

Package ‘MSBVAR’

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Title Markov-Switching, Bayesian, Vector Autoregression Models

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Depends R (>= 2.12.0), KernSmooth, xtable, coda, bit, mvtnorm, lattice

Description Provides methods for estimating frequentist and Bayesian Vector Autoregression (VAR) models and Markov-switching Bayesian VAR (MSBVAR). Functions for reduced form and structural VAR models are also available. Includes methods for the generating posterior inferences for these models, forecasts, impulse responses (using likelihood-based error bands), and forecast error decompositions. Also includes utility functions for plotting forecasts and impulse responses, and generating draws from Wishart and singular multivariate normal densities. Current version includes functionality to build and evaluate models with Markov switching.

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`A02mcmc`*Converts A0 objects to coda MCMC objects*

Description

Converts A0 objects from `gibbs.A0.BSVAR` into `mcmc` objects for analysis with `coda`

Usage

```
A02mcmc(x)
```

Arguments

`x` $N2 \times$ number of free parameters in $A(0)$ MCMC Gibbs sample object for the B-SVAR model A_0 from `gibbs.A0`. This matrix is a column major to row major version of $A(0)$ that can be used to diagnose convergence and summarize the elements of $A(0)$

Details

Returns an object of the class `mcmc`, an $N2 \times$ number free parameters in $A(0)$ matrix. This can then be fed into `coda` for further analysis of the posterior.

Value

Object with class `mcmc`

Author(s)

Patrick T. Brandt

See Also

[gibbs.A0,mcmc](#)

`BCFdata`*Subset of Data from Brandt, Colaresi, and Freeman (2008)*

Description

This data set in two matrices about the Israeli-Palestinian conflict. The first matrix is a set of endogenous variables that gives 1) monthly Goldstein scaled means that summarize the Israeli-Palestinian conflict from April 1996 - March 2005, 2) average Jewish peace index score [0 = no support to 100=full support] that measure Jewish public support of the peace process based on polls of Jewish respondents from the Tami Steinmetz Center for Peace Research. The conflict measures are dyadic or directed actions from one party towards the other. Positive values indicate an average of more cooperation and less conflict and negative values indicate an average with more conflict than cooperation. These are a subset of the Levant dataset from the Kansas / Penn State Event Data Project Levant dataset. The data are from AFP news sources and encoded into the World Event Interaction Survey (WEIS) coding system and Goldstein scalings using the Penn State Event Data Project TABARI program. Source data can be found on the site below.

Usage

```
data(BCFdata)
```

Format

Two matrices containing 108 observations. The first matrix "Y" is a multiple ts object of the endogenous series that measure the average conflict-cooperation level and the public opinion data. This matrix has three columns. Column one, "I2P", is average Goldstein scaled Israeli actions towards the Palestinians; column two, "P2I" is average Goldstein scaled Palestinian actions towards the Israelis; column three is the average Jewish peace index value for the month, "JPI".

The second matrix, "z2" is a set of nine control variables for shifts in the conflict, the Israeli prime ministerial regime, and election trends. The columns of this matrix are 1) a dummy variable for the period from the start of the second Intifada to the start of the Battle of Jenin (October 2000–April 2002, end of the second Intifada). 2) a dummy variable for the post-Battle of Jenin period (May 2002–March 2005), 3-5) dummy variables for the identities of the Israeli prime ministers in each month (one each for Netanyahu, Barak, and Sharon, with Rabin/Peres treated as the reference category). 6-9) a separate time counter that starts at the value 1 in the month after each Israeli election and increases until the time of the next constitutionally mandated election.

Source

Brandt, Patrick T., Michael P. Colaresi and John R. Freeman. 2008. "The Dynamics of Reciprocity, Accountability and Credibility." *Journal of Conflict Resolution*. 52(3): 343-374.

Replication materials at http://www.utdallas.edu/~pbrandt/pbrandt/Replication_files/BrandtColaresiFreemanJCR08.tar.gz

References

Goldstein, Joshua. S. 1992. "A Conflict-Cooperation Scale for WEIS Event Data" *Journal of Conflict Resolution*. 36:369-385.

Penn State Event Data Project <http://eventdata.psu.edu>

`BHLK.filter`*Baum-Hamilton-Lindgren-Kim state-space filter*

Description

Implements a Baum-Hamilton-Lindgren-Kim state-space filter for a multivariate Markov-switching model.

Usage

```
BHLK.filter(u, Sigma, Q)
```

Arguments

`u` $T \times m \times h$ dimensional array of the regime-specific residuals to be filtered for the MS process.

`Sigma` $m \times m \times h$ dimensional array of the regime-specific error covariances.

`Q` The $h \times h$ Markov transition matrix.

Details

Estimates the Markov-switching regime probabilities for an MSBVAR model. Conditional on the BVAR(p) model, the residuals are used to filter the data. The estimation is done using compiled C++ code for speed.

Value

`x` $T \times h$ matrix of the filtered regime probabilities.

Author(s)

Patrick T. Brandt

References

Sims, Christopher A. and Daniel F. Waggoner and Tao Zha. 2008. "Methods for inference in large multiple-equation Markov-switching models" *Journal of Econometrics* 146(2):255–274.

Kim, C.J. and C.R. Nelson. 1999. *State-space models with regime switching*. Cambridge, Mass: MIT Press.

Krolzig, Hans-Martin. 1997. *Markov-Switching Vector Autoregressions: Modeling, Statistical Inference, and Application to Business Cycle Analysis*.

See Also

[msbvar](#)

Examples

```
# Sets up and estimates a set of filter probabilities
h <- 2
m <- 2
TT <- 100
u <- array(rnorm(TT*m*h), c(TT, m, h))
Sigma <- array(diag(m), c(m, m, h))
Q <- matrix(c(0.99, 0.2, 0.01, 0.8), h, h)
x <- BHLK.filter(u, Sigma, Q)
```

cf.forecasts

Compare VAR forecasts to each other or real data

Description

Computes the root mean squared error and mean absolute error for a series of forecasts or for forecasts and real data.

Usage

```
cf.forecasts(m1, m2)
```

Arguments

m1	Matrix of VAR forecasts produced by <code>forecast.VAR</code> .
m2	Matrix of VAR forecasts or a matrix of real data to compare to forecasts.

Details

Simple RMSE and MAE computation for the forecasts. The reported values are summed over the series and time points.

Value

An object with two elements:

rmse	Forecast RMSE
mae	Forecast MAE

Author(s)

Patrick T. Brandt

See Also

[forecast](#) for forecast computations

Examples

```
data(IsraelPalestineConflict)
Y.sample1 <- window(IsraelPalestineConflict, end=c(2002, 52))
Y.sample2 <- window(IsraelPalestineConflict, start=c(2003,1))

# Fit a BVAR model
fit.bvar <- szbvar(Y.sample1, p=6, lambda0=0.6, lambda1=0.1, lambda3=2,
                  lambda4=0.25, lambda5=0, mu5=0, mu6=0, prior=0)

# Forecast -- this gives back the sample PLUS the forecasts!

forecasts <- forecast(fit.bvar, nsteps=nrow(Y.sample2))

# Compare forecasts to real data
cf.forecasts(forecasts[(nrow(Y.sample1)+1):nrow(forecasts)], Y.sample2)
```

decay.spec

Lag decay specification check

Description

Provides a quick way to visualize the lag decay specification in a BVAR model for given parameters by computing the variance of the prior VAR coefficients across various lags.

Usage

```
decay.spec(qm, p, lambda)
```

Arguments

qm	Periodicity parameter: either 4 or 12 for quarterly or monthly data.
p	Number of lags
lambda	Lag decay parameter [>0], which is lambda3 in the Sims-Zha BVAR specification in szbvar

Details

Computes the relative decay in the prior variance of the VAR prior across the lags from 1 to p. Useful for visualizing the rate of decay or how tight the prior becomes at higher order lags.

Value

A time series of length p of the prior variances for each lag.

Author(s)

Patrick T. Brandt

References

Sims, C.A. and Tao Zha. 1998. "Bayesian Methods for Dynamic Multivariate Models." *International Economic Review*. 39(4):949-968.

See Also

[szbvar](#)

Examples

```
# Harmonic lag decay example
harmonic <- decay.spec(4, 6, 1)

# Quadratic lag decay example
quadratic <- decay.spec(4, 6, 2)

plot(cbind(harmonic,quadratic))
```

dfev

*Decompositions of Forecast Error Variance (DFEV) for
VAR/BVAR/BSVAR models*

Description

Computes the m dimensional decomposition of forecast error variance (DFEV) for a VAR, BVAR, and BSVAR models. User can specify the decomposition of the contemporaneous innovations.

Usage

```
dfev(varobj, A0 = NULL, k)
```

Arguments

varobj	VAR/BVAR/BSVAR object created from fitting a VAR/BVAR/BSVAR model using szbvar, szbsvar, or reduced.form.var.
A0	Decomposition of the contemporaneous error covariance matrix. Default is to use the (lower) Cholesky decomposition of the residual error covariance matrix for VAR and BVAR models, or the inverse of A_0 in B-SVAR models.
k	Number of periods over which to compute the decomposition.

Details

The decomposition of the forecast error variance (DFEV) provides a measure of the relationship among forecast errors or impact of shocks to a VAR/BVAR/BSVAR system. It is computed by finding the moving average representation (MAR) of the VAR/BVAR/BSVAR model and then tracing out the path of innovations through the system. For each of the M innovations in a VAR/BVAR/BSVAR, the amount of the variance in these forecast errors or innovations is computed and returned in a table. The table can be accessed via the `print.dfev` and `summary.dfev` functions.

Value

Returns a list with

<code>errors</code>	$M \times M \times K$ of the percentage of the innovations in variable i explained by the other M variables.
<code>std.err</code>	$M \times k$ dimension matrix of the forecast standard errors.
<code>names</code>	Variable names

Note

The interpretation of the DFEV depends on the decomposition of the contemporaneous residuals. In the default case of a Cholesky decomposition, this means that the ordering of the variables in the decomposition determines the effect of each innovation on the subsequent DFEVs. For high correlated series, this will mean that the DFEV is not very robust to the ordering.

Author(s)

Patrick T. Brandt

References

Brandt, Patrick T. and John T. Williams. Multiple Time Series Models. Thousand Oaks, CA; Sage Press.

See Also

See also `print.dfev` and `summary.dfev` for a nicely formatted tables and an output example

Examples

```
data(IsraelPalestineConflict)
varnames <- colnames(IsraelPalestineConflict)
fitted.BVAR <- szbvar(IsraelPalestineConflict, p=6, z=NULL,
                    lambda0=0.6, lambda1=0.1,
                    lambda3=2, lambda4=0.25, lambda5=0, mu5=0,
                    mu6=0, nu=3, qm=4, prior=0,
                    posterior.fit=FALSE)

A0 <- t(chol(fitted.BVAR$mean.S))
dat.dfev <- dfev(fitted.BVAR, A0, 24)
```

```
print(dat.dfev)
summary(dat.dfev)
```

`forc.ecdf`*Empirical CDF computations for posterior forecast samples*

Description

Computes (pointwise over time) empirical density (error bands) and mean forecasts for a Monte Carlo or Bayesian posterior sample of forecasts.

Usage

```
forc.ecdf(forecasts, probs = c(0.05, 0.95), start = c(0, 1), ...)
```

Arguments

<code>forecasts</code>	Posterior sample of VAR forecasts produced by <code>hc.forecast.VAR()</code> or <code>uc.forecast.VAR()</code>
<code>probs</code>	Error band width in percentiles, default is 90% error band.
<code>start</code>	Start value for the time series – as in the <code>ts()</code> for the forecast horizon
<code>...</code>	Other <code>ecdf()</code> parameters

Details

For each endogenous variable in the VAR and each point in the forecast horizon this function estimates the percentile based confidence interval. It then returns a time series matrix beginning at `start` of the mean forecast and the limits of the confidence region for each variable in the forecast sample.

Value

A multiple time series object is returned where the first column is the mean estimate followed by the upper and lower bounds of the confidence region.

Author(s)

Patrick T. Brandt

forecast	<i>Generate forecasts for fitted VAR objects</i>
----------	--

Description

Forecasting for VAR/BVAR/BSVAR objects with structural (endogenous) and exogenous shocks.

Usage

```
forecast(varobj, nsteps, A0=t(chol(varobj$mean.S)),
        shocks=matrix(0,nrow=nsteps,ncol=dim(varobj$ar.coefs)[1]),
        exog.fut=matrix(0,nrow=nsteps,ncol=nrow(varobj$exog.coefs)))
```

Arguments

varobj	Fitted VAR model of the class VAR, BVAR, or BSVAR produced by reduced.form.var , szbvar , or szbsvar (Not yet implemented for msbvar .)
nsteps	Number of periods in the forecast horizon
A0	$m \times m$ matrix of the decomposition of the contemporaneous endogenous forecast innovations
shocks	Structural shocks to the VAR model. These must be scaled consistent with the structural identification in A_0
exog.fut	nsteps x number of exogenous variables matrix of the future values of exogenous variable shocks.

Details

This function computes forecasts for both classical and Bayesian (S)VARs. Users can specify shocks to the system over the forecast horizon (both structural and exogenous shocks). The forecasting model is that described by Waggoner and Zha (1999) and can be used to construct unconditional forecasts based on these structural shocks and the contemporaneous decomposition of the innovation variance, A_0 .

Value

A matrix time series object, $((T + nsteps) \times m)$ of the original series and forecasts.

Note

The forecasts can be easily plotted by using the `plot.forecast()` command to select the appropriate sample-forecast horizon

Author(s)

Patrick T. Brandt

References

Waggoner, Daniel F. and Tao Zha. 1999. "Conditional Forecasts in Dynamic Multivariate Models" *Review of Economics and Statistics*, 81(4):639-651.

