

Package ‘tensorTS’

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Title Factor and Autoregressive Models for Tensor Time Series

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Description Factor and autoregressive models for matrix and tensor valued time series.

We provide functions for estimation, simulation and prediction. The models are discussed in Chen et al (2020) <DOI:10.1016/j.jeconom.2020.07.015>, Chen et al (2020) <arXiv:1905.07530>, and Han et al (2020) <arXiv:2006.02611>.

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R topics documented:

matAR.RR.est	2
matAR.RR.se	3
mplot	4

tenAR.est	5
tenAR.predict	7
tenAR.sim	8
tenFM.est	9
tenFM.rank	10
tenFM.sim	12

Index	14
--------------	-----------

matAR.RR.est	<i>Estimation for Reduced Rank MAR(1) Model</i>
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Description

Estimation of the reduced rank MAR(1) model, using least squares (RRLSE) or MLE (RRMLE), as determined by the value of method.

Usage

```
matAR.RR.est(xx, method, A1.init=NULL, A2.init=NULL, Sig1.init=NULL, Sig2.init=NULL,
k1=NULL, k2=NULL, niter=100, tol=1e-6)
```

Arguments

xx	$T \times d_1 \times d_2$ matrix-valued time series, T is the length of the series.
method	character string, specifying the method of the estimation to be used. "RRLSE", Least squares. "RRMLE", MLE under a separable $\text{cov}(\text{vec}(E_t))$.
A1.init	initial value of A_1 . The default is the identity matrix.
A2.init	initial value of A_2 . The default is the identity matrix.
Sig1.init	only if method=RRMLE, initial value of Σ_1 . The default is the identity matrix.
Sig2.init	only if method=RRMLE, initial value of Σ_2 . The default is the identity matrix.
k1	rank of A_1 , a positive integer.
k2	rank of A_2 , a positive integer.
niter	maximum number of iterations if error stays above tol.
tol	relative Frobenius norm error tolerance.

Details

The reduced rank MAR(1) model takes the form:

$$X_t = A_1 X_{t-1} A_2' + E_t,$$

where A_i are $d_i \times d_i$ coefficient matrices of ranks $\text{rank}(A_i) = k_i \leq d_i$, $i = 1, 2$. For the MLE method we also assume

$$\text{Cov}(\text{vec}(E_t)) = \Sigma_2 \otimes \Sigma_1$$

Value

return a list containing the following:

A1 estimator of A_1 , a d_1 by d_1 matrix

A2 estimator of A_2 , a d_2 by d_2 matrix

Sig1 only if method=MLE, when $\text{Cov}(\text{vec}(E_t)) = \Sigma_2 \otimes \Sigma_1$.

Sig2 only if method=MLE, when $\text{Cov}(\text{vec}(E_t)) = \Sigma_2 \otimes \Sigma_1$.

res residuals.

Sig covariance matrix $\text{cov}(\text{vec}(E_t))$

cov covariance matrix \hat{A}_1 and \hat{A}_2 . If method=RRLSE or method=RRMLE, then it is a list containing

Sigma asymptotic covariance matrix of $(\text{vec}(\hat{A}_1), \text{vec}(\hat{A}_2^T))$.

Theta1.u, Theta1.v asymptotic covariance matrix of $\text{vec}(\hat{U}_1), \text{vec}(\hat{V}_1)$.

Theta2.u, Theta2.v asymptotic covariance matrix of $\text{vec}(\hat{U}_2), \text{vec}(\hat{V}_2)$.

sd standard errors of \hat{A}_1 and \hat{A}_2 , returned in a list aligned with \hat{A}_1 and \hat{A}_2 .

niter number of iterations.

BIC value of the extended Bayesian information criterion.

References

Reduced Rank Autoregressive Models for Matrix Time Series, by Han Xiao, Yuefeng Han, Rong Chen and Chengcheng Liu.

Examples

```
set.seed(333)
dim <- c(3,3)
xx <- tenAR.sim(t=500, dim, R=2, P=1, rho=0.5, cov='iid')
est <- matAR.RR.est(xx, method="RRLSE", k1=1, k2=1)
```

matAR.RR.se

Asymptotic Covariance Matrix of One-Term Reduced rank MAR(1) Model

Description

Asymptotic covariance matrix of the reduced rank MAR(1) model. If Sigma1 and Sigma2 is provided in input, we assume a separable covariance matrix, $\text{Cov}(\text{vec}(E_t)) = \Sigma_2 \otimes \Sigma_1$.

