triangular matrix as
# relation between structural and reduced form errors
R <- rbind(c(0,0,0,1,0,0,0,0,0), c(0,0,0,0,0,0,1,0,0),
           c(0,0,0,0,0,0,0,1,0))
c.test <- js.test(bb, R)
summary(c.test)
```

---

mb.boot — *Moving block bootstrap for IRFs of identified SVARs*

Description

Calculating confidence bands for impulse response via moving block bootstrap

Usage

```
mb.boot(x, b.length = 15, horizon, nboot, nc = 1, dd = NULL,
  signrest = NULL, itermax = 300, steptol = 200, iter2 = 50)
```

Arguments

`x`	SVAR object of class "svars"
`b.length`	Length of each block
`horizon`	Time horizon of impulse response functions
`nboot`	Number of bootstrap iterations
`nc`	Number of processor cores (Not available on windows machines)
`dd`	Object of class 'indepTestDist'. A simulated independent sample of the same size as the data. If not supplied, it will be calculated by the function
`signrest`	A list with vectors containing 1 and -1, e.g. c(1,-1,1), indicating a sign pattern of specific shocks to be tested with the help of the bootstrap samples.
`itermax`	Maximum number of iterations for DEoptim
`steptol`	Tolerance for steps without improvement for DEoptim
`iter2`	Number of iterations for the second optimization

Value

A list of class "sboot" with elements

boot_mean
: Mean of bootstrapped covariance decompositions

sign_complete
: Frequency of bootstrapped covariance decompositions which conform the complete predetermined sign pattern. If signrest=NULL, the frequency of bootstrapped covariance decompositions that hold the same sign pattern as the point estimate is provided.

sign_part
: Frequency of single shocks in all bootstrapped covariance decompositions which accord to a specific predetermined sign pattern

References

Brueggemann, R., Jentsch, C., and Trenkler, C. (2016). Inference in VARs with conditional heteroskedasticity of unknown form. Journal of Econometrics 191, 69-85.
Herwartz, H., 2017. Hodges Lehmann detection of structural shocks - An analysis of macroeconomic dynamics in the Euro Area, Oxford Bulletin of Economics and Statistics

See Also

id.cvm, id.dc, id.ngml or id.cv

Examples

```
# data contains quarterly observations from 1965Q1 to 2008Q3
# x = output gap
# pi = inflation
# i = interest rates
set.seed(23211)
v1 <- vars::VAR(USA, lag.max = 10, ic = "AIC" )
x1 <- id.dc(v1)
summary(x1)

# impulse response analysis with confidence bands
# Checking how often theory based impact relations appear
signrest <- list(demand = c(1,1,1), supply = c(-1,1,1), money = c(-1,-1,1))
bb <- mb.boot(x1, b.length = 15, nboot = 500, horizon = 30, nc = 1, signrest = signrest)
summary(bb)
plot(bb, lowerq = 0.16, upperq = 0.84)
```

USA — US macroeconomic time series

Description

The time series of output gap (x), inflation (pi) and interest rate (r) are taken from the FRED database and transformed as in Herwartz & Ploedt (2016). The trivariate time series model is commonly used to analyze monetary policy shocks.
Quarterly observations from 1965Q1 to 2008Q3:

x	Percentage log-deviation of real GDP wrt the estimate of potential output by the Congressional Budget Office
pi	Annualized quarter-on-quarter growth of the GDP deflator
i	Interest rate on Federal funds

A more detailed description of the data and a corresponding VAR model implementation can be found in Herwartz & Ploedt (2016).

Usage

```
USA
```

Format

A `data.frame` containing 174 observations on 3 variables.

Source

Herwartz, H. & Ploedt, M., 2016. Simulation Evidence on Theory-based and Statistical Identification under Volatility Breaks, Oxford Bulletin of Economics and Statistics, 78, 94-112.
Data originally from FRED database of the Federal Reserve Bank of St. Louis.

wild.boot — Wild bootstrap for IRFs of identified SVARs

Description

Calculating confidence bands for impulse response functions via wild bootstrap techniques (Goncalves and Kilian, 2004).

Usage

```
wild.boot(x, rademacher = TRUE, horizon, nboot, nc = 1, dd = NULL,
  signrest = NULL, itermax = 300, steptol = 200, iter2 = 50)
```

Arguments

`x`	SVAR object of class "svars"
`rademacher`	If rademacher="TRUE", the Rademacher distribution is used to generate the bootstrap samples
`horizon`	Time horizon for impulse response functions
`nboot`	Number of bootstrap iterations
`nc`	Number of processor cores (Not available on windows machines)
`dd`	Object of class 'indepTestDist'. A simulated independent sample of the same size as the data. roxIf not supplied, it will be calculated by the function
`signrest`	A list with vectors containing 1 and -1, e.g. c(1,-1,1), indicating a sign pattern of specific shocks to be tested with the help of the bootstrap samples.
`itermax`	Maximum number of iterations for DEoptim
`steptol`	Tolerance for steps without improvement for DEoptim
`iter2`	Number of iterations for the second optimization

Value

A list of class "sboot" with elements

`boot_mean`	Mean of bootstrapped covariance decompositions
`sign_complete`	Frequency of appearance of the complete sign pattern in all bootstrapped covaraince decompositions
`sign_part`	Frequency of bootstrapped covariance decompositions which conform the complete predetermined sign pattern. If signrest=NULL, the frequency of bootstrapped covariance decompositions that hold the same sign pattern as the point estimate is provided.
`sign_part`	Frequency of single shocks in all bootstrapped covariance decompositions which accord to a specific predetermined sign pattern

References

Goncalves, S., Kilian, L., 2004. Bootstrapping autoregressions with conditional heteroskedasticity of unknown form. Journal of Econometrics 123, 89-120.
Herwartz, H., 2017. Hodges Lehmann detection of structural shocks - An analysis of macroeconomic dynamics in the Euro Area, Oxford Bulletin of Economics and Statistics

See Also

`id.cvm`, `id.dc`, `id.ngml` or `id.cv`

Examples

```
# data contains quarterly observations from 1965Q1 to 2008Q3
# x = output gap
# pi = inflation
# i = interest rates
set.seed(23211)
v1 <- vars::VAR(USA, lag.max = 10, ic = "AIC" )
x1 <- id.dc(v1)
summary(x1)

# impulse response analysis with confidence bands
# Checking how often theory based impact relations appear
signrest <- list(demand = c(1,1,1), supply = c(-1,1,1), money = c(-1,-1,1))
bb <- wild.boot(x1, rademacher = TRUE, nboot = 500, horizon = 30, nc = 1, signrest = signrest)
summary(bb)
plot(bb, lowerq = 0.16, upperq = 0.84)
```

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