See Also

[reduced.form.var](#), [szbvar](#) and [szbsvar](#) for estimation methods that create the elements needed to forecast

Examples

```
data(IsraelPalestineConflict)
Y.sample1 <- window(IsraelPalestineConflict, end=c(2002, 52))
Y.sample2 <- window(IsraelPalestineConflict, start=c(2003,1))

# Fit a BVAR model
fit.bvar <- szbvar(Y.sample1, p=6, lambda0=0.6, lambda1=0.1, lambda3=2,
                  lambda4=0.25, lambda5=0, mu5=0, mu6=0, prior=0)

# Forecast -- this gives back the sample PLUS the forecasts!

forecasts <- forecast(fit.bvar, nsteps=nrow(Y.sample2))
forecasts.only <- forecasts[(nrow(Y.sample1)+1):nrow(forecasts),]

# Plot forecasts and actual data
i2p <- ts(cbind(Y.sample2[,1], forecasts.only[,1]),
          start=c(2003,1), freq=52)

p2i <- ts(cbind(Y.sample2[,2], forecasts.only[,2]),
          start=c(2003,1), freq=52)

par(mfrow=c(2,1))
plot(i2p, plot.type=c("single"))
plot(p2i, plot.type=c("single"))
```

gibbs.A0

Gibbs sampler for posterior of Bayesian structural vector autoregression models

Description

Samples from the structural contemporaneous parameter matrix A_0 of a Bayesian Structural Vector Autoregression (B-SVAR) model.

Usage

```
gibbs.A0(varobj, N1, N2, thin=1, normalization="DistanceMLA")
```

Arguments

varobj	A structural BVAR object created by szbsvar
N1	Number of burn-in iterations for the Gibbs sampler (should probably be greater than or equal to 1000).
N2	Number of iterations in the posterior sample.
thin	Thinning parameter for the Gibbs sampler.
normalization	Normalization rule as defined in normalize.svar . Default is "DistanceMLA" as recommended in Waggoner and Zha (2003b).

Details

Samples the posterior pdf of an A_0 matrix for a Bayesian structural VAR using the algorithm described in Waggoner and Zha (2003a). This function is meant to be called after [szbsvar](#), so one should consult that function for further information. The function draws $N2 * thin$ draws from the sampler and returns the $N2$ draws that are the $thin$ 'th elements of the Gibbs sampler sequence.

The computations are done using compiled C++ code as of version 0.3.0. See the package source code for details about the implementation.

Value

A list of five elements:

A0.posterior	A list of three elements containing the results of the $N2$ A_0 draws. The list contains a vector storing all of the draws, the location of the drawn elements in and the dimension of A_0 . <code>A0.posterior\$A0</code> is a vector of length equal to the number of parameters in A_0 times $N2$. <code>A0.posterior\$struct</code> is a vector of length equal to the number of free parameters in A_0 that gives the index positions of the elements in A_0 . <code>A0.posterior\$m</code> is m , an integer, the number of equations in the system.
W.posterior	A list of three elements that describes the vectorized W matrices that characterize the covariance of the restricted parameter space of each column of A_0 . <code>W.posterior\$W</code> is a vector of the elements of all the sampled W matrices. <code>W.posterior\$W.index</code> is a cumulative index of the elements of W that defines how the W matrices for each iteration of the sampler are stored in the vector. <code>W.posterior\$m</code> is m , an integer, the number of equations in the system.
ident	ident matrix from the varobj of binary elements that defined the free and restricted parameters, as specified in szbsvar
thin	thin value that was input into the function for thinning the Gibbs sampler.
N2	$N2$, size of the posterior sample.

Note

You must have called / loaded an [szbsvar](#) object to use this Gibbs sampler.

Author(s)

Patrick T. Brandt

References

Waggoner, Daniel F. and Tao A. Zha. 2003a. "A Gibbs sampler for structural vector autoregressions" *Journal of Economic Dynamics & Control*. 28:349–366.

Waggoner, Daniel F. and Tao A. Zha, 2003b. "Likelihood Preserving Normalization in Multiple Equation Models" *Journal of Econometrics*, 114: 329–347

See Also

[szbsvar](#) for estimation of the posterior moments of the B-SVAR model,

[normalize.svar](#) for a discussion of and references on A_0 normalization.

[posterior.fit](#) for computing the marginal log likelihood for the model after sampling the posterior

Examples

```
# SZ, B-SVAR model for the Levant data
data(BCFdata)
m <- ncol(Y)
ident <- diag(m)
ident[1,] <- 1
ident[2,1] <- 1

# estimate the model's posterior moments
set.seed(123)
model <- szbsvar(Y, p=2, z=z2, lambda0=0.8, lambda1=0.1, lambda3=1,
                 lambda4=0.1, lambda5=0.05, mu5=0, mu6=5,
                 ident, qm=12)

# Set length of burn-in and size of posterior. These are only an
# example. Production runs should set these much higher.
N1 <- 1000
N2 <- 1000

A0.posterior.obj <- gibbs.A0(model, N1, N2, thin=1)

# Use coda to look at the posterior.
A0.free <- A02mcmc(A0.posterior.obj)

plot(A0.free)
```

gibbs.msbvar

Gibbs sampler for a Markov-switching Bayesian reduced form vector autoregression model

Description

Draws a Bayesian posterior sample for a Markov-switching Bayesian reduced form vector autoregression model based on the setup from the [msbvar](#) function.

Usage

```
gibbs.msbvar(x, N1 = 1000, N2 = 1000, permute = TRUE,
             Beta.idx = NULL, Sigma.idx = NULL, posterior.fit=FALSE)
```

Arguments

x	MSBVAR setup and posterior mode estimate generated using the <code>msbvar</code> function.
N1	Number of burn-in iterations for the Gibbs sampler (should probably be greater than or equal to 1000)
N2	Number of iterations in the posterior sample.
permute	Logical (default = TRUE). Should random permutation sampling be used to explore the $h!$ posterior modes?
Beta.idx	A two element vector indicating the MSBVAR coefficient matrix that is to be ordered for non-permutation sampling, i.e., the ordering of the states. The states will be put into ascending order for the parameter selected. The two elements provide are for the two-dimensional array of the VAR coefficients. The first number gives the coefficient, the second the equation numbers. Coefficients are ordered by lag, then variable. So for an m equation VAR where we want the AR(1) coefficient on the second variable's equation, use <code>c(2, 2)</code> . The intercept is the last value, or $mp + 1$. So the intercept for the first equation in a 4 variable model with two lags is <code>c(9, 1)</code> .
Sigma.idx	Scalar integer giving the equation variance that is to be ordered for non-permutation sampling, i.e., the ordering of the states. The states will be put into ascending order for the variance parameter selected.
posterior.fit	logical (default=FALSE). Should the loglikelihood and log marginal data density be computed (using the method of Chib [1995] from the posterior sample)

Details

This function implements a Gibbs sampler for the posterior of a MSBVAR model setup with `msbvar`. This is a reduced form MSBVAR model. The estimation is done in a mixture of native R code and C++. The sampling of the BVAR coefficients, the transition matrix, and the error covariances for each regime are done in native R code. The forward-filtering-backward-sampling of the Markov-switching process (The most computationally intensive part of the estimation) is handled in compiled C++ code. As such, this model is reasonably fast for small samples / small numbers of regimes (say less than 2000 observations and 2-4 regimes). The reason for this mixed implementation is that it is easier to setup variants of the model (some coefficients switching, others not; different sampling methods; etc.)

The random permutation of the states is done using a multinomial step: at each draw of the Gibbs sampler, the states are permuted using a multinomial draw. This generates a posterior sample where the states are unidentified. This makes sense, since the user may have little idea of how to select among the $h!$ posterior models of the reduced form MSBVAR model (see e.g., Fruhwirth-Schnatter (2006)). Once a posterior sample has been draw with random permutation, a clustering algorithm can be used to identify the states, for example, by examining the intercepts or covariances across the regimes (see the example below for details).

Only the `Beta.idx` or `Sigma.idx` value is followed. If the first is given the second will be ignored. So variance ordering for identification can only be used when `Beta.idx=NULL`.

The Gibbs sampler is estimated using six steps:

Drawing the state-space for the Markov process This step uses compiled C++ code to draw the 0-1 matrix of the regimes. It uses the Baum-Hamilton-Lee-Kim (BHLK) filter and smoother to estimate the regime probabilities. Draws are based on the standard forward-filter-backward-sample algorithm.

Drawing the Markov transition matrix Q Conditional on the other parameters, this takes a draw from a Dirichlet posterior with the `alpha.prior` prior.

Regression step update Conditional on the state-space and the Markov-switching process data augmentation steps, estimate a set of h regressions, one for each regime.

Draw the error covariances, Σ_h Conditional on the other steps, compute and draw the error covariances from an inverse Wishart pdf.

Draw the regression coefficients For each set of classified observations' (based on the previous step) BVAR regression coefficients, take a draw from their multivariate normal posterior.

Permute the states If `permute = TRUE`, then permute the states and the respective coefficients.

The state-space for the MS process is a $T \times h$ matrix of zeros and ones. Since this matrix classifies the observations infor states for the N2 posterior draws, it does not make sense to store it in double precisions. We use the `bit` package to compress this matrix into a 2-bit integer representation for more efficient storage. Functions are provided (see below) for summarizing and plotting the resulting state-space of the MS process.

Value

A list summarizing the reduced form MSBVAR posterior:

<code>Beta.sample</code>	$N2 \times h(m^2p + m)$ of the BVAR regression coefficients for each regime. The ordering is based on regime, equation, intercept (and in the future covariates). So the first p coefficients are the the first equation in the first regime, ordered by lag, not variable; the next is the intercept. This pattern repeats for the remaining coefficients across the regimes.
<code>Sigma.sample</code>	$N2 \times h(\frac{m(m+1)}{2})$ matrix of the covariance parameters for the error covariances Σ_h . Since these matrices are symmetric p.d., we only store the upper (or lower) portion. The elements in the matrix are the first, second, etc. columns / rows of the lower / upper version of the matrix.
<code>Q.sample</code>	$N2 \times h^2$
<code>transition.sample</code>	An array of $N2 h \times h$ transition matrices.
<code>ss.sample</code>	List of class SS for the N2 estimates of the state-space matrices coded as <code>bit</code> objects for compression / efficiency.
<code>pfit</code>	A list of the posterior fit statistics for the MSBVAR model.
<code>h</code>	integer, number of regimes fit in the model.

Note

Users need to call this function twice (unless they have really good a priori identification information!) The first call will be using the random permutation sampler (so with `permute = TRUE`) and then some exploration of the clustering of the posterior. Then, once the posterior is identified (i.e., you have chosen one of the $h!$ posterior modes), the function is called with `permute = FALSE` and values specified for `Beta.idx` or `Sigma.idx`. See the example below for usage.

Author(s)

Patrick T. Brandt

References

- Brandt, Patrick T. 2009. "Empirical, Regime-Specific Models of International, Inter-group Conflict, and Politics"
- Fruhwirth-Schnatter, Sylvia. 2001. "Markov Chain Monte Carlo Estimation of Classical and Dynamic Switching and Mixture Models". *Journal of the American Statistical Association*. 96(153):194–209.
- Fruhwirth-Schnatter, Sylvia. 2006. *Finite Mixture and Markov Switching Models*. Springer Series in Statistics New York: Springer.
- Sims, Christopher A. and Daniel F. Waggoner and Tao Zha. 2008. "Methods for inference in large multiple-equation Markov-switching models" *Journal of Econometrics* 146(2):255–274.
- Krolzig, Hans-Martin. 1997. *Markov-Switching Vector Autoregressions: Modeling, Statistical Inference, and Application to Business Cycle Analysis*.

See Also

[msbvar](#), [plot.SS](#), [mean.SS](#), [plotregimeid](#)

Examples

```
## Not run:
# This example can be pasted into a script or copied into R to run. It
# takes a few minutes, but illustrates how the code can be used

data(IsraelPalestineConflict)

# Find the mode of an msbvar model
# Initial guess is based on random draw, so set seed.
set.seed(123)

xm <- msbvar(y=IsraelPalestineConflict, p=1, h=2,
             lambda0=0.8, lambda1=0.15,
             lambda3=2, lambda4=1, lambda5=0, mu5=0,
             mu6=0, qm=12,
             alpha.prior=matrix(c(5,2,2,10), 2, 2))

# Plot out the initial mode
plot(ts(xm$fp))
```

```
print(xm$Q)

# Now sample the posterior
N1 <- 100
N2 <- 500

# First, so this with random permutation sampling
x1 <- gibbs.msbvar(xm, N1=N1, N2=N2, permute=TRUE)

# Identify the regimes using clustering in plotregimeid()
plotregimeid(xm, x1, type="all")

# Now re-estimate based on desired regime identification seen in the
# plots. Here we are using the variance of the first equation, so
# Sigma.idx=1.

x2 <- gibbs.msbvar(xm, N1=N1, N2=N2, permute=FALSE, Sigma.idx=1)

## End(Not run)
```

granger.test

Bivariate Granger causality testing

Description

Bivariate Granger causality testing for multiple time series.

Usage

```
granger.test(y, p)
```

Arguments

y	T x m time series or matrix.
p	Lag length to be used for computing the test

Details

Estimates all possible bivariate Granger causality tests for m variables. Bivariate Granger causality tests for two variables X and Y evaluate whether the past values of X are useful for predicting Y once Y's history has been modeled. The null hypothesis is that the past p values of X do not help in predicting the value of Y.

The test is implemented by regressing Y on p past values of Y and p past values of X. An F-test is then used to determine whether the coefficients of the past values of X are jointly zero.

This produces a matrix with $m*(m-1)$ rows that are all of the possible bivariate Granger causal relations. The results include F-statistics and p-values for each test. Tests are estimated using single equation OLS models.

Value

A matrix with 2 columns. Column 1 are the F-statistic values. Column 2 are the p-values for the F-tests. Row labels specifying the Granger causality relationship tested will be included if variables in the input time series y include variable or dimnames.

Note

These are bivariate tests – not block exogeneity tests for a fitted VAR model. Note also that these tests are highly sensitive to lag length (p) and the presence of unit roots. Results in the matrix include row labels for nice printing with `xtable()`

Author(s)

Patrick T. Brandt

References

Granger, C.W.J. 1969. "Investigating Causal Relations by Econometric Models and Cross-Spectral Methods" *Econometrica* 37:424-438.

Sims, C.A. 1972. "Money, Income, and Causality" *American Economic Review*. 62:540-552.

See Also

[reduced.form.var](#) for frequentist VAR estimation, [szbvar](#) for Bayesian VAR estimation with Sims-Zha prior, [var.lag.specification](#) for VAR lag length testing.

Examples

```
data(IsraelPalestineConflict)
granger.test(IsraelPalestineConflict, p=6)
```

hc.forecast

Forecast density estimation of hard condition forecasts for VAR models via MCMC

Description

Implements a "hard condition" forecast density estimator for VAR/BVAR/B-SVAR models as described in Waggoner and Zha (1999). A "hard condition" forecast is one where the forecast path of one or more variables in a VAR is constrained to be an exact value. The forecast densities are estimated as the posterior sample for the VAR model using Markov Chain Monte Carlo with data augmentation to account for the uncertainty of the forecasts and the parameters. This function DOES account for parameter uncertainty in the MCMC algorithm.