Usage

```
matAR.RR.se(A1,A2,k1,k2,method,Sigma.e=NULL,Sigma1=NULL,Sigma2=NULL,RU1=diag(k1),
RV1=diag(k1),RU2=diag(k2),RV2=diag(k2),mpower=100)
```

Arguments

A1	left coefficient matrix.
A2	right coefficient matrix.
k1	rank of A_1 .
k2	rank of A_2 .
method	character string, specifying the method of the estimation to be used. "RRLSE", Least squares. "RRMLE", MLE under a separable $\text{cov}(\text{vec}(E_t))$.
Sigma.e	only if method = "RRLSE". $\text{Cov}(\text{vec}(E_t)) = \text{Sigma.e}$: covariance matrix of dimension $(d_1 d_2) \times (d_1 d_2)$
Sigma1, Sigma2 RU1, RV1, RU2, RV2	only if method = "RRMLE". $\text{Cov}(\text{vec}(E_t)) = \Sigma_2 \otimes \Sigma_1$. Σ_i is $d_i \times d_i$, $i = 1, 2$. orthogonal rotations of U_1, V_1, U_2, V_2 , e.g., $\text{new_U1} = U_1 \text{RU1}$
mpower	truncate the $\text{VMA}(\infty)$ representation of $\text{vec}(X_t)$ at <code>mpower</code> for the purpose of calculating the autocovariances. The default is 100.

Value

a list containing the following:

Sigma asymptotic covariance matrix of $(\text{vec}(\hat{A}_1), \text{vec}(\hat{A}_2^T))$.

Theta1.u asymptotic covariance matrix of $\text{vec}(\hat{U}_1)$.

Theta1.v asymptotic covariance matrix of $\text{vec}(\hat{V}_1)$.

Theta2.u asymptotic covariance matrix of $\text{vec}(\hat{U}_2)$.

Theta2.v asymptotic covariance matrix of $\text{vec}(\hat{V}_2)$.

References

Han Xiao, Yuefeng Han, Rong Chen and Chengcheng Liu, Reduced Rank Autoregressive Models for Matrix Time Series.

mplot

Plot Matrix-Valued Time Series

Description

Plot matrix-valued time series, can be also used to plot a given slice of a tensor-valued time series.

Usage

```
mplot(xx)
```

Arguments

xx $T \times d_1 \times d_2$ matrix-valued time series. Note that the number of mode is 3, where the first mode is time.

Value

a figure.

Examples

```
dim <- c(3,3,3)
xx <- tenAR.sim(t=50, dim, R=2, P=1, rho=0.5, cov='iid')
mplot(xx[1:30,,1])
```

tenAR.est

Estimation for Autoregressive Model of Tensor-Valued Time Series

Description

Estimation function for tensor autoregressive models. Methods include projection (PROJ), Least Squares (LSE), maximum likelihood estimation (MLE) and vector autoregressive model (VAR), as determined by the value of method.

Usage

```
tenAR.est(xx,R=1,P=1,method="LSE",init.A=NULL,init.sig=NULL,niter=500,tol=1e-6)
```

Arguments

xx $T \times d_1 \times \dots \times d_K$ tensor-valued time series, T is the length of the series.

R Kronecker rank for each lag.

P Autoregressive order.

method character string, specifying the type of the estimation method to be used.
 "PROJ", Projection method.
 "LSE", Least squares.
 "MLE", MLE under a separable $\text{cov}(\text{vec}(E_t))$.
 "VAR", VAR(P) model for the $\text{vec}(E_t)$.

init.A initial values of coefficient matrices $A_k^{(ir)}$ in estimation algorithms, which is a multi-layer list such that the first layer for the lag $1 \leq i \leq P$, the second the term $1 \leq r \leq R$, and the third the mode $1 \leq k \leq K$. See "Details". By default, we use PROJ estimators as initial values.

init.sig only if method=MLE, a list of initial values of $\Sigma_1, \dots, \Sigma_K$. The default are identity matrices.

niter maximum number of iterations if error stays above tol.

tol error tolerance in terms of the Frobenius norm.

