Package ‘HDMFA’

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Title High-Dimensional Matrix Factor Analysis

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Description High-dimensional matrix factor models have drawn much attention in view of the fact that observations are usually well structured to be an array such as in macroeconomics and finance. In addition, data often exhibit heavy-tails and thus it is also important to develop robust procedures. We aim to address this issue by replacing the least square loss with Huber loss function. We propose two algorithms to do robust factor analysis by considering the Huber loss. One is based on minimizing the Huber loss of the idiosyncratic error’s Frobenius norm, which leads to a weighted iterative projection approach to compute and learn the parameters and thereby named as Robust-Matrix-Factor-Analysis (RMFA), see the details in He et al. (2023) <doi:10.1080/07350015.2023.2191676>. The other one is based on minimizing the element-wise Huber loss, which can be solved by an iterative Huber regression algorithm (IHR), see the details in He et al. (2023) <arXiv:2306.03317>. In this package, we also provide the algorithm for alpha-PCA by Chen & Fan (2021) <doi:10.1080/01621459.2021.1970569>, the Projected estimation (PE) method by Yu et al. (2022) <doi:10.1016/j.jeconom.2021.04.001>. In addition, the methods for determining the pair of factor numbers are also given.

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Description

This function is to fit the matrix factor model via the $\alpha$-PCA method by conducting eigen-analysis of a weighted average of the sample mean and the column (row) sample covariance matrix through a hyper-parameter $\alpha$.

Usage

alpha_PCA(X, m1, m2, alpha = 0)

Arguments

- **X**: Input an array with $T \times p_1 \times p_2$, where $T$ is the sample size, $p_1$ is the row dimension of each matrix observation and $p_2$ is the column dimension of each matrix observation.
- **m1**: A positive integer indicating the row factor numbers.
- **m2**: A positive integer indicating the column factor numbers.
- **alpha**: A hyper-parameter balancing the information of the first and second moments ($\alpha \geq -1$). The default is 0.

Details

For the matrix factor models, Chen & Fan (2021) propose an estimation procedure, i.e. $\alpha$-PCA. The method aggregates the information in both first and second moments and extract it via a spectral method. In detail, for observations $X_t$, $t = 1, 2, \cdots, T$, define

$$\hat{M}_R = \frac{1}{p_1 p_2} \left( (1 + \alpha)XX^\top + \frac{1}{T} \sum_{t=1}^{T} (X_t - \bar{X})(X_t - \bar{X})^\top \right),$$

$$\hat{M}_C = \frac{1}{p_1 p_2} \left( (1 + \alpha)XX^\top + \frac{1}{T} \sum_{t=1}^{T} (X_t - \bar{X})^\top (X_t - \bar{X}) \right),$$
where $\alpha \in [-1, +\infty]$, $\bar{X} = \frac{1}{T} \sum_{t=1}^{T} X_t$, $\frac{1}{T} \sum_{t=1}^{T} (X_t - \bar{X})(X_t - \bar{X})^T$ and $\frac{1}{T} \sum_{t=1}^{T} (X_t - \bar{X})^T(X_t - \bar{X})$ are the sample row and column covariance matrix, respectively. The loading matrices $R$ and $C$ are estimated as $\sqrt{p_1}$ times the top $k_1$ eigenvectors of $\hat{M}_R$ and $\sqrt{p_2}$ times the top $k_2$ eigenvectors of $\hat{M}_C$, respectively. For details, see Chen & Fan (2021).

Value

The return value is a list. In this list, it contains the following:

- **F**: The estimated factor matrix of dimension $T \times m_1 \times m_2$.
- **R**: The estimated row loading matrix of dimension $p_1 \times m_1$, satisfying $R^T R = p_1 I_{m_1}$.
- **C**: The estimated column loading matrix of dimension $p_2 \times m_2$, satisfying $C^T C = p_2 I_{m_2}$.

Author(s)

Yong He, Changwei Zhao, Ran Zhao.