Usage

```
hc.forecast(varobj, yconst, nsteps, burnin,
            gibbs, exog = NULL)
```

Arguments

varobj	VAR object produced for an unrestricted VAR or BVAR using <code>szbvar</code> or <code>reduced.form.var</code>
yconst	nsteps x m matrix of the constrained forecasts that matches the variables in the endogenous variables of the VAR object. Unconstrained forecasts should be set to NA or zero.
nsteps	Number of periods in the forecast horizon
burnin	Burnin cycles for the MCMC algorithm
gibbs	Number of cycles of the Gibbs sampler after the burnin that are returned in the output
exog	num.exog x nsteps matrix of the exogenous variable values for the forecast horizon. If left at the NULL default, they are set to zero.

Details

"Hard conditions" are restrictions of the future forecast path of a variable in a VAR. Once a variable has been constrained along the forecast path, the paths of the other variables in the VAR forecasts must be re-estimated to satisfy the forecast constraint, since the constrained variable has a forecast variance of zero (it is assumed known). Thus, an MCMC algorithm must be used to determine the posterior of the forecasts and a consistent set of VAR parameter estimates that satisfy the forecast constraints. This function accounts for the uncertainty of the VAR parameters by sampling from them in the computation of the VAR forecasts.

Value

A list with two components:

forecast	gibbs x nsteps x m array of the samples of the VAR forecasts
orig.y	T x m time series object of the original endogenous variables

Author(s)

Patrick T. Brandt

References

Brandt, Patrick T. and John R. Freeman. 2006. "Advances in Bayesian Time Series Modeling and the Study of Politics: Theory Testing, Forecasting, and Policy Analysis" *Political Analysis* 14(1):1-36.

Waggoner, Daniel F. and Tao Zha. 1999. "Conditional Forecasts in Dynamic Multivariate Models" *Review of Economics and Statistics*, 81(4):639-651.

See Also

[plot.forecast](#) for plotting, [forecast](#) for unconditional forecasting of forecast means, [uc.forecast](#) for MCMC estimation of forecast densities for unconstrained or unconditional forecasts

Examples

```
## Not run:
## Uses the example from Brandt and Freeman 2006. Will not run unless
## you have their data from http://yule.utdallas.edu or the Political
## Analysis website!
library(MSBVAR)

# Read the data and set up as a time series
data <- read.dta("levant.weekly.79-03.dta")
attach(data)

# Set up KEDS data
KEDS.data <- ts(cbind(a2i,a2p,i2a,p2a,i2p,p2i),
               start=c(1979,15),
               freq=52,
               names=c("A2I","A2P","I2A","P2A","I2P","P2I"))

# Select the sample we want to use.
KEDS <- window(KEDS.data, end=c(1988,50))

#####
# Estimate the BVAR models
#####

# Fit a flat prior model
KEDS.BVAR.flat <- szbvar(KEDS, p=6, z=NULL, lambda0=1,
                       lambda1=1, lambda3=1, lambda4=1, lambda5=0,
                       mu5=0, mu6=0, nu=0, qm=4, prior=2,
                       posterior.fit=F)

# Reference prior model -- Normal-IW prior pdf
KEDS.BVAR.informed <- szbvar(KEDS, p=6, z=NULL, lambda0=0.6,
                            lambda1=0.1, lambda3=2, lambda4=0.5,
                            lambda5=0, mu5=0, mu6=0,
                            nu=ncol(KEDS)+1, qm=4, prior=0,
                            posterior.fit=F)

# Set up conditional forecast matrix conditions
nsteps <- 12
a2i.condition <- rep(mean(KEDS[,1]) + sqrt(var(KEDS[,1])), nsteps)

yhat<-matrix(c(a2i.condition,rep(0, nsteps*5)), ncol=6)

# Set the random number seed so we can replicate the results.
set.seed(11023)
```

```

# Conditional forecasts
conditional.forcs.ref <- hc.forecast(KEDS.BVAR.informed, yhat, nsteps,
                                   burnin=3000, gibbs=5000, exog=NULL)

conditional.forcs.flat <- hc.forecast(KEDS.BVAR.flat, yhat, nsteps,
                                     burnin=3000, gibbs=5000, exog=NULL)

# Unconditional forecasts
unconditional.forcs.ref <-uc.forecast(KEDS.BVAR.informed, nsteps,
                                     burnin=3000, gibbs=5000)

unconditional.forcs.flat <- uc.forecast(KEDS.BVAR.flat, nsteps,
                                       burnin=3000, gibbs=5000)

# Set-up and plot the unconditional and conditional forecasts. This
# code pulls for the forecasts for I2P and P2I and puts them into the
# appropriate array for the figures we want to generate.
uc.flat <- NULL
hc.flat <- NULL
uc.ref <- NULL
hc.ref <- NULL

uc.flat$forecast <- unconditional.forcs.flat$forecast[, ,5:6]
hc.flat$forecast <- conditional.forcs.flat$forecast[, ,5:6]
uc.ref$forecast <- unconditional.forcs.ref$forecast[, ,5:6]
hc.ref$forecast <- conditional.forcs.ref$forecast[, ,5:6]

par(mfrow=c(2,2), omi=c(0.25,0.5,0.25,0.25))
plot(uc.flat,hc.flat, probs=c(0.16, 0.84), varnames=c("I2P", "P2I"),
     compare.level=KEDS[nrow(KEDS),5:6], lwd=2)
plot(hc.ref,hc.flat, probs=c(0.16, 0.84), varnames=c("I2P", "P2I"),
     compare.level=KEDS[nrow(KEDS),5:6], lwd=2)

## End(Not run)

```

irf

Impulse Response Function (IRF) Computation for a VAR

Description

Computes the impulse response function (IRF) or moving average representation (MAR) for an m-dimensional set of VAR/BVAR/B-SVAR coefficients.

Usage

```
irf(varobj, nsteps, A0=NULL)
```

Arguments

varobj	VAR, BVAR, or BSVAR objects for a fitted VAR, BVAR, or BSVAR model from <code>szbvar</code> , <code>szbsvar</code> or <code>reduced.form.var</code>
nsteps	Number or steps, or the horizon over which to compute the IRFs (typically 1.5 to 2 times the lag length used in estimation)
A0	Decomposition contemporaneous error covariance of a VAR/BVAR/BSVAR, default is a Cholesky decomposition of the error covariance matrix for VAR and BVAR models, $A_0 = \text{chol}(\text{varobj}\$mean.S)$, and the inverse of A_0 for B-SVAR models, $A_0 = \text{solve}(\text{varobj}\$A_0.mode)$

Details

This function should rarely be called by the user. It is a working function to compute the IRFs for a VAR model. Users will typically want to use one of the simulation functions that also compute error bands for the IRF, such as `mc.irf` which calls this function and simulates its multivariate posterior distribution.

Value

A list of the AR coefficients used in computing the IRF and the impulse response matrices:

B	$m \times m \times nstep$ Autoregressive coefficient matrices in lag order. Note that all AR coefficient matrices for $nstep > p$ are zero.
mhat	$m \times m \times nstep$ impulse response matrices. <code>mhat[, , i]</code> are the impulses for the i 'th period for the m variables.

Note

The IRF depends on the ordering of the variables and the structure of the decomposition in A_0 .

Author(s)

Patrick T. Brandt

References

- Sims, C.A. and Tao Zha. 1999. "Error Bands for Impulse Responses." *Econometrica* 67(5): 1113-1156.
- Hamilton, James. 1994. *Time Series Analysis*. Chapter 11.

See Also

See also [dfev](#) for the related decompositions of the forecast error variance, [mc.irf](#) for Bayesian and frequentist computations of IRFs and their variances (which is what you probably really want).

Examples

```
data(IsraelPalestineConflict)
rf.var <- reduced.form.var(IsraelPalestineConflict, p=6)
plot(irf(rf.var, nsteps = 12))
```

IsraelPalestineConflict

Weekly Goldstein Scaled Israeli-Palestinian Conflict Data, 1979-2003

Description

This data set gives Goldstein scaled totals that summarize the Israeli-Palestinian conflict from April 1979 - December 2003. These are dyadic or directed actions from one party towards the other. Data are weekly starting April 15, 1979. Positive values indicate cooperation, negative values indicate aggression. These are a subset of the Levant dataset from the Kansas / Penn State Event Data System Levant dataset. The data are from Reuters and AFP news sources and encoded into the World Event Interaction Survey (WEIS) coding system and Goldstein scalings using the Penn State Event Data System TABARI program. Source data can be found on the KEDS site below.

Usage

```
data(IsraelPalestineConflict)
```

Format

A matrix containing 1278 observations. Column one, "i2p", is the Israeli actions towards the Palestinians and column two, "p2i" is the Palestinian actions towards the Israelis.

Source

Brandt, Patrick T. and John R. Freeman. 2006. "Advances in Bayesian Time Series Modeling and the Study of Politics: Theory Testing, Forecasting, and Policy Analysis" *Political Analysis* 14(1):1-36.

References

Brandt, Patrick T. and John R. Freeman. 2006. "Advances in Bayesian Time Series Modeling and the Study of Politics: Theory Testing, Forecasting, and Policy Analysis" *Political Analysis* 14(1):1-36.

Goldstein, Joshua. S. 1992. "A Conflict-Cooperation Scale for WEIS Event Data" *Journal of Conflict Resolution*. 36:369-385.

Penn State Event Data Project <http://eventdata.psu.edu>

`ldwishart`*Log density for a Wishart variate*

Description

Computes log density for a Wishart random variable.

Usage

```
ldwishart(W, v, S)
```

Arguments

<code>W</code>	Wishart variate for which the log density is to be computed
<code>v</code>	degrees of freedom for the Wishart variate
<code>S</code>	scale factor for the Wishart variate (typically the inverse covariance if you are working with a multivariate random normal setup)

Details

Computes the log density for a Wishart variate with mean S and degrees of freedom v . Special care has been taken to avoid underflow in the computation.

Value

A scalar, the value of the log density for the variate W with mean S and degrees of freedom v .

Note

This is modified from the log density function in `MCMCpack`. It better handles underflows.

Author(s)

Patrick T. Brandt

See Also

[rwishart](#)

Examples

```
x <- matrix(rnorm(100), 50, 2)
XX <- crossprod(x)
ldwishart(solve(XX), 50, diag(2))
```

<code>list.print</code>	<i>Prints a list object for the VAR and BVAR models in MSBVAR</i>
-------------------------	---

Description

Provides a smartly formatted print method for the list objects created by MSBVAR objects. This will provide a table of estimates for the VAR and BVAR methods in this package.

Usage

```
list.print(x)
```

Arguments

`x` Fitted model object from [szbvar](#) or [szbsvar](#)

Details

This is a way to view the coefficients from a B(S)-VAR model fit with this package.

Value

None. Results are send to STDOUT.

Author(s)

Patrick T. Brandt and Justin Appleby.

See Also

[szbvar](#), [szbsvar](#)

<code>mae</code>	<i>Mean absolute error of VAR forecasts</i>
------------------	---

Description

Computes the mean absolute error of VAR forecasts

Usage

```
mae(m1, m2)
```

Arguments

`m1` $nsteps \times m$ matrix of VAR forecasts
`m2` $nsteps \times m$ matrix of VAR forecasts or true values

Details

Computes the mean absolute error (MAE) across a series of VAR forecasts.

Value

MAE value

Author(s)

Patrick T. Brandt

See Also

[cf. forecasts](#), [rmse](#)

Examples

```
data(IsraelPalestineConflict)
Y.sample1 <- window(IsraelPalestineConflict, end=c(2002, 52))
Y.sample2 <- window(IsraelPalestineConflict, start=c(2003,1))

# Fit a BVAR model
fit.bvar <- szbvar(Y.sample1, p=6, lambda0=0.6, lambda1=0.1, lambda3=2,
                  lambda4=0.25, lambda5=0, mu5=0, mu6=0, prior=0)

# Forecast -- this gives back the sample PLUS the forecasts!

forecasts <- forecast(fit.bvar, nsteps=nrow(Y.sample2))

# Compare forecasts to real data
mae(forecasts[(nrow(Y.sample1)+1):nrow(forecasts)], Y.sample2)
```

 mc.irf

Monte Carlo Integration / Simulation of Impulse Response Functions

Description

Simulates a posterior of impulse response functions (IRF) by Monte Carlo integration. This can handle Bayesian and frequentist VARs and Bayesian (structural) VARs estimated with the `szbvar`, `szbsvar` or `reduced.form.var` functions. The decomposition of the contemporaneous innovations is handled by a Cholesky decomposition of the error covariance matrix in reduced form (B)VAR object, or for the contemporaneous structure in S-VAR models. Simulations of IRFs from the Bayesian model utilize the posterior estimates for that model.

Usage

```
mc.irf(varobj, nsteps, draws=0, A0.posterior=NULL,
       sign.list=rep(1, ncol(varobj$Y)))
```

Arguments

varobj	VAR objects for a fitted VAR model from either <code>reduced.form.var</code> , <code>szbvar</code> or <code>szbsvar</code> .
nsteps	Number of periods over which to compute the impulse responses
draws	Number of draws for the simulation of the posterior distribution of the IRFs (if not a <code>szbsvar</code> object)
A0.posterior	Posterior sample objects generated by <code>gibbs.A0()</code> for B-SVAR models, based on the structural identification in <code>varobj\$ident</code> .
sign.list	A list of signs (length = number of variables) for normalization given as either 1 or -1.

Details**VAR/BVAR:**

Draws a set of posterior samples from the VAR coefficients and computes impulse responses for each sample. These samples can then be summarized to compute MCMC-based estimates of the responses using the error band methods described in Sims and Zha (1999).

B-SVAR: Generates a set of $N2$ draws from the impulse responses for the Bayesian SVAR model in `varobj`. The function takes as its arguments the posterior moments of the B-SVAR model in `varobj`, the draws of the contemporaneous structural coefficients A_0 from `gibbs.A0`, and a list of signs for normalization. This function then computes a posterior sample of the impulse responses based on the Schur product of the sign list and the draws of A_0 and draws from the normal posterior pdf for the other coefficients in the model.

The computations are done using compiled C++ code as of version 0.3.0. See the package source code for details about the implementation.