Details

Tensor autoregressive model (of autoregressive order one) has the form:

$$X_t = \sum_{r=1}^R X_{t-1} \times_1 A_1^{(r)} \times_2 \cdots \times_K A_K^{(r)} + E_t,$$

where $A_k^{(r)}$ are $d_k \times d_k$ coefficient matrices, $k = 1, \dots, K$, and E_t is a tensor white noise. R is the Kronecker rank. The model of autoregressive order P takes the form

$$X_t = \sum_{i=1}^P \sum_{r=1}^{R_i} X_{t-i} \times_1 A_1^{(ir)} \times_2 \cdots \times_K A_K^{(ir)} + E_t.$$

For the "MLE" method, we also assume,

$$\text{Cov}(\text{vec}(E_t)) = \Sigma_K \otimes \Sigma_{K-1} \otimes \cdots \otimes \Sigma_1,$$

Value

return a list containing the following:

A a list of estimated coefficient matrices $A_k^{(ir)}$. It is a multi-layer list, the first layer for the lag $1 \leq i \leq P$, the second the term $1 \leq r \leq R$, and the third the mode $1 \leq k \leq K$. See "Details".

SIGMA only if method=MLE, a list of estimated $\Sigma_1, \dots, \Sigma_K$.

res residuals

Sig covariance matrix $\text{cov}(\text{vec}(E_t))$.

cov grand covariance matrix of all estimated entries of $A_k^{(ir)}$

sd standard errors of the coefficient matrices $A_k^{(ir)}$, returned as a list aligned with A.

niter number of iterations.

BIC value of extended Bayesian information criterion.

References

Rong Chen, Han Xiao, and Dan Yang. "Autoregressive models for matrix-valued time series". Journal of Econometrics, 2020.

Examples

```
set.seed(333)
dim <- c(2,2,2)
xx <- tenAR.sim(t=100, dim,R=2,P=1,rho=0.5, cov='iid')
est <- tenAR.est(xx, R=2, P=1, method="LSE")
A <- est$A # A is a multi-layer list

length(A) == 1 # TRUE, since the order P = 1
length(A[[1]]) == 2 # TRUE, since the number of terms R = 2
length(A[[1]][[1]]) == 3 # TRUE, since the mode K = 3
```

tenAR.predict	<i>Predictions for Tensor Autoregressive Models</i>
---------------	---

Description

Prediction based on the tensor autoregressive model or reduced rank MAR(1) model. If `rolling = TRUE`, returns the rolling forecasts.

Usage

```
tenAR.predict(object, xx, n.head, rolling = FALSE, n0 = NULL)
```

Arguments

<code>object</code>	a model object returned by <code>tenAR.est()</code> .
<code>xx</code>	$T' \times d_1 \times \dots \times d_K$ tensor time series.
<code>n.head</code>	prediction horizon.
<code>rolling</code>	TRUE or FALSE, rolling forecast, is FALSE by default.
<code>n0</code>	only if <code>rolling = TRUE</code> , the starting point of rolling forecast.

Value

a tensor time series of length `n.head` if `rolling = FALSE`;
a tensor time series of length $T' - n_0 - n.head + 1$ if `rolling = TRUE`.

See Also

'predict.ar' or 'predict.arima'

Examples

```
set.seed(333)
dim <- c(2,2,2)
t = 20
xx <- tenAR.sim(t, dim, R=2, P=1, rho=0.5, cov='iid')
est <- tenAR.est(xx, R=1, P=1, method="LSE")
pred <- tenAR.predict(est, xx, n.head = 1)
# rolling forecast
n0 = t - min(50,t/2)
pred.rolling <- tenAR.predict(est, xx, n.head = 5, rolling=TRUE, n0)

# prediction for reduced rank MAR(1) model
dim <- c(2,2)
t = 20
xx <- tenAR.sim(t, dim, R=1, P=1, rho=0.5, cov='iid')
est <- matAR.RR.est(xx, method="RRLSE", k1=1, k2=1)
pred <- tenAR.predict(est, xx, n.head = 1)
```

```
# rolling forecast
n0 = t - min(50,t/2)
pred.rolling <- tenAR.predict(est, xx, n.head = 5, rolling=TRUE, n0)
```

tenAR.sim

Generate TenAR(p) tensor time series

Description

Simulate from the TenAR(p) model.

Usage

```
tenAR.sim(t, dim, R, P, rho, cov, A = NULL)
```

Arguments

t	length of output series, a strictly positive integer.
dim	dimension of the tensor at each time.
R	Kronecker rank for each lag.
P	autoregressive order.
rho	spectral radius of coefficient matrix Φ .
cov	covariance matrix of the error term: diagonal ("iid"), separable ("mle"), random ("svd").
A	coefficient matrices. If not provided, they are randomly generated according to given dim, R, P and rho. It is a multi-layer list, the first layer for the lag $1 \leq i \leq P$, the second the term $1 \leq r \leq R$, and the third the mode $1 \leq k \leq K$. See "Details" of tenAR.est .