References


Examples

```r
set.seed(11111)
T=20;p1=20;p2=20;k1=3;k2=3
R=matrix(rnorm(p1*k1,min=-1,max=1),p1,k1)
C=matrix(rnorm(p2*k2,min=-1,max=1),p2,k2)
X=array(0,c(T,p1,p2))
Y=X+E
F=array(0,c(T,k1,k2))
for(t in 1:T){
  F[t,,]=matrix(rnorm(k1*k2),k1,k2)
  E[t,,]=matrix(rnorm(p1*p2),p1,p2)
  Y[t,,]=R%*%F[t,,]%*%t(C)
}

#Estimate the factor matrices and loadings
fit=alpha_PCA(X, k1, k2, alpha = 0)
Rhat=fit$R
Chat=fit$C
Fhat=fit$F

#Estimate the common component
CC=array(0,c(T,p1,p2))
for (t in 1:T){
  CC[t,,]=Rhat%*%Fhat[t,,]%*%t(Chat)
}
```
KMHFA

Estimating the Pair of Factor Numbers via Eigenvalue Ratios or Rank Minimization.

Description

The function is to estimate the pair of factor numbers via eigenvalue-ratio corresponding to RMFA method or rank minimization and eigenvalue-ratio corresponding to Iterative Huber Regression (IHR).

Usage

KMHFA(X, W1 = NULL, W2 = NULL, kmax, method, max_iter = 100, c = 1e-04, ep = 1e-04)

Arguments

X
Input an array with \( T \times p_1 \times p_2 \), where \( T \) is the sample size, \( p_1 \) is the the row dimension of each matrix observation and \( p_2 \) is the the column dimension of each matrix observation.

W1
Only if method=“E_RM” or method=“E_ER”, the initial value of row loadings matrix. The default is NULL, which is randomly chosen and all entries from a standard normal distribution.

W2
Only if method=“E_RM” or method=“E_ER”, the initial value of column loadings matrix. The default is NULL, which is randomly chosen and all entries from a standard normal distribution.

kmax
The user-supplied maximum factor numbers. Here it means the upper bound of the number of row factors and column factors.

method
Character string, specifying the type of the estimation method to be used.

“P”, the robust iterative eigenvalue-ratio based on RMFA

“E_RM”, the rank-minimization based on IHR

“E_ER”, the eigenvalue-ratio based on IHR

max_iter
Only if method=“E_RM” or method=“E_ER”, the maximum number of iterations in the iterative Huber regression algorithm. The default is 100.

c
A constant to avoid vanishing denominators. The default is \( 10^{-4} \).

ep
Only if method=“E_RM” or method=“E_ER”, the stopping criterion parameter in the iterative Huber regression algorithm. The default is \( 10^{-4} \times T p_1 p_2 \).
Details

If method=“P”, the number of factors $k_1$ and $k_2$ are estimated by

$$
\hat{k}_1 = \arg \max_{j \leq k_{max}} \frac{\lambda_j(M_w^u)}{\lambda_{j+1}(M_w^u)} , \hat{k}_2 = \arg \max_{j \leq k_{max}} \frac{\lambda_j(M_w^w)}{\lambda_{j+1}(M_w^w)},
$$

where $k_{max}$ is a predetermined value larger than $k_1$ and $k_2$. $\lambda_j(\cdot)$ is the j-th largest eigenvalue of a nonnegative definitive matrix. See the function \texttt{MHFA} for the definition of $M_w^u$ and $M_w^w$. For details, see He et al. (2023).

Define $D = \min(\sqrt{Tp_1}, \sqrt{Tp_2}, \sqrt{p_1p_2})$.

$$
\hat{\Sigma}_1 = \frac{1}{T} \sum_{t=1}^{T} \hat{F}_t \hat{F}_t^\top , \hat{\Sigma}_2 = \frac{1}{T} \sum_{t=1}^{T} \hat{F}_t^\top \hat{F}_t,
$$

where $\hat{F}_t, t = 1, \ldots, T$ is estimated by IHR under the number of factor is $k_{max}$.

If method=“E_RM”, the number of factors $k_1$ and $k_2$ are estimated by

$$
\hat{k}_1 = \sum_{i=1}^{k_{max}} I \left( \text{diag}(\hat{\Sigma}_1) > P_1 \right) , \hat{k}_2 = \sum_{j=1}^{k_{max}} I \left( \text{diag}(\hat{\Sigma}_2) > P_2 \right),
$$

where $I$ is the indicator function. In practice, $P_1$ is set as $\max \left( \text{diag}(\hat{\Sigma}_1) \right) \cdot D^{-2/3}$, $P_2$ is set as $\max \left( \text{diag}(\hat{\Sigma}_2) \right) \cdot D^{-2/3}$.