MSBVAR:

At present these are not implemented in the package. Email the package maintainer if you are interest in this feature.

Value**VAR/BVAR:**

An `mc.irf.VAR` or `mc.irf.BVAR` class object object that is the array of impulse response samples for the Monte Carlo samples

`impulse` $draws \times nsteps \times m^2$ array of the impulse responses

B-SVAR: `mc.irf.BSVAR` object which is an $(N2, nsteps, m^2)$ array of the impulse responses for the associated B-SVAR model in `varobj` and the posterior A_0 .

Note

Users need to think carefully about the number of steps and the size of the posterior sample in A_0 , since enough memory needs to be available to store and process the posterior of the impulse responses. The number of bytes consumed by the impulse responses will be approximately $m^2 \times nsteps \times N2 \times 16$ where $N2$ is the number of draws of A_0 from the `gibbs.A0`. Be sure you have enough memory available to store the object you create!

Author(s)

Patrick T. Brandt

References

Brandt, Patrick T. and John R. Freeman. 2006. "Advances in Bayesian Time Series Modeling and the Study of Politics: Theory Testing, Forecasting, and Policy Analysis" *Political Analysis* 14(1):1-36.

Sims, C.A. and Tao Zha. 1999. "Error Bands for Impulse Responses." *Econometrica* 67(5): 1113-1156.

Hamilton, James. 1994. Time Series Analysis. Chapter 11.

Waggoner, Daniel F. and Tao A. Zha. 2003. "A Gibbs sampler for structural vector autoregressions" *Journal of Economic Dynamics & Control*. 28:349–366.

See Also

See also as [plot.mc.irf](#) for plotting methods and error band construction for the posterior of the impulse response functions, [szbsvar](#) for estimation of the posterior moments of the B-SVAR model, [gibbs.A0](#) for drawing posterior samples of A_0 for the B-SVAR model before the IRF computations, and [plot.mc.irf](#) for a plotting method for the posterior of the impulse responses.

Examples

```
# Example 1
data(IsraelPalestineConflict)
varnames <- colnames(IsraelPalestineConflict)

fit.BVAR <- szbvar(Y=IsraelPalestineConflict, p=6, z=NULL,
                  lambda0=0.6, lambda1=0.1,
                  lambda3=2, lambda4=0.25, lambda5=0, mu5=0,
                  mu6=0, nu=3, qm=4,
                  prior=0, posterior.fit=FALSE)

# Draw from the posterior pdf of the impulse responses.
posterior.impulses <- mc.irf(fit.BVAR, nsteps=10, draws=5000)

# Plot the responses
plot(posterior.impulses, method=c("Sims-Zha2"), component=1,
     probs=c(0.16,0.84), varnames=varnames)

# Example 2
ident <- diag(2)
varobj <- szbsvar(Y=IsraelPalestineConflict, p=6, z = NULL,
                 lambda=0.6, lambda1=0.1, lambda3=2, lambda4=0.25,
                 lambda5=0, mu5=0, mu6=0, ident, qm = 4)

A0.posterior <- gibbs.A0(varobj, N1=1000, N2=1000)

# Note you need to explicitly reference the sampled A0.posterior object
# in the following call for R to find it in the namespace!
```

```
impulse.sample <- mc.irf(varobj, nsteps=12, A0.posterior=A0.posterior)

plot(impulse.sample, varnames=colnames(IsraelPalestineConflict),
     probs=c(0.16,0.84))
```

mcmc.szbsvar

Gibbs sampler for coefficients of a B-SVAR model

Description

Draws a posterior sample of the reduced form coefficients for a Bayesian SVAR model

Usage

```
mcmc.szbsvar(varobj, A0.posterior)
```

Arguments

varobj A B-SVAR object created by [szbsvar](#)
A0.posterior A posterior sample object generated by [gibbs.A0](#)

Details

This function draws the parameters from the Bayesian SVAR model described by Waggoner and Zha (2003). The details can be found in [szbsvar](#). The draws are done for the SVAR model and then translated into the reduced form parameters.

Value

A list of the class "mcmc.bsvr.posterior" with the following components:

A0.posterior $m \times m \times N2$ array of the posterior matrices A_0 .
B.sample $N2 \times ncoef$ matrix of the reduced form coefficients for the SVAR.

Author(s)

Patrick T. Brandt

References

Waggoner, Daniel F. and Tao A. Zha. 2003. "A Gibbs sampler for structural vector autoregressions" *Journal of Economic Dynamics & Control*. 28:349–366.

See Also

[szbsvar](#)

Examples

```
## Not run:
varobj <- szbsvar(Y, p, z = NULL, lambda0, lambda1, lambda3, lambda4,
                 lambda5, mu5, mu6, ident, qm = 4)
posterior <- mcmc.szbsvar(varobj, N1, N2)

## End(Not run)
```

 mean.SS

Summary measures and plots for MS-B(S)VAR state-spaces

Description

Provides a summary and plotting methods for the SS class objects produced from sampling the posterior of an MSBVAR model. These functions provide the mean regime probabilities and a plotting method for them.

Usage

```
mean.SS(x, ...)
sum.SS(x, ...)

plot.SS(x, ylab="State Probabilities", ...)
```

Arguments

x	SS class object produced by sampling the posterior of a Markov-switching BVAR model in MSBVAR. These are produced by gibbs.msbvar .
ylab	y-axis label for the regime plot.
...	Other argument or graphics parameters for plot.

Details

The first two provide the sum and mean of the number of time periods in each state of Markov-process. The last produces a time series plot of the regime or state probabilities. These are computed from the Markov Chain Monte Carlo sample computed from [gibbs.msbvar](#)

Value

Mean and sum are $T \times h$ matrices for the first two summary functions. The plot function generates a plot in the current device. These are the posterior probability measures of the Markov process regimes across T periods.

Author(s)

Patrick T. Brandt

See Also

[gibbs.msbvar](#), [msbvar](#)

mountains

Mountain plots for summarizing forecast densities

Description

"Mountain plots" summarize the bivariate density of 2 variables for two competing forecasts of those variables.

Usage

```
mountains(fcasts1, fcasts2, varnames, pts, ...)
```

Arguments

fcasts1	<i>gibbs</i> × 2 set of forecasts from model 1
fcasts2	<i>gibbs</i> × 2 set of forecasts from model 2
varnames	c("name1", "name2") object of the variable names
pts	c(pt1, pt2) which are reference points to be plotted.
...	Other graphics parameters.

Details

A "mountain plot" provide a 2×2 graph of plots that summarize the bivariate forecasts for two competing forecasts. This function presents four perspectives on the bivariate density or 'hills' for a set of forecasts. Starting from the bottom right plot and working counter-clockwise, the first plot is the bivariate density of the two competing forecasts. The next plot is a contour map that provide the topography of the densities. The third and fourth plots are projections of densities in each variable. The first forecast in the function is presented in black, the second in red. The densities are estimated from the Gibbs Monte Carlo sample of forecasts using the `bkde2D` bivariate kernel density estimator with an optimal plug-in bandwidth selected using `dpi11`.

Value

None. Produces the mountain plot described above in the current graphics device.

Note

This function requires the bivariate kernel smoother in the package [bkde2D](#)

Author(s)

Patrick T. Brandt

References

Brandt, Patrick T. and John R. Freeman. 2006. "Advances in Bayesian Time Series Modeling and the Study of Politics: Theory Testing, Forecasting, and Policy Analysis" *Political Analysis* 14(1):1-36.

See Also

[bkde2D](#) for details of the density estimators

Examples

```
## Not run:
data(IsraelPalestineConflict)

# Fit a BVAR model
fit.BVAR <- szbvar(IsraelPalestineConflict, p=6, z=NULL, lambda0=0.6,
                  lambda1=0.1, lambda3=2, lambda4=0.5, lambda5=0,
                  mu5=0, mu6=0, nu=3, qm=4, prior=0,
                  posterior.fit=FALSE)

# Fit a flat prior / MLE model
fit.FREQ <- szbvar(IsraelPalestineConflict, p=6, z=NULL, lambda0=0.6,
                  lambda1=0.1, lambda3=2, lambda4=0.5, lambda5=0,
                  mu5=0, mu6=0, nu=3, qm=4, prior=2,
                  posterior.fit=FALSE)

# Generate unconditional forecasts for both models
forecast.BVAR <- uc.forecast.var(fit.BVAR, nsteps=2,
                                burnin=100, gibbs=1000)

forecast.FREQ <- uc.forecast.var(fit.FREQ, nsteps=2,
                                burnin=100, gibbs=1000)

# Plot the densities for the forecasts in period of the forecast horizon
mountains(forecast.BVAR$forecast[,2,1:2],
          forecast.FREQ$forecast[,2,1:2], varnames=c("I2P","P2I"), pts=c(0,0))

## End(Not run)
```

msbvar

*Markov-switching Bayesian reduced form vector autoregression
model setup and posterior mode estimation*

Description

Sets up and estimates the posterior mode of a reduced form Markov-switching Bayesian vector autoregression model with a Sims-Zha prior. This is the setup and input function for the Gibbs sampler for this model.

Usage

```
msbvar(y, z = NULL, p, h, lambda0, lambda1, lambda3, lambda4,
       lambda5, mu5, mu6, qm,
       alpha.prior = 100 * diag(h) + matrix(2, h, h),
       prior=0, max.iter = 40)
```

Arguments

y	$T \times m$ multiple time series object created with <code>ts()</code> .
z	NOT IMPLEMENTED AT PRESENT: THIS SHOULD BE A $T \times k$ matrix of exogenous variables. Can be <code>z = NULL</code> if there are none (the default).
p	Lag length, an integer
h	Number of regimes / states, an integer
lambda0	[0, 1], Overall tightness of the prior (discounting of prior scale).
lambda1	Lag decay (> 0 , with 1=harmonic)
lambda3	Lag decay (> 0 , with 1=harmonic)
lambda4	Standard deviation or tightness around the intercept > 0
lambda5	Standard deviation or tightness around the exogenous variable coefficients > 0
mu5	Sum of coefficients prior weight ≥ 0 . Larger values imply difference stationarity.
mu6	Dummy initial observations or drift prior ≥ 0 . Larger values allow for common trends.
qm	Frequency of the data for lag decay equivalence. Default is 4, and a value of 12 will match the lag decay of monthly to quarterly data. Other values have the same effect as "4"
alpha.prior	Prior for the Dirichlet process for the MS process. Default is $100 * \text{diag}(h) + \text{matrix}(2, h, h)$, but the model will be sensitive to this.
prior	One of three values: 0 = Normal-Wishart prior, 1 = Normal-flat prior, 2 = flat-flat prior (i.e., akin to MLE). The conjugate prior is the first one, which is the default.
max.iter	Maximum number of iterations for the block EM algorithm used to fit an initial guess of the model posterior. Default value is 40 iterations. Larger problems will need more iterations.

Details

This function estimates the posterior mode of a reduced form Bayesian Markov-switching VAR model. The MSBVAR mode is estimated using block EM algorithm where the blocks are 1) the MS state-space, 2) the BVAR regression step for each regime and 3) the transition matrix. Starting values are randomly drawn, so a random number seed should be set prior to calling the function in order to make the results replicable.

This function should NOT be used for inference, since it only finds the posterior mode of the model. This function is intended to generate starting values for the Gibbs sampling of the model. See [gibbs.msbvar](#) for further details of the Gibbs sampling.

Value

A list describing the posterior mode of the MSBVAR model and the inputs necessary for the subsequent Gibbs sampler.

<code>init.model</code>	An object of the class BVAR that describes the setup of the model. See szbvar for details.
<code>hreg</code>	A list containing the regime-specific moment matrices, VAR coefficients, and error covariances
<code>Q</code>	The $h \times h$ Markov transition matrix.
<code>fp</code>	The $T \times h$ matrix of the filtered regime probabilities. First column is the first regime, etc.
<code>m</code>	Integer, the number of endogenous variables in the system.
<code>p</code>	Integer, the lag length of the VAR.
<code>h</code>	Integer, the number of regimes in the MS process.
<code>alpha.prior</code>	The $h \times h$ matrix for the prior for the Dirichlet density for the MS process.

Note

Users should consult the reference papers and the (coming) package vignette to see how this function is used to setup an MSBVAR model. An example is currently in [gibbs.msbvar](#).

Author(s)

Patrick T. Brandt

References

- Brandt, Patrick T. 2009. "Empirical, Regime-Specific Models of International, Inter-group Conflict, and Politics"
- Fruhworth-Schnatter, Sylvia. 2001. "Markov Chain Monte Carlo Estimation of Classical and Dynamic Switching and Mixture Models". *Journal of the American Statistical Association*. 96(153):194–209.
- Fruhworth-Schnatter, Sylvia. 2006. *Finite Mixture and Markov Switching Models*. Springer Series in Statistics New York: Springer.
- Sims, Christopher A. and Daniel F. Waggoner and Tao Zha. 2008. "Methods for inference in large multiple-equation Markov-switching models" *Journal of Econometrics* 146(2):255–274.
- Sims, Christopher A. and Tao A. Zha. 1998. "Bayesian Methods for Dynamic Multivariate Models" *International Economic Review* 39(4):949-968.
- Sims, Christopher A. and Tao A. Zha. 2006. "Were There Regime Switches in U.S. Monetary Policy?" *American Economic Review*. 96(1):54–81.

See Also

[gibbs.msbvar](#), [szbvar](#)

normalize.svar	<i>Likelihood normalization of SVAR models</i>
----------------	--

Description

Computes various sign normalizations of Bayesian structural VAR (B-SVAR) models.

Usage

```
normalize.svar(A0unnormalized, A0mode,
              method = c("DistanceMLA", "DistanceMLAhat",
                        "Euclidean", "PositiveDiagA",
                        "PositiveDiagAinv", "Unnormalized"),
              switch.count = 0)
```

Arguments

<code>A0unnormalized</code>	$m \times m$ unnormalized matrix value of A_0 in an B-SVAR
<code>A0mode</code>	$m \times m$ matrix of the A_0 to normalize around
<code>method</code>	string that selects the normalization method
<code>switch.count</code>	counter that counts the number of sign switches. Can be non-zero if you want to track the sign switches iteratively.

Details

The likelihood of VAR models are invariant to sign changes of the structural equation coefficients across equations. Thus a VAR with m equations has a likelihood with 2^m identical peaks, each a different set of signs (but with the same posterior peak). Normalization is used to choose among these peaks. The most common choice is to select the peak where the diagonal elements of A_0 are all positive, but will not be possible in all cases since no such normalization may exist. Thus, one should select a single peak and map all of the draws back to that peak.