Value

A tensor-valued time series generated by the TenAR(p) model.

See Also

[tenFM.sim](#)

Examples

```
set.seed(123)
dim <- c(3,3,3)
xx <- tenAR.sim(t=500, dim, R=2, P=1, rho=0.5, cov='iid')
```

tenFM.est	<i>Estimation for Tucker structure Factor Models of Tensor-Valued Time Series</i>
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Description

Estimation function for Tucker structure factor models of tensor-valued time series. Two unfolding methods of the auto-covariance tensor, Time series Outer-Product Unfolding Procedure (TOPUP), Time series Inner-Product Unfolding Procedure (TIPUP), are included, as determined by the value of method.

Usage

```
tenFM.est(x,r,h0=1,method='TIPUP',iter=TRUE,vmax=FALSE,tol=1e-5,maxiter=100)
```

Arguments

<code>x</code>	$T \times d_1 \times \dots \times d_K$ tensor-valued time series.
<code>r</code>	input rank of the factor tensor.
<code>h0</code>	the number of lags used in auto-covariance tensor.
<code>method</code>	character string, specifying the type of the estimation method to be used. "TIPUP", TIPUP method. "TOPUP", TOPUP method.
<code>iter</code>	boolean, specifying using an iterative approach or an non-iterative approach.
<code>vmax</code>	boolean, specifying using varimax rotation on the factor matrix or not.
<code>tol</code>	tolerance in terms of the Frobenius norm.
<code>maxiter</code>	maximum number of iterations if error stays above <code>tol</code> .

Details

Tensor factor model with Tucker structure has the following form,

$$X_t = F_t \times_1 A_1 \times_2 \dots \times_K A_k + E_t,$$

where A_k is the deterministic loading matrix of size $d_k \times r_k$ and $r_k \ll d_k$, the core tensor F_t itself is a latent tensor factor process of dimension $r_1 \times \dots \times r_K$, and the idiosyncratic noise tensor E_t is uncorrelated (white) across time. Two estimation approaches, named TOPUP and TIPUP, are studied. Time series Outer-Product Unfolding Procedure (TOPUP) are based on

$$\text{TOPUP}_k(X_{1:T}) = \left(\sum_{t=h+1}^T \frac{\text{mat}_k(X_{t-h}) \otimes \text{mat}_k(X_t)}{T-h}, h = 1, \dots, h_0 \right),$$

where h_0 is a predetermined positive integer, \otimes is tensor product. Note that $\text{TOPUP}_k(\cdot)$ is a function mapping a tensor time series to an order-5 tensor. Time series Inner-Product Unfolding Procedure (TIPUP) replaces the tensor product in TOPUP with the inner product:

$$\text{TIPUP}_k(X_{1:T}) = \text{mat}_1 \left(\sum_{t=h+1}^T \frac{\text{mat}_k(X_{t-h}) \text{mat}_k^\top(X_t)}{T-h}, h = 1, \dots, h_0 \right).$$

Value

return a list containing the following:

`Ft` estimated factor processes of dimension $T \times r_1 \times r_2 \times \cdots \times r_k$.

`Ft.all` Summation of factor processes over time, of dimension r_1, r_2, \cdots, r_k .

`Q` a list of estimated factor loading matrices Q_1, Q_2, \cdots, Q_K .

`x.hat` fitted signal tensor, of dimension $T \times d_1 \times d_2 \times \cdots \times d_k$.

`niter` number of iterations.

`fnorm.resid` Frobenius norm of residuals, divide the Frobenius norm of the original tensor.

References

Chen, Rong, Dan Yang, and Cun-Hui Zhang. "Factor models for high-dimensional tensor time series." *Journal of the American Statistical Association* (2021): 1-59.

Han, Yuefeng, Rong Chen, Dan Yang, and Cun-Hui Zhang. "Tensor factor model estimation by iterative projection." *arXiv preprint arXiv:2006.02611* (2020).