The available normalization methods are 1) "DistanceMLA" : normalize around the ML peak of A_0 mode, 2) "DistanceMLAhat" : normalize around the ML peak of $\text{inv}(A_0 \text{ mode})$ 3) "Euclidean" : normalize by minimizing the distance between the two matrices. 4) "PositiveDiagA" : normalize by making the diagonal positive 5) "PositiveDiagAinv" : normalize by making the diagonal of $\text{inv}(A_0)$ positive. 6) "Unnormalized" : no normalization is performed and the function returns A_0 unnormalized.

Value

A list with two elements

<code>A0normalized</code>	$m \times m$ matrix, the normalized value of A_0 according to the selected normalization rule.
<code>switch.count</code>	Number of signs changed in the normalization

Note

This function is called in `gibbs.A0.BSVAR`, the Gibbs sampling of `szbsvar` models. In those functions, the A_0 produced by `szbsvar` is unnormalized. The Gibbs sampled draws are then normalized using the "DistanceMLA" method, which is consistent with the positive system shocks typically seen in the literature, if such a normalization exists. Note that Waggoner and Zha prefer the "DistanceMLA" method.

Author(s)

Patrick T. Brandt

References

Waggoner, Daniel F. and Tao A. Zha. 2003a. "A Gibbs sampler for structural vector autoregressions" *Journal of Economic Dynamics & Control*. 28:349–366.

Waggoner, Daniel F. and Tao A. Zha. 2003b. "Likelihood preserving normalization in multiple equation models". *Journal of Econometrics*. 114: 329–347.

See Also

[szbsvar](#), [gibbs.A0](#)

null.space

Find the null space of a matrix

Description

Computes the null space of A for an arbitrary linear system of the form $Ax = b$.

Usage

`null.space(x)`

Arguments

x $m \times n$ A matrix of a linear system $Ax = b$

Details

Computes the null space via singular value decomposition (SVD) of A by finding the columns of the SVD of A that correspond to the non-singular column vectors that span A .

Value

Returns an $m \times q$ matrix that is the null space, where q is the rank of A .

Author(s)

Patrick T. Brandt

See Also[svd](#)

`plot.forc.ecdf`*Plots VAR forecasts and their empirical error bands*

Description

Plots mean VAR forecasts and pointwise error bands

Usage

```
plot.forc.ecdf(x, probs = c(0.05, 0.95),  
              xlab = "", ylab = "", ylim = NA, ...)
```

Arguments

<code>x</code>	N x nstep matrix of forecasts
<code>probs</code>	width of error band probabilities, default is 90% quantiles or <code>c(0.05, 0.95)</code>
<code>xlab</code>	x-axis labels
<code>ylab</code>	y-axis labels
<code>ylim</code>	Bounds for y-axis in standard format <code>c(lower, upper)</code>
<code>...</code>	other plot parameters

Details

Plots the mean forecast and the pointwise empirical confidence region for a posterior sample of VAR forecasts.

Value

None.

Author(s)

Patrick T. Brandt

See Also[plot.forecast](#)

Examples

```
## Not run:
data(IsraelPalestineConflict)

# Fit a BVAR model
fit.BVAR <- szbvar(IsraelPalestineConflict, p=6, z=NULL, lambda0=0.6,
                  lambda1=0.1, lambda3=2, lambda4=0.5, lambda5=0,
                  mu5=0, mu6=0, nu=3, qm=4, prior=0,
                  posterior.fit=FALSE)

# Generate unconditional forecasts for both models
forecast.BVAR <- uc.forecast(fit.BVAR, nsteps=12,
                             burnin=100, gibbs=1000)

# Plot the forecasts
par(mfrow=c(2,1))

plot(forecast.BVAR$forecast[,1], probs=c(0.16,0.84),
     main="I2P Forecast")
abline(h=0)

plot(forecast.BVAR$forecast[,2], probs=c(0.16,0.84),
     main="P2I Forecast")
abline(h=0)

## End(Not run)
```

plot.forecast

Plot function for forecasts

Description

Generates simple plots of forecasts obtained from forecast.VAR / forecast.BVAR / forecast.B-SVAR

Usage

```
plot.forecast(x, ...)
```

Arguments

x	Plots generated from forecast generated through fitted VAR, BVAR, or B-SVAR model from forecast .
...	Other graphics parameters

Details

Generates a plot in the current graphics device for the m time series in the respective (B)VAR model.

Value

None. Generates a plot in the current graphics device.

Author(s)

Patrick T. Brandt

See Also

[summary](#)

Examples

```
## Not run:
plot(x)

## End(Not run)
```

plot.gibbs.A0

Plot a parameter density summary for B-SVAR $A(0)$ objects

Description

Generates an $m \times m$ matrix of density plots for each free parameter in an `szbsvar` A_0 object produced by `gibbs.A0`, with associated highest posterior density (HPD) regions.

Usage

```
plot.gibbs.A0(x, hpd = 0.68, varnames=attr(x, "eqnames"), ...)
```

Arguments

<code>x</code>	An A_0 posterior object created by <code>szbsvar</code> .
<code>hpd</code>	Probability width of the highest posterior density region, default is 0.68 or approximately one standard deviation around the mode of the parameter
<code>varnames</code>	List of variable names for labeling the equations and variables. Default are the names of the variables for the input data to <code>szbsvar</code> as fed through <code>gibbs.A0</code> . For an SVAR, users often want to relabel these as economic sectors or groups of actors for the time series and this is the place this can be done.
<code>...</code>	optional graphics arguments

Details

This function plots an $m \times m$ matrix of densities for the posterior of the A_0 free parameters for a B-SVAR model. The plot is arranged such that the unrestricted parameters for each contemporaneous effect of each variable on an equation are in the row for that equation. So the first row shows densities for the contemporaneous effects of the column variables (as in an impulse response plot like `plot.irf` or `plot.mc.irf`). Elements of A_0 that were restricted to zero are left empty in the matrix of densities. The pattern of the densities will match the `*tranpose*` of the `ident` matrix passed to `szbsvar`.

Highest posterior density regions are plotted using Hyndman's 91996) density quantile algorithm. These HPDs are defined by a set of vertical bars over the HPD interval. The vertical line in each plot measures the value of the density at the boundaries of the HPD region. The HDR is superimposed at the bottom of each density.

Value

None. Main purposed is to plot density summaries and HPDs for each of the free parameters in an A_0 matrix.

Note

The plot will tend to be large, so be sure to adjust the size of your plotting device accordingly so things are visible.

Author(s)

Patrick T. Brandt

References

Hyndman, Rob J. 1996. "Computing and Graphical Highest Density Regions", *The American Statistician*, 50(2):120–126

HPD code is borrowed from Hyndman's `hdrcode` package, version 2.07.

See Also

[plot.mcmc](#), [summary.mcmc](#), and [A02mcmc](#).

Examples

```
# SZ, B-SVAR model for the Levant data
data(BCFdata)
m <- ncol(Y)
ident <- diag(m)
ident[1,] <- 1
ident[2,1] <- 1

# estimate the model's posterior moments
set.seed(123)
model <- szbsvar(Y, p=2, z=z2, lambda0=0.8, lambda1=0.1, lambda3=1, lambda4=0.1,
```

```

lambda5=0.05, mu5=0, mu6=5, ident, qm=12)

# Set length of burn-in and size of posterior. These are only an
# example. Production runs should set these much higher.
N1 <- 1000
N2 <- 10000

A0.posterior.obj <- gibbs.A0(model, N1, N2, thin=1)

# Plot the matrix of the densities
dev.new()
plot.gibbs.A0(A0.posterior.obj, hpd=0.68, varnames=colnames(Y))

```

plot.irf

Plots impulse responses

Description

Plots the $m \times m$ matrix of impulse responses produced by `irf`.

Usage

```
plot.irf(x, varnames = attr(x, "eqnames"), ...)
```

Arguments

<code>x</code>	Impulse response object produced by <code>irf</code>
<code>varnames</code>	Names of equations and shocks in the format <code>c("name1", "name2", ...)</code> . Default is to use the names of the input variables from the estimation method.
<code>...</code>	other plot arguments

Details

Generates a plot in the current plotting device of the impulse responses in `irf`. See below for functions that allow one to add error bands and confidence regions to the impulse responses. Impulses or shocks are in the columns and the rows are the responses.

Value

None. Draws a graph in the current device.

Note

This function should NOT be used for Monte Carlo samples of IRFs. Use `plot.mc.irf` for this purpose.

Author(s)

Patrick T. Brandt

References

Hamilton, James. 1994. Time Series Analysis, Chapter 11.
 Sims, C.A. 1980. "Macroeconomics and Reality" Econometrica.

See Also

[irf](#) to produce impulse responses from a VAR object, [mc.irf](#), and [plot.mc.irf](#) for methods that allow frequentist and Bayesian error bands in the impulse responses

Examples

```
data(IsraelPalestineConflict)
rf.var <- reduced.form.var(IsraelPalestineConflict, p=6)
plot(irf(rf.var, nsteps = 12))
```

 plot.mc.irf

Plotting posteriors of Monte Carlo simulated impulse responses

Description

Provides a plotting method for the mc.irf Monte Carlo sample of impulse responses. Responses can be plotted with classical or Bayesian error bands, as suggested by Sims and Zha (1999).

Usage

```
plot.mc.irf(x, method=c("Sims-Zha2"), component=1,
            probs=c(0.16,0.84), varnames = attr(x, "eqnames"), ...)
```

Arguments

x	Output of the mc.irf function
method	Method to be used for the error band construction. Default method is to use the eigendecomposition method proposed by Sims and Zha. Defined methods are "Percentile" (error bands are based on percentiles specified in probs), "Normal Approximation" (Gaussian approximation for interval of width probs), "Sims-Zha1" (Gaussian approximation with linear eigendecomposition), "Sims-Zha2" (Percentiles with eigendecomposition for each impulse response function), "Sims-Zha3" (Percentiles with eigendecomposition of the full stacked impulse responses)
component	If using one of the eigendecomposition methods, the eigenvector component to be used for the error band construction. Default is the first or largest eigenvector component.

probs	probs is the width of the error bands. Default is <code>c(0.16, 0.84)</code> which is a 68% band that is approximately one standard deviation, as suggested by Sims and Zha.
varnames	List of variable names of length m for labeling the impulse responses. Default are the input variable names from the relevant estimation method.
...	Other graphics parameters

Details

This function plots the output of a Monte Carlo simulation of (B)(BS)VAR impulse response functions produced by `mc.irf`. The function allows the user to choose among a variety of frequentist (normal approximation and percentile) and Bayesian (eigendecomposition) methods for constructing error bands around a set of impulse responses. Impulses or shocks are in the columns and the rows are the responses.

Value

The primary reason for this function is to plot impulse responses and their error bands. Secondly, it returns an invisible list of the impulses responses, their error bands, and summary measures of the fractions of the variance in the eigenvector methods that explain the total variation of each response.

responses	Responses and their error bands
eigenvector.fractions	Fraction of the variation in each response that is explained by the chosen eigenvectors. NULL for non-eigenvector methods.

Author(s)

Patrick T. Brandt

References

- Brandt, Patrick T. and John R. Freeman. 2006. "Advances in Bayesian Time Series Modeling and the Study of Politics: Theory Testing, Forecasting, and Policy Analysis" *Political Analysis* 14(1):1-36.
- Sims, C.A. and Tao Zha. 1999. "Error Bands for Impulse Responses." *Econometrica*. 67(5): 1113-1156.

See Also

See Also `mc.irf` for the computation of Monte Carlo samples of impulse responses, `szbsvar` for estimation of the posterior moments of the B-SVAR model, `gibbs.A0` for Gibbs sampling the posterior of the A_0 for the model, and

Examples

```
## Not run:
data(IsraelPalestineConflict)
fit.BVAR <- szbvar(IsraelPalestineConflict, p=6, z=NULL, lambda0=0.6,
                 lambda1=0.1, lambda3=2, lambda4=0.5, lambda5=0,
                 mu5=0, mu6=0, nu=3, qm=4, prior=0,
                 posterior.fit=FALSE)

posterior.impulses <- mc.irf(fit.BVAR, nsteps=12, draws=1000)
plot(posterior.impulses, method = c("Percentile"))

## End(Not run)
```

plotregimeid

*Clustering and plotting function for msbvar permuted sample output***Description**

Identifies and plots regime-specific coefficients from the random permutation sampler for regime identification

Usage

```
plotregimeid(m1, m1p, type = c("all", "intercepts", "Sigma", "Q"),
            ask = TRUE, ...)
```

Arguments

m1	Model object produced by <code>msbvar</code> with the posterior mode of an MSBVAR model.
m1p	Gibbs sample from the posterior of an MSBVAR model. Object is produced by a call to the <code>gibbs.msbvar</code> function. Should be produced by the same <code>msbvar</code> object used to generate the posterior sample in the <code>gibbs.msbvar</code> call.
type	Items to be clustered and plots to be produced to identify the posterior regimes / modes of the Gibbs sampler based on the randomly permuted draws. The type can be "intercepts" where the clustering of the posterior draws and the plots are based on the intercepts in each equation (so a change in equilibrium model), "Sigma" or the variances of the equations across the regimes, or "Q" based on the elements of the transition matrix, Q . The option "all" generates the plots and clustering for all of the above options and is the default.
ask	logical, default=TRUE. Ask about which plots to show, ala the syntax in coda. If TRUE then all relevant responses are displayed on the current graphical device with user input. Otherwise, all plots run by in the current device as generated.
...	Optional graphical and lattice parameters to be fed to the plots. There is no assurance that these will work. E-mail <code>pbrandt@utdallas.edu</code> if you have inputs on this that do not work, but that you think should.

Details

The posterior of a Markov-switching (MS) model estimated by an unrestricted Gibbs sampler has $h!$ identical posterior modes. The modes are identical in the sense that they are merely relabelings of the regime labels. Since the analyst may not apriori know what defines or separates the regimes in the parameter space, this function allows one to explore the randomly permuted labelings that are generated by the `gibbs.msbvar` function.

This function takes the output of `gibbs.msbvar` and shows colored scatter, densityplots, and tra-ceplots for the posterior. The coloring follow standard R color pallates. The determination of how the regimes are identified is based on a `kmeans` clustering of either the "intercepts", "Sigma" (variances), or "Q" transition probabilities. This is the method suggested by Fruhwirth-Schanatter (2001, 2006). The utility here is that this function handles subsetting the data, setting up the clustering and plotting and labeling the results for the user.

Regime identification and labeling is necessary so that one can sample from a single mode of the posterior to get sensible regime classification plots from say `plot.SS` or regime probabilities from say `mean.SS`.

Value

None. A series of plots are produced in the current graphics device.

Note

This is the first version of this function. Future versions may use a slightly different syntax and only use one input argument.

Author(s)

Patrick T. Brandt

References

- Fruhwirth-Schnatter, Sylvia. 2001. "Markov Chain Monte Carlo Estimation of Classical and Dynamic Switching and Mixture Models". *Journal of the American Statistical Association*. 96(153):194–209.
- Fruhwirth-Schnatter, Sylvia. 2006. *Finite Mixture and Markov Switching Models*. Springer Series in Statistics New York: Springer.

See Also

`msbvar`, `plot.SS`, `mean.SS`, `gibbs.msbvar`

Examples

```
## Not run:
# This example can be pasted into a script or copied into R to run. It
# takes a few minutes, but illustrates how the code can be used

data(IsraelPalestineConflict)
```

```

# Find the mode of an msbvar model
# Initial guess is based on random draw, so set seed.
set.seed(123)

xm <- msbvar(y=IsraelPalestineConflict, p=1, h=2,
             lambda0=0.8, lambda1=0.15,
             lambda3=2, lambda4=1, lambda5=0, mu5=0,
             mu6=0, qm=12,
             alpha.prior=matrix(c(5,2,2,10), 2, 2))

# Plot out the initial mode
plot(ts(xm$fp))
print(xm$Q)

# Now sample the posterior
N1 <- 100
N2 <- 500

# First, so this with random permutation sampling
x1 <- gibbs.msbvar(xm, N1=N1, N2=N2, permute=TRUE)

# Identify the regimes using clustering in plotregimeid()
plotregimeid(xm, x1, type="all")

# Now re-estimate based on desired regime identification seen in the
# plots. Here we are using the variance of the first equation, so
# Sigma.idx=1.

x2 <- gibbs.msbvar(xm, N1=N1, N2=N2, permute=FALSE, Sigma.idx=1)

# Plot the variances. Note the strict hyperplane between the variances
# for the first equation versus the others.
plotregimeid(xm, x2, type="Sigma")

## End(Not run)

```

posterior.fit	<i>Estimates the marginal likelihood and posterior probability for VAR, BVAR, and BSVAR models</i>
---------------	--

Description

Computes the marginal log likelihood other posterior fit measures for VAR, BVAR, and BSVAR models fit with `szbsvar` and `szbvar`.

Usage

```
posterior.fit(varobj, A0.posterior.obj=NULL)
```

Arguments

varobj BVAR or BSVAR object from fitting a model with `szbsvar` or `szbvar`
A0.posterior.obj MCMC Gibbs object for the B-SVAR model A_0 from `gibbs.A0`

Details

Estimates the marginal log likelihood, log prior, log posterior for the A_0 and A_1, \dots, A_p parameters of the model, and the log data density for the sample (after integrating out the model parameters). The approach used is that of Chib (1995).

The computations are done using compiled C++ code as of version 0.3.0. See the package source code for details about the implementation.

Value

BVAR:

A list of the class "posterior.fit.VAR" that includes the following elements:

data.marg.llf Log marginal density, the probability of the data after integrating out the parameters in the model.
data.marg.post Predictive marginal posterior density
coefficient.post Contribution to the posterior fit from the pdf of the coefficients.

BSVAR:

A list of the class "posterior.fit.BSVAR" that includes the following elements:

log.prior Log prior probability
log.llf $T \times 1$ list of the log probabilities for each observation conditional on the parameters.
log.posterior.Aplus Log marginal probability of A_1, \dots, A_p conditional on the data and A_0
log.marginal.data.density Log data density or marginal log likelihood, the probability of the data after integrating out the parameters in the model.
log.marginal.A0k $m \times 1$ list of the log probabilities of each column (corresponding to the equations) of A_0 conditional on the other columns.

Note

The log Bayes factor for two model can be computed using the `log.marginal.data.density`:

`log BF = log.marginal.data.density.1 - log.marginal.data.density.2`

Note that at present, the scale factors for the BVAR and B-SVAR models are different (one used the concentrated likelihood, the other does NOT). Thus, one cannot compare fit measures across the two functions. To compare a recursive B-SVAR to a non-recursive B-SVAR model, one should estimate the recursive model with `szbsvar` using the appropriate `ident` matrix and then call `posterior.fit` on the two B-SVAR models!

Author(s)

Patrick T. Brandt

References

Chib, Siddhartha. 1995. "Marginal Likelihood from the Gibbs Output." *Journal of the American Statistical Association*. 90(432): 1313–1321.

Waggoner, Daniel F. and Tao A. Zha. 2003. "A Gibbs sampler for structural vector autoregressions" *Journal of Economic Dynamics & Control*. 28:349–366.

See Also

[szbvar](#), [szbsvar](#), [gibbs.A0](#), [mc.irf](#), [print.posterior.fit](#)

Examples

```
## Not run:
varobj <- szbsvar(Y, p, z = NULL, lambda0, lambda1, lambda3, lambda4,
                 lambda5, mu5, mu6, ident, qm = 4)
A0.posterior <- gibbs.A0(varobj, N1, N2)
fit <- posterior.fit(varobj, A0.posterior)
print(fit)

## End(Not run)
```

print.dfev

Printing DFEV tables

Description

Prints decomposition of forecast error variance tables

Usage

```
print.dfev(x, latex = F, file = NULL, ...)
```

```
summary.dfev(object, latex = F, file = NULL, ...)
```

Arguments

x	DFEV object created by dfev
object	DFEV object created by dfev
latex	Logical. T = format results in LaTeX tables, default is F, text output
file	File for the results. If NULL, prints to standard output device.
...	Other print and summary arguments

Details

Prints DFEV results in a table using `xtable` functions.

Value

None.

Author(s)

Patrick T. Brandt

See Also

See [dfev](#) for an example.

`print.posterior.fit` *Print method for posterior fit measures*

Description

Prints objects of the classes "posterior.fit.VAR", "posterior.fit.BVAR", and "posterior.fit.BSVAR".

Usage

```
print.posterior.fit(x, ...)
```

Arguments

<code>x</code>	object produced by posterior.fit ,
<code>...</code>	other print options

Details

Called for its side effect — printing the output of [posterior.fit](#)

Value

None

Author(s)

Patrick T. Brandt

See Also

[szbvar](#), [szbsvar](#), [gibbs.A0](#), [gibbs.msbvar](#), [mc.irf](#), [posterior.fit](#)

Examples

```
## Not run:
varobj <- szbsvar(Y, p, z = NULL, lambda0, lambda1, lambda3, lambda4,
                 lambda5, mu5, mu6, ident, qm = 4)
A0.posterior <- gibbs.A0(varobj, N1, N2)
fit <- posterior.fit(varobj, A0.posterior)
print(fit)

## End(Not run)
```

rdirichlet

Random draws from and density for Dirichlet distribution

Description

Generate draws from a random Dirichlet distribution or compute its density.

Usage

```
rdirichlet(n, alpha)
ddirichlet(x, alpha)
```

Arguments

n	Number of draws
alpha	Scale matrix, $h \times h$
x	value to compute density

Details

Draws n values for an $h \times h$ Dirichlet random variable or computes the density.

Value

x An $n \times h$ matrix of the draws

Note

Based on code from Kevin Quinn in the MCMCpack package and the gregmisc package.

References

MCMCpack and gregmisc

Examples

```
rdirichlet(2, matrix(rep(1, 4), 2, 2))
```

reduced.form.var	<i>Estimation of a reduced form VAR model</i>
------------------	---

Description

Estimates a reduced form VAR using equation-by-equation seemingly unrelated regression (SUR).

Usage

```
reduced.form.var(Y, p, z=NULL)
```

Arguments

Y	$T \times m$ multiple time series object created with <code>ts()</code> .
p	Lag length
z	$T \times k$ exogenous variables in a matrix of T rows. Can be NULL if there are none.

Details

This is a frequentist VAR estimator. This is a workhorse function — you will want to use other functions such as [irf](#), [mc.irf](#) or [dfev](#) to report and interpret the results of this object.

Value

List of class "VAR" with elements,

intercept	Row vector of the m intercepts.
ar.coefs	$m \times m \times p$ array of the AR coefficients. The first $m \times m$ array is for lag 1, the p 'th array for lag p .
Bhat	$(mp + k + 1) \times m$ matrix of the coefficients, where the columns correspond to the variables in the VAR. Intercepts follow the AR coefficients, etc.
exog.coefs	$k \times m$ matrix of exogenous coefficients, or NA if $z=NULL$
vcv	$m \times m$ matrix of the maximum likelihood estimate of the residual covariance
mean.S	$m \times m$ matrix of the posterior residual covariance.
hstar	$mp \times mp$ right hand side variables crossproduct.
X	Right hand side variables for the estimation of BVAR
Y	Left hand side variables for the estimation of BVAR
y	Input data (Y)

Author(s)

Patrick T. Brandt

References

Sims, C.A. 1980. "Macroeconomics and Reality" *Econometrica* 48(1): 1-48.

See Also

See also [szbvar](#) for BVAR models with the Sims-Zha prior and [szbsvar](#) for Bayesian SVAR models with the Sims-Zha prior.

Examples

```
data(IsraelPalestineConflict)
rf.var <- reduced.form.var(IsraelPalestineConflict, p=6)
plot(irf(rf.var, nsteps=12))
```

restmtx	<i>Utility function for generating the restriction matrix for hard condition forecasting</i>
---------	--

Description

Generates the restriction matrix for a set of hard condition forecasts. See [hc.forecast](#) for details.

Usage

```
restmtx(nsteps, m)
```

Arguments

nsteps	Number of periods in the forecast horizon
m	Number of endogenous variables in the VAR.

Details

Builds the appropriately dimensioned and filled restriction matrix of zeros and ones for hard condition forecasting.

Value

A matrix of dimensions (nsteps x m*nsteps) that can be used to represent the restrictions in hard condition forecasting using `hc.forecast`

Author(s)

Patrick T. Brandt

References

Waggoner, Daniel F. and Tao Zha. 1999. "Conditional Forecasts in Dynamic Multivariate Models" *Review of Economics and Statistics*, 81(4):639-651.

See Also

[hc.forecast](#)

rmse

Root mean squared error of a Monte Carlo / MCMC sample of forecasts

Description

Computes the root mean squared error (RMSE) of a Monte Carlo sample of forecasts.

Usage

```
rmse(m1, m2)
```

Arguments

m1	Forecast sample for model 1
m2	Forecast sample for model 2

Details

User needs to subset the forecasts if necessary.

Value

Forecast RMSE.

Author(s)

Patrick T. Brandt

See Also

[mae](#), [forecast](#)

Examples

```

data(IsraelPalestineConflict)
Y.sample1 <- window(IsraelPalestineConflict, end=c(2002, 52))
Y.sample2 <- window(IsraelPalestineConflict, start=c(2003,1))

# Fit a BVAR model
fit.bvar <- szbvar(Y.sample1, p=6, lambda0=0.6, lambda1=0.1, lambda3=2,
                  lambda4=0.25, lambda5=0, mu5=0, mu6=0, prior=0)

# Forecast -- this gives back the sample PLUS the forecasts!

forecasts <- forecast(fit.bvar, nsteps=nrow(Y.sample2))

# Compare forecasts to real data
rmse(forecasts[(nrow(Y.sample1)+1):nrow(forecasts)], Y.sample2)

```

 rmultnorm

Multivariate Normal Random Number Generator

Description

Generates multivariate normal random variates for give mean and covariance vectors. Can also handle generation of multivariate normal deviates with singular covariance distributions via singular value decomposition (SVD).

Usage

```
rmultnorm(n, mu, vmat, tol = 1e-10)
```

Arguments

n	Number of variates to draw.
mu	m column matrix of multivariate means
vmat	$m \times m$ covariance matrix
tol	Tolerance level used for SVD of the covariance. Default is 1e-10

Details

Generates n draws from a multivariate normal distribution with mean matrix μ and covariance matrix vmat .

Value

Matrix of the random draw that is conformable with the input μ .

Note

Based on code by Jeff Gill. This function is called in the hard condition forecasting in [hc.forecast](#) for simulating the structural innovations.

Author(s)

Patrick T. Brandt

See Also

[rnorm](#)

Examples

```
rmultnorm(1, matrix(c(1,2),2,1), vmat=matrix(c(1,1,0,1),2,2))
```

rwishart

Random deviates from a Wishart distribution

Description

Draws random deviates from a Wishart pdf.

Usage

```
rwishart(N, df, Sigma)
```

Arguments

N	Number of random deviates to draw.
df	Degrees of freedom for Wishart distribution
Sigma	Mean of the Wishart from which to draw the deviates

Details

Draws N matrices of draws from a Wishart with mean Sigma. This is used to draw error covariances for the VAR and BVAR models which are distributed inverse Wisharts deviates.

Value

Returns an N dimensional array of dim(Sigma) square matrices for the Wishart random deviates. If N=1, it returns a single matrix.

Author(s)

Patrick T. Brandt

See Also

See also [rmultnorm](#) for multivariate normal deviates, [rgamma](#) for the univariate analog to drawing Wishart deviates, and [ldwishart](#) for computing the log density for a Wishart variate.

Examples

```
x <- matrix(rnorm(100), 50, 2)
XX <- crossprod(x)
tmp <- rwishart(1, 50, XX)
```

SS.draw

State-space filter and sampler for a Markov-switching VAR model

Description

This function estimates the h state probabilities for all of the observations for a Gaussian likelihood

Usage

```
SS.draw(u, TT, m, h, Sik, Q)
```

Arguments

<code>u</code>	$TT \times m \times h$ array of the residuals for an MSBVAR process
<code>TT</code>	integer, number of observations in the model
<code>m</code>	integer, number of equations or variables in the MSBVAR model
<code>h</code>	integer, number of regimes in the MSBVAR model
<code>Sik</code>	$m \times m \times h$ array of the covariances for each regime (can be the same for each of the h regimes)
<code>Q</code>	$h \times h$ first order Markov transition matrix; each row must sum to 1

Details

The estimation of an MSBVAR model requires an efficient classifier of the states for the observed filtered probabilities. This function provides a way to accomplish this and is one of the workhorses in the estimation in the [msbvar](#) and [gibbs.msbvar](#) function.