Examples

```
set.seed(333)
dims <- c(16,18,20) # dimensions of tensor time series
r <- c(3,3,3) # dimensions of factor series
Ft <- tenAR.sim(t=100, dim=r, R=1, P=1, rho=0.9, cov='iid')
lambda <- sqrt(prod(dims))
x <- tenFM.sim(Ft,dims=dims,lambda=lambda,A=NULL,cov='iid') # generate t*dims tensor time series
result <- tenFM.est(x,r,method='TIPUP') # Estimation
Ft <- result$Ft
```

tenFM.rank

Rank Determination for Tensor Factor Models with Tucker Structure

Description

Function for rank determination of tensor factor models with Tucker Structure. Two unfolding methods of the auto-covariance tensor, Time series Outer-Product Unfolding Procedure (TOPUP), Time series Inner-Product Unfolding Procedure (TIPUP), are included, as determined by the value of `method`. Different penalty functions for the information criterion (BIC) and the eigen ratio criterion (ER) can be used, which should be specified by the value of `rank` and `penalty`. The information criterion resembles BIC in the vector factor model literature. And the eigen ratio criterion is similar to the eigenvalue ratio based methods in the vector factor model literature.

Usage

```
tenFM.rank(x,r,h0=1,rank='BIC',method='TIPUP',inputr=FALSE,iter=TRUE,penalty=1,
delta1=0,tol=1e-5,maxiter=100)
```

Arguments

x	$T \times d_1 \times \cdots \times d_K$ tensor-valued time series.
r	input rank of the factor tensor.
h0	the number of lags used in auto-covariance tensor.
rank	character string, specifying the type of the rank determination method to be used. "BIC", information criterion. "ER", eigen ratio criterion.
method	character string, specifying the type of the factor estimation method to be used. "TIPUP", TIPUP method. "TOPUP", TOPUP method.
inputr	boolean, if TRUE, use input rank for each iteration; if FALSE, update the rank r in each iteration.
iter	boolean, specifying using an iterative approach or a non-iterative approach.
penalty	takes value in 1,2,3,4,5, decide which penalty function to use for each tensor mode k . Here ν is a tuning parameter defined in the argument "delta1", and $d = \prod_{i=1}^K d_i$. When rank= 'BIC': if penalty=1, $g_1 = \frac{h_0 d^{2-2\nu}}{T} \log(\frac{dT}{d+T})$; if penalty=2, $g_2 = h_0 d^{2-2\nu} (\frac{1}{T} + \frac{1}{d}) \log(\frac{dT}{d+T})$; if penalty=3, $g_3 = \frac{h_0 d^{2-2\nu}}{T} \log(\min(d, T))$; if penalty=4, $g_4 = h_0 d^{2-2\nu} (\frac{1}{T} + \frac{1}{d}) \log(\min(d, T))$; if penalty=5, $g_5 = h_0 d^{2-2\nu} (\frac{1}{T} + \frac{1}{d}) \log(\min(d_k, T))$. When rank= 'ER': if penalty=1, $h_1 = c_0 h_0$; if penalty=2, $h_2 = \frac{h_0 d^2}{T^2}$; if penalty=3, $h_3 = \frac{h_0 d^2}{T^2 d_k^2}$; if penalty=4, $h_4 = \frac{h_0 d^2}{T^2 d_k^2} + \frac{h_0 d_k^2}{T^2}$; if penalty=5, $h_5 = \frac{h_0 d^2}{T^2 d_k^2} + \frac{h_0 d d_k^2}{T^2}$.
delta1	weakest factor strength, a tuning parameter used for BIC method only, default value is 0.
tol	tolerance in terms of the Frobenius norm.
maxiter	maximum number of iterations if error stays above tol.

Details

Let W be a $p \times p$ symmetric and non-negative definite matrix and \widehat{W} be its sample version, $\hat{\lambda}_j$ be the eigenvalues of \widehat{W} such that $\hat{\lambda}_1 \geq \hat{\lambda}_2 \geq \cdots \hat{\lambda}_p$. The rank determination methods using the information criterion ("IC") and the eigen ratio criterion ("ER") are defined as follows:

$$IC(\widehat{W}) = \operatorname{argmin}_{0 \leq m \leq m^*} \left\{ \sum_{j=m+1}^p \hat{\lambda}_j + mg(\widehat{W}) \right\},$$

$$ER(\widehat{W}) = \operatorname{argmin}_{0 \leq m \leq m^*} \left\{ \frac{\hat{\lambda}_{m+1} + h(\widehat{W})}{\hat{\lambda}_m + h(\widehat{W})} \right\},$$

where m^* is a predefined upper bound, g and h are some appropriate positive penalty functions. We have provided 5 choices for g and h ; see more details in the argument "penalty". For non-iterative TOPUP and TIPUP methods, \widehat{W} is $\operatorname{mat}_1(\operatorname{TOPUP}_k(X_{1:T}))\operatorname{mat}_1(\operatorname{TOPUP}_k(X_{1:T}))^\top$ or $(\operatorname{TIPUP}_k(X_{1:T}))(\operatorname{TIPUP}_k(X_{1:T}))^\top$, for each tensor mode k , $1 \leq k \leq K$, where $\operatorname{TOPUP}_k(X_{1:T})$ and $\operatorname{TIPUP}_k(X_{1:T})$ are defined in the Details section of the function `tenFM.est`. For iterative TOPUP and TIPUP methods, we refer to the literature in the References section for more information.