This function uses compiled C++ code to draw the 0-1 matrix of the regimes. It uses the Baum-Hamilton-Lee-Kim (BHLK) filter and smoother to estimate the regime probabilities. Draws are based on the standard forward-filter-backward-sample algorithm.

Value

A $T \times h$ matrix of the sampled regimes. Each row corresponds to an identity matrix element giving the regime classification for the observation.

Note

This function assumes that the innovation in the MSBVAR model are multivariate normal. The resulting filter and sample follows that in the references listed above. This function is provided so users can build their own customized MSBVAR models. Users can write functions to generate the (B)VAR residuals for their own customized MSBVAR models than then provide the residuals and their covariances and transition matrix Q . This function can then be used to estimate / sample the regime probabilities. So if you need an MSBVAR model where only certain parameters change — rather than all of them as in the existing `msbvar` and `gibbs.msbvar` functions — you can build your own estimator using this function. This function takes care of the hard part of building an MSBVAR model.

Author(s)

Patrick T. Brandt

References

- Kim, C.J. and C.R. Nelson. 1999. State-space models with regime switching. Cambridge, Mass: MIT Press.
- Krolzig, Hans-Martin. 1997. Markov-Switching Vector Autoregressions: Modeling, Statistical Inference, and Application to Business Cycle Analysis.
- Sims, Christopher A. and Daniel F. Waggoner and Tao Zha. 2008. "Methods for inference in large multiple-equation Markov-switching models" *Journal of Econometrics* 146(2):255–274.

See Also

[BHLK.filter](#), [msbvar](#), [gibbs.msbvar](#)

Examples

```
# Simple example to show how data are input to the filter-sampler.
# Assumes a simple bivariate regression model with switching means and
# variances.

TT <- 100
h <- 2
m <- 2
set.seed(123)
x1 <- rnorm(TT)
x2 <- rnorm(TT)
y1 <- 5 + 2*x1 + rnorm(TT)
y2 <- 1 + x2 + 5*rnorm(TT)

Y <- rbind(cbind(y1[1:(0.5*TT)], y2[1:(0.5*TT)]),
           cbind(y2[((0.5*TT)+1):TT], y1[((0.5*TT)+1):TT]))
X <- rbind(cbind(x1[1:(0.5*TT)], x2[1:(0.5*TT)]),
           cbind(x2[((0.5*TT)+1):TT], x1[((0.5*TT)+1):TT]))

u1 <- Y - tcrossprod(cbind(rep(1,TT), X), matrix(c(5,2,0,1,1,0), 2, 3))
u2 <- Y - tcrossprod(cbind(rep(1,TT), X), matrix(c(1,1,0,5,2,0), 2, 3))
```

```

u <- array(0, c(TT, m, h))
u[, ,1] <- u1
u[, ,2] <- u2

Sik <- array(0, c(m,m,h))
Sik[, ,1] <- diag(c(1,25))
Sik[, ,2] <- diag(c(25,1))

Q <- matrix(c(0.9,0.2,0.1,0.8), h, h)

# estimate the states 100 times
ss <- replicate(100, SS.draw(u, TT, m, h, Sik, Q), simplify=FALSE)

# Get the state estimates from the 100 simulations
ss.est <- matrix(unlist(ss), nrow=(h*TT + h^2))

ss.prob <- matrix(rowMeans(ss.est[1:(h*TT),]), ncol=h)
ss.transition <- matrix(rowMeans(ss.est[((h*TT)+1):((h*TT) + h^2),]),
                        h, h)

```

summary

Summary functions for VAR / BVAR / B-SVAR model objects

Description

Prints a summary of the coefficient matrices for various VAR / BVAR / B-SVAR model objects to standard output.

Usage

```
summary(object, ...)
```

Arguments

object	Fitted VAR, BVAR, or B-SVAR model from either reduced form <code>var</code> , <code>szbvar</code> , or <code>szbsvar</code>
...	other arguments

Details

Prints (posterior) coefficient matrices for each lag and error covariance summaries as appropriate.

Value

None.

Author(s)

Patrick T. Brandt

See Also[summary](#)**Examples**

```
## Not run:
summary(x)

## End(Not run)
```

summary.forecast	<i>Summary functions for forecasts obtained through VAR / BVAR / B-SVAR model objects</i>
------------------	---

Description

Prints a summary of the mean and quantile values for the forecasts generated through VAR / BVAR / B-SVAR model objects to standard output.

Usage

```
summary.forecast(object, probs = c(0.16,0.84), ...)
```

Arguments

object	Forecast object generated through fitting a VAR, BVAR, or B-SVAR model from either forecast.VAR, forecast.BVAR, or forecast.BSVAR
probs	vector list of probability range for quantiles. default: c(0.16,0.84) or a 68% region (approximately one standard deviation on each side of the mean)
...	optional arguments (ignored, but included for S3 consistency)

Details

Prints a summary of the mean and quantile values for the forecasts.

Value

Returns the mean forecast and the specified posterior probability interval for the forecasts.

Author(s)

Patrick T. Brandt

See Also[summary](#)**Examples**

```
## Not run:
summary(x)

## End(Not run)
```

SZ.prior.evaluation *Sims-Zha Bayesian VAR Prior Specification Search*

Description

Estimates posterior and in-sample fit measures for a reduced form vector autoregression model with different specifications of the Sims-Zha hyperparameters values.

Usage

```
SZ.prior.evaluation(Y, p,
                    lambda0, lambda1, lambda3, lambda4, lambda5,
                    mu5, mu6, z = NULL, nu = ncol(Y) + 1, qm,
                    prior = 0, nsteps, y.future)
```

Arguments

Y	T x m matrix of endogenous variables for the VAR
p	Lag length
lambda0	List of values, e.g, c(0.7, 0.8, 0.9) in [0,1], Overall tightness of the prior (discounting of prior scale).
lambda1	List of values, e.g, c(0.05, 0.1, 0.2) in [0,1], Standard deviation or tightness of the prior around the AR(1) parameters.
lambda3	List of values, e.g, c(0, 1, 2) for Lag decay (>0, with 1=harmonic)
lambda4	List of values, e.g, c(0.15, 0.2, 0.5) for Standard deviation or tightness around the intercept [>0]
lambda5	Single value for the standard deviation or tightness around the exogeneous variable coefficients [>0]
mu5	Single value for sum of coefficients prior weight [>=0]
mu6	Single value for dummy Initial observations or cointegration prior [>=0]
z	Exogenous variables

nu	Prior degrees of freedom = m+1
qm	Frequency of the data for lag decay equivalence. Default is 4, and a value of 12 will match the lag decay of monthly to quarterly data. Other values have the same effect as "4"
prior	One of three values: 0 = Normal-Wishart prior, 1 = Normal-flat prior, 2 = flat-flat prior (i.e., akin to MLE)
nsteps	Number of periods in the forecast horizon
y.future	Future values of the series, nsteps x m for computing the root mean squared error and mean absolute error for the fit

Details

This function fits a series of BVAR models for the combinations of lambda0, lambda1, lambda3, and lambda4 provided. For each possible value of these parameters specified, a Sims-Zha prior BVAR model is fit, posterior fit measures are computed, and forecasts are generated over nsteps. These nstep forecasts are then compared to a new set of data in y.future and root mean squared error and mean absolute error measures are computed.

Value

A matrix of the results with columns corresponding to the values of "lambda0", "lambda1", "lambda3", "lambda4", "lambda5", "mu5", "mu6", "RMSE", "MAE", "MargLLF", "MargPosterior".

Note

The matrix of the results can be usefully plotted using the lattice package. See the example below.

Author(s)

Patrick T. Brandt

References

Brandt, Patrick T. and John R. Freeman. 2006. "Advances in Bayesian Time Series Modeling and the Study of Politics: Theory Testing, Forecasting, and Policy Analysis" *Political Analysis* 14(1):1-36.

See Also

[szbvar](#)

Examples

```
Y <- EuStockMarkets
results <- SZ.prior.evaluation(window(Y, start=c(1998, 1),
                                     end=c(1998,149)),
                              p=3,
                              lambda0=c(1,0.9),
```

```

lambda1=c(0.1,0.2),
lambda3=c(0,1),
lambda4=c(0.1,0.25),
lambda5=0,
mu5=4,
mu6=4, z=NULL,
nu=ncol(Y)+1, qm=4,
prior=0,
nstep=20,
y.future=window(Y, start=c(1998,150)))

# Now plot the RMSE and marginal posterior of the data for each of the
# 6 period forecasts as a function of the prior parameters. This can
# easily be done using a lattice graphic.

library(lattice)

attach(as.data.frame(results))
dev.new()
xyplot(RMSE ~ lambda0 | lambda1 + lambda3)
dev.new()
xyplot(logMDD ~ lambda0 | lambda1 + lambda3)
dev.new()
xyplot(LLF ~ lambda0 | lambda1 + lambda3)

```

szbsvar

*Structural Sims-Zha Bayesian VAR model estimation***Description**

Estimates the posterior mode for a Bayesian Structural Vector Autoregression (B-SVAR) model using the prior specified by Sims and Zha (1998)

Usage

```
szbsvar(Y, p, z = NULL,
        lambda0, lambda1, lambda3, lambda4, lambda5,
        mu5, mu6, ident, qm = 4)
```

Arguments

Y	$T \times m$ multiple time series object created with <code>ts()</code> with no NAs.
p	integer lag length for the model
z	$T \times k$ matrix of exogenous variables (not including an intercept)
lambda0	[0, 1], Overall tightness of the prior (discounting of prior scale).
lambda1	[0, 1], Standard deviation or tightness of the prior around the AR(1) parameters.
lambda3	Lag decay (> 0 , with 1=harmonic)

lambda4	Standard deviation or tightness around the intercept > 0
lambda5	Standard deviation or tightness around the exogenous variable coefficients > 0
mu5	Sum of coefficients prior weight ≥ 0 . Larger values imply difference stationarity.
mu6	Dummy Initial observations or drift prior ≥ 0 . Larger values allow for common trends.
ident	$m \times m$ matrix of binary indicators for the identification of the free and restricted contemporaneous parameters in A_0 .
qm	Frequency of the data for lag decay equivalence. Default is 4, and a value of 12 will match the lag decay of monthly to quarterly data. Other values have the same effect as "4"

Details

This function estimates the posterior mode for the Bayesian structural VAR (B-SVAR) model described by Sims and Zha (1998) and Waggoner and Zha (2003). This B-SVAR model is based a specification of the dynamic simultaneous equation representation of the model. The prior is constructed for the structural parameters.

The basic SVAR model has the form of Waggoner and Zha (2003):

$$y_t' A_0 = \sum_{\ell=1}^p Y_{t-\ell}' A_\ell + z_t' D + \epsilon_t', t = 1, \dots, T,$$

where A_i are $m \times m$ parameter matrices for the contemporaneous and lagged effects of the endogenous variables, D is an $h \times m$ parameter matrix for the exogenous variables (including an intercept), y_t is the $m \times 1$ matrix of the endogenous variables, z_t is a $h \times 1$ vector of exogenous variables (including an intercept) and ϵ_t is the $m \times 1$ matrix of structural shocks. NOTE that in this representation of the model, the columns of the A_ℓ matrices refer to the equations!

The structural shocks are normal with mean and variance equal to the following:

$$E[\epsilon_t | y_1, \dots, y_{t-1}, z_1, \dots, z_{t-1}] = 0$$

$$E[\epsilon_t \epsilon_t' | y_1, \dots, y_{t-1}, z_1, \dots, z_{t-1}] = I$$

The *reduced form representation* of the SVAR model can be found by post-multiplying through by A_0^{-1} :

$$y_t' A_0 A_0^{-1} = \sum_{\ell=1}^p Y_{t-\ell}' A_\ell A_0^{-1} + z_t' D A_0^{-1} + \epsilon_t' A_0^{-1}$$

$$y_t' = \sum_{\ell=1}^p Y_{t-\ell}' B_\ell + z_t' \Gamma + \epsilon_t' A_0^{-1}.$$

The reduced form error covariance matrix is found from the crossproduct of the reduced form innovations:

$$\Sigma = E[(\epsilon'_t A_0^{-1})(\epsilon'_t A_0^{-1})'] = [A_0 A_0']^{-1}.$$

Restrictions on the contemporaneous parameters in A_0 are expressed by the specification of the ident matrix that defines the shocks that "hit" each equation in the contemporaneous specification. If ident is defined as in the following table,

Variables	Equations		
	Eqn 1	Eqn 2	Eqn 3
Var. 1	1	0	0
Var. 2	1	1	0
Var. 3	0	1	1

then the corresponding A_0 is restricted to

Variables	Equations		
	Eqn 1	Eqn 2	Eqn 3
Var. 1	a_{11}	0	0
Var. 2	a_{12}	a_{22}	0
Var. 3	0	a_{23}	a_{33}

which is interpreted as shocks in variables 1 and 2 hit equation 1 (the first column); shocks in variables 2 and 3 hit the second equation (column 2); and, shocks in variable 3 hit the third equation (column 3).

As in Sims and Zha (1998) and Waggoner and Zha (2003), the prior for the model is formed for each of the equations. To illustrate the prior, the model is written in the more compact notation

$$y'_t A_0 = x'_t F + \epsilon'_t$$

where

$$x'_t = [y'_{t-1} \cdots y'_{t-p}, z'_t], F' = [A'_1 \cdots A'_p D']$$

are the matrices of the right hand side variables and the right hand side coefficients for the SVAR model.

The general form of this prior is then

$$a_i \sim N(0, \bar{S}_i) \quad \text{and} \quad f_i | a_i \sim N(\bar{P}_i a_i, \bar{H}_i)$$

where \bar{S}_i is an $m \times m$ prior covariance of the contemporaneous parameters, and \bar{H}_i is the $k \times k$ prior covariance of the parameters in $f_i | a_i$. The prior means of a_i are zero in the structural model, while the "random walk" component is in $\bar{P}_i a_i$.

The prior covariance matrix of the errors, \bar{S}_i , is initially estimated using a VAR(p) model via OLS, with an intercept and no demeaning of the data.

The Bayesian prior is constructed for the unrestricted VAR model and then mapped into the restricted prior parameter space, as discussed in Waggoner and Zha (2003a).

Value

A list of the class "BSVAR" that summarizes the posterior mode of the B-SVAR model

XX	$X'X + H_0$ crossproduct moment matrix for the predetermined variables in the model plus the prior
XY	$X'Y$ for the model, including the dummy observations for mu5 and mu6
YY	$m \times m$ Crossproduct for the Y's in the model
y	$T \times m$ input data in dat plus the m dummy observations for dat
structural.innovations	$T \times m$ structural innovations for the SVAR model
Ui	$m \times q_i$ Null space matrices that map the columns of A_0 to the free parameters of the columns
Hpinv.tilde	Prior covariance for the predetermined and exogenous regression in the B-SVAR
H0inv.tilde	m dimensional list of the prior covariances for the free parameters of the i 'th equation in the model's A_0 matrix
Pi.tilde	list of $(m^2p + 1 + h) \times q_i$ matrices of the prior for the parameters for the predetermined variables in the model
Hpinv.posterior	$(m^2p + 1 + h) \times m$ matrix of the posterior of the structural parameters for the predetermined variables
P.posterior	list of $(m^2p + 1 + h) \times m$ matrices of the posterior of the paramters for the predetermined variables in the model
H0inv.posterior	m dimensional list of the posterior covariances for the free parameters of the i 'th equation in the model's A_0 matrix
A0.mode	posterior mode of the A_0 matrix
F.posterior	$(m^2p + 1 + h) \times m$ matrix of the posterior of the structural parameters for the predetermined variables
B.posterior	$(m^2p + 1 + h) \times m$ matrix of the posterior of the reduced form parameters for the predetermined variables
ar.coefs	$(m^2p) \times m$ matrix of the posterior of the reduced form autoregressive parameters
intercept	m dimensional vector of the reduced form intercepts
exog.coefs	$h \times m$ matrix of the reduced form exogenous variable coefficients
prior	List of the prior parameter: c(lambda0, lambda1, lambda3, lambda4, lambda5, mu5, mu6).
df	Degrees of freedom for the model: T + number of dummy observations - lag length.
n0	m dimensional list of the number of free parameters for the A_0 matrix for equation i .
ident	$m \times m$ identification matrix ident.

Warning

If you do not understand the model described here, you probably want the models described in [szbvar](#) or [reduced.form.var](#)

Author(s)

Patrick T. Brandt

References

- Sims, C.A. and Tao A. Zha. 1998. "Bayesian Methods for Dynamic Multivariate Models." *International Economic Review*. 39(4):949-968.
- Waggoner, Daniel F. and Tao A. Zha. 2003a. "A Gibbs sampler for structural vector autoregressions" *Journal of Economic Dynamics & Control*. 28:349–366.
- Waggoner, Daniel F. and Tao A. Zha. 2003b. "Likelihood preserving normalization in multiple equation models". *Journal of Econometrics*. 114: 329–347.
- Brandt, Patrick T. and John R. Freeman. 2006. "Advances in Bayesian Time Series Modeling and the Study of Politics: Theory Testing, Forecasting, and Policy Analysis". *Political Analysis* 14(1):1-36.

See Also

[szbvar](#) for reduced form Bayesian VAR models, [reduced.form.var](#) for non-Bayesian reduced form VAR models, [gibbs.A0](#) for drawing from the posterior of this model using a Gibbs sampler, [posterior.fit](#) for assessing the posterior fit of the model, and [mc.irf](#) for computing impulse responses for this model.

Examples

```
# SZ, B-SVAR model for the Levant data
data(BCFdata)
m <- ncol(Y)
ident <- diag(m)
ident[1,] <- 1
ident[2,1] <- 1

# estimate the model's posterior moments
model <- szbsvar(Y, p=2, z=z2, lambda0=0.8, lambda1=0.1,
                lambda3=1, lambda4=0.1, lambda5=0.05,
                mu5=0, mu6=5, ident, qm=12)
```

szbvar

*Reduced form Sims-Zha Bayesian VAR model estimation***Description**

Estimation of the Bayesian VAR model for just identified VARs described in Sims and Zha (1998)

Usage

```
szbvar(Y, p, z = NULL, lambda0, lambda1, lambda3, lambda4, lambda5,
       mu5, mu6, nu = ncol(Y)+1, qm = 4, prior = 0,
       posterior.fit = FALSE)
```

Arguments

Y	$T \times m$ multiple time series object created with <code>ts()</code> .
p	Lag length
z	$T \times k$ matrix of exogenous variables. Can be <code>z = NULL</code> if there are none.
lambda0	[0, 1], Overall tightness of the prior (discounting of prior scale).
lambda1	[0, 1], Standard deviation or tightness of the prior around the AR(1) parameters.
lambda3	Lag decay (> 0 , with 1=harmonic)
lambda4	Standard deviation or tightness around the intercept > 0
lambda5	Standard deviation or tightness around the exogeneous variable coefficients > 0
mu5	Sum of coefficients prior weight ≥ 0 . Larger values imply difference stationarity.
mu6	Dummy initial observations or drift prior ≥ 0 . Larger values allow for common trends.
nu	Prior degrees of freedom, $m + 1$
qm	Frequency of the data for lag decay equivalence. Default is 4, and a value of 12 will match the lag decay of monthly to quarterly data. Other values have the same effect as "4"
prior	One of three values: 0 = Normal-Wishart prior, 1 = Normal-flat prior, 2 = flat-flat prior (i.e., akin to MLE)
posterior.fit	logical, F = do not estimate log-posterior fit measures, T = estimate log-posterior fit measures.

Details

This function estimates the Bayesian VAR (BVAR) model described by Sims and Zha (1998). This BVAR model is based a specification of the dynamic simultaneous equation representation of the model. The prior is constructed for the structural parameters. The basic SVAR model used here is documented in [szbsvar](#).

The prior covariance matrix of the errors, \bar{S}_i , is initially estimated using a VAR(p) model via OLS, with an intercept and no demeaning of the data.

Value

Returns a list of multiple elements. This is a workhorse function to get the estimates, so nothing is displayed to the screen. The elements of the list are intended as inputs for the various post-estimation functions (e.g., impulse response analyses, forecasting, decompositions of forecast error variance, etc.)

Returns a list of the class "BVAR" with the following elements:

intercept	$m \times 1$ row vector of the m intercepts
ar.coefs	$m \times m \times p$ array of the AR coefficients. The first $m \times m$ array is for lag 1, the p 'th array for lag p .
exog.coefs	$k \times m$ matrix of the coefficients for any exogenous variables
Bhat	$(mp + k + 1) \times m$ matrix of the coefficients, where the columns correspond to the variables in the VAR
vcv	$m \times m$ matrix of the maximum likelihood estimate of the residual covariance
vcv.Bh	Posterior estimate of the parameter covariance that is conformable with Bhat.
mean.S	$m \times m$ matrix of the posterior residual covariance.
St	$m \times m$ matrix of the degrees of freedom times the posterior residual covariance.
hstar	$(mp + k + 1) \times (mp + k + 1)$ prior precision plus right hand side variables crossproduct.
hstarinv	$(mp + k + 1) \times (mp + k + 1)$ prior covariance crossproduct solve(hstar)
H0	$(mp + k + 1) \times (mp + k + 1)$ prior precision for the parameters
S0	$m \times m$ prior error covariance
residuals	$(T - p) \times m$ matrix of the residuals
X	$T \times (mp + 1 + k)$ matrix of right hand side variables for the estimation of BVAR
Y	$T \times m$ matrix of the left hand side variables for the estimation of BVAR
y	$T \times m$ input data in dat
z	$T \times k$ exogenous variables matrix
p	Lag length
num.exog	Number of exogenous variables
qm	Value of parameter to match quarterly to monthly lag decay (4 or 12)
prior.type	Numeric code for prior type: 0 = Normal-Wishart, 1 = Normal-Flat, 2 = Flat-Flat (approximate MLE)
prior	List of the prior parameter: c(lambda0,lambda1,lambda3,lambda4,lambda5, mu5, mu6, nu)
marg.llf	Value of the in-sample marginal log-likelihood for the data, if posterior.fit=T
marg.post	Value of the in-sample marginal log posterior of the data, if posterior.fit=T
coef.post	Value of the marginal log posterior estimate of the coefficients, if posterior.fit=T

Note

This is a work horse function. You will probably want to use other functions to summarize and report the BVAR results.

Author(s)

Patrick T. Brandt, based on code from Robertson and Tallman and Sims and Zha.

References

Sims, C.A. and Tao Zha. 1998. "Bayesian Methods for Dynamic Multivariate Models." *International Economic Review*. 39(4):949-968.

Brandt, Patrick T. and John R. Freeman. 2006. "Advances in Bayesian Time Series Modeling and the Study of Politics: Theory Testing, Forecasting, and Policy Analysis". *Political Analysis*.

See Also

[reduced.form.var szbsvar](#)

Examples

```
## Not run:
data(IsraelPalestineConflict)
varnames <- colnames(IsraelPalestineConflict)

fit.BVAR <- szbvar(IsraelPalestineConflict, p=6, z=NULL,
                  lambda0=0.6, lambda1=0.1,
                  lambda3=2, lambda4=0.25, lambda5=0, mu5=0,
                  mu6=0, nu=3, qm=4,
                  prior=0, posterior.fit=FALSE)

# Draw from the posterior pdf of the impulse responses.
posterior.impulses <- mc.irf(fit.BVAR, nsteps=10, draws=5000)

# Plot the responses
plot(posterior.impulses, method=c("Sims-Zha2"), component=1,
     probs=c(0.16,0.84), varnames=varnames)

## End(Not run)
```

uc.forecast

*Forecast density estimation unconditional forecasts for
VAR/BVAR/BSVAR models via MCMC*

Description

Implements unconditional forecast density estimator for VAR/BVAR/BSVAR models described in Waggoner and Zha (1999). The unconditional forecasts place no restriction on the paths of the forecasts (cf. `hc.forecast`). The forecast densities are estimated as the posterior sample for the VAR/BVAR/BSVAR model using Markov Chain Monte Carlo with data augmentation to account for the uncertainty of the forecasts and the parameters. This function DOES account for parameter uncertainty in the MCMC algorithm.

Usage

```
uc.forecast(varobj, nsteps, burnin, gibbs, exog = NULL)
```

Arguments

varobj	VAR or BVAR object produced for a VAR or BVAR using <code>szbvar</code> or <code>reduced.form.var</code>
nsteps	Number of periods in the forecast horizon
burnin	Burnin cycles for the MCMC algorithm
gibbs	Number of cycles of the Gibbs sampler after the burnin that are returned in the output
exog	num.exog x nsteps matrix of the exogenous variable values for the forecast horizon. If left at the NULL default, they are set to zero.

Details

Produces a posterior sample of unconstrained VAR/BVAR/BSVAR forecasts via MCMC. This function accounts for the uncertainty of the VAR/BVAR/BSVAR parameters by sampling from them in the computation of the VAR/BVAR/BSVAR forecasts and then regenerating the forecasts. Data augmentation is used to account for the impact of the forecast uncertainty on the parameters.

Value

A list with three components:

yforc	Forecast sample
orig.y	Original endogenous variables time series
hyperp	values of the hyperparameters used in the BVAR estimation / MCMC

Author(s)

Patrick T. Brandt

References

- Brandt, Patrick T. and John R. Freeman. 2006. "Advances in Bayesian Time Series Modeling and the Study of Politics: Theory Testing, Forecasting, and Policy Analysis" *Political Analysis* 14(1):1-36.
- Waggoner, Daniel F. and Tao Zha. 1999. "Conditional Forecasts in Dynamic Multivariate Models" *Review of Economics and Statistics*, 81(4):639-651.

See Also

[hc.forecast](#)


```

# Unconditional forecasts
unconditional.forcs.ref <-uc.forecast(KEDS.BVAR.informed, nsteps,
                                     burnin=3000, gibbs=5000)

unconditional.forcs.flat <- uc.forecast(KEDS.BVAR.flat, nsteps,
                                       burnin=3000, gibbs=5000)

# Set-up and plot the unconditional and conditional forecasts. This
# code pulls for the forecasts for I2P and P2I and puts them into the
# appropriate array for the figures we want to generate.
uc.flat <- NULL
hc.flat <- NULL
uc.ref <- NULL
hc.ref <- NULL

uc.flat$forecast <- unconditional.forcs.flat$forecast[, ,5:6]
hc.flat$forecast <- conditional.forcs.flat$forecast[, ,5:6]
uc.ref$forecast <- unconditional.forcs.ref$forecast[, ,5:6]
hc.ref$forecast <- conditional.forcs.ref$forecast[, ,5:6]

par(mfrow=c(2,2), omi=c(0.25,0.5,0.25,0.25))
plot(uc.flat,hc.flat, probs=c(0.16, 0.84), varnames=c("I2P", "P2I"),
     compare.level=KEDS[nrow(KEDS),5:6], lwd=2)
plot(hc.ref,hc.flat, probs=c(0.16, 0.84), varnames=c("I2P", "P2I"),
     compare.level=KEDS[nrow(KEDS),5:6], lwd=2)

## End(Not run)

```

var.lag.specification *Automated VAR lag specification testing*

Description

Estimates a series of test statistics and measures for VAR lag length selection.

Usage

```
var.lag.specification(y, lagmax = 20)
```

Arguments

y	T x m multiple time series
lagmax	Maximum lag order to be evaluated. Function will return lag length tests for all lag orders less than lagmax.

Details

Estimates a series of frequentist VAR models for 1 to lagmax and returns a sequence of χ^2 tests, AIC, BIC and Hannan-Quinn criterion values for each lag length.

Value

Results are printed to standard output (screen or file). In addition, a list of two matrices is returned:

ldets	Lag length, log-determinants, χ^2 tests, and p-values for each lag length, compared to the null of the next shorter lag length
results	Lag length, AIC, BIC, and HQ criteria for each lag length. Selection criteria should be minimized.

Note

Sizes of p-values are uncorrected for multiple testing. Use cautiously.

Author(s)

Patrick T. Brandt

References

Lutkepohl, Helmut 2004. "Vector Autoregressive and Vector Error Correction Models", Chapter 3. In Applied Time Series Econometrics. Lutkepohl, Helmut and Markus Kratzig eds. Cambridge: CUP.

See Also

See Also [reduced.form.var](#) for frequentist VAR estimation, [szbvar](#) for Bayesian VAR estimation, and [szbsvar](#) for Bayesian Structural VAR estimation.

Examples

```
data(IsraelPalestineConflict)
var.lag.specification(IsraelPalestineConflict, lagmax=12)
```

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