Value

return a list containing the following:

`path` a $K \times (\text{niter} + 1)$ matrix of the estimated Tucker rank of the factor process as a path of the maximum number of iteration (`niter`) used. The i -th column is the estimated rank $\hat{r}_1, \hat{r}_2, \dots, \hat{r}_K$ at $(i - 1)$ -th iteration.

`factor.num` final solution of the estimated Tucker rank of the factor process $\hat{r}_1, \hat{r}_2, \dots, \hat{r}_K$.

References

Han, Yuefeng, Cun-Hui Zhang, and Rong Chen. "Rank Determination in Tensor Factor Model." Available at SSRN 3730305 (2020).

Examples

```
set.seed(333)
dims <- c(16,18,20) # dimensions of tensor time series
r <- c(3,3,3) # dimensions of factor series
Ft <- tenAR.sim(t=100, dim=r, R=1, P=1, rho=0.9, cov='iid')
lambda <- sqrt(prod(dims))
x <- tenFM.sim(Ft,dims=dims,lambda=lambda,A=NULL,cov='iid') # generate t*dims tensor time series
rank <- tenFM.rank(x,c(4,4,4),h0=1,rank='ER',method='TIPUP') # Estimate the rank
```

tenFM.sim	<i>Generate Tensor Time series using given Factor Process and Factor Loading Matrices</i>
-----------	---

Description

Simulate tensor time series X_t using a given factor process F_t . The factor process F_t can be generated by the function `tenAR.sim`.

Usage

```
tenFM.sim(Ft,dims=NULL,lambda=1,A=NULL,cov='iid',rho=0.2)
```

Arguments

Ft	input of the factor process, of dimension $T \times r_1 \times r_2 \times \dots \times r_k$. It can be TenAR(p) tensor time series generated by the function tenAR.sim .
dims	dimensions of the output tensor at each time, $d_1 \times d_2 \dots \times d_K$.
lambda	signal strength parameter of the tensor factor models, see Details section for more information.
A	a list of the factor loading matrices A_1, A_2, \dots, A_K . The default is random orthogonal matrices A_k of dimension $d_k \times r_k$.
cov	covariance matrix of the error tensor: identity ("iid"), separable Kronecker structure ("separable"), random ("random").
rho	a parameter only for "separable" covariance matrix of the error tensor. It is the off-diagonal element of the error matrices, with the diagonal being 1.

Details

Simulate from the model :

$$X_t = \lambda F_t \times_1 A_1 \times_2 \dots \times_K A_k + E_t,$$

where A_k is the deterministic loading matrix of size $d_k \times r_k$ and $r_k \ll d_k$, the core tensor F_t itself is a latent tensor factor process of dimension $r_1 \times \dots \times r_K$, λ is an additional signal strength parameter, and the idiosyncratic noise tensor E_t is uncorrelated (white) across time. In this function, by default A_k are orthogonal matrices.

Value

A tensor-valued time series of dimension $T \times d_1 \times d_2 \dots \times d_K$.

See Also

[tenAR.sim](#)

Examples

```
set.seed(333)
dims <- c(16,18,20) # dimensions of tensor time series
r <- c(3,3,3) # dimensions of factor series
Ft <- tenAR.sim(t=100, dim=r, R=1, P=1, rho=0.9, cov='iid')
lambda <- sqrt(prod(dims))
# generate t*dims tensor time series with iid error covariance structure
x <- tenFM.sim(Ft,dims=dims,lambda=lambda,A=NULL,cov='iid')
# generate t*dims tensor time series with separable error covariance structure
x <- tenFM.sim(Ft,dims=dims,lambda=lambda,A=NULL,cov='separable',rho=0.2)
```

Index

matAR.RR.est, [2](#)

matAR.RR.se, [3](#)

mplot, [4](#)

tenAR.est, [5](#), [8](#)

tenAR.predict, [7](#)

tenAR.sim, [8](#), [12](#), [13](#)

tenFM.est, [9](#), [12](#)

tenFM.rank, [10](#)

tenFM.sim, [8](#), [12](#)