If method=“E_ER”, the number of factors $k_1$ and $k_2$ are estimated by

$$
\hat{k}_1 = \arg \max_{i \leq k_{max}} \frac{\lambda_i(\hat{\Sigma}_1)}{\lambda_{i+1}(\hat{\Sigma}_1) + cD^{-2}}, \hat{k}_2 = \arg \max_{j \leq k_{max}} \frac{\lambda_j(\hat{\Sigma}_2)}{\lambda_{j+1}(\hat{\Sigma}_2) + cD^{-2}}.
$$

Value

- $k_1$ The estimated row factor number.
- $k_2$ The estimated column factor number.

Author(s)

Yong He, Changwei Zhao, Ran Zhao.

References


Examples

```r
set.seed(11111)
T=20;p1=20;p2=20;k1=3;k2=3
R=matrix(runif(p1*k1,min=-1,max=1),p1,k1)
C=matrix(runif(p2*k2,min=-1,max=1),p2,k2)
X=array(0,c(T,p1,p2))
Y=X;E=Y
F=array(0,c(T,k1,k2))
for(t in 1:T){
  F[t,,]=matrix(rnorm(k1*k2),k1,k2)
  E[t,,]=matrix(rnorm(p1*p2),p1,p2)
  Y[t,,]=R%*%F[t,,]%*%t(C)
}
X=Y+E
KMHFA(X, kmax=6, method="P")
KMHFA(X, W1 = NULL, W2 = NULL, 6, "E_RM")
KMHFA(X, W1 = NULL, W2 = NULL, 6, "E_ER")
```

KPCA

Estimating the Pair of Factor Numbers via Eigenvalue Ratios Corresponding to $\alpha$-PCA

**Description**

The function is to estimate the pair of factor numbers via eigenvalue ratios corresponding to $\alpha$-PCA.

**Usage**

`KPCA(X, kmax, alpha = 0)`

**Arguments**

- **X**: Input an array with $T \times p_1 \times p_2$, where $T$ is the sample size, $p_1$ is the row dimension of each matrix observation and $p_2$ is the column dimension of each matrix observation.
- **kmax**: The user-supplied maximum factor numbers. Here it means the upper bound of the number of row factors and column factors.
- **alpha**: A hyper-parameter balancing the information of the first and second moments ($\alpha \geq -1$). The default is 0.
KPCA

Details

The function KPCA uses the eigenvalue-ratio idea to estimate the number of factors. In details, the number of factors $k_1$ is estimated by

$$\hat{k}_1 = \arg \max_{j \leq k_{\text{max}}} \frac{\lambda_j(\hat{M}_R)}{\lambda_{j+1}(\hat{M}_R)},$$

where $k_{\text{max}}$ is a given upper bound. $k_2$ is defined similarly with respect to $\hat{M}_C$. See the function alpha_PCA for the definition of $\hat{M}_R$ and $\hat{M}_C$. For more details, see Chen & Fan (2021).

Value

- $k_1$ The estimated row factor number.
- $k_2$ The estimated column factor number.

Author(s)

Yong He, Changwei Zhao, Ran Zhao.

References


Examples

```r
set.seed(11111)
T=20; p1=20; p2=20; k1=3; k2=3
R=matrix(runif(p1*k1,min=-1,max=1),p1,k1)
C=matrix(runif(p2*k2,min=-1,max=1),p2,k2)
X=array(0,c(T,p1,p2))
Y=X; E=Y
F=array(0,c(T,k1,k2))
for(t in 1:T){
  F[t,]=matrix(rnorm(k1*k2),k1,k2)
  E[t,]=matrix(rnorm(p1*p2),p1,p2)
  Y[t,]=R%*%F[t,]%*%t(C)
}
X=Y+E
KPCA(X, 8, alpha = 0)
```
KPE

Estimating the Pair of Factor Numbers via Eigenvalue Ratios Corresponding to PE

Description

The function is to estimate the pair of factor numbers via eigenvalue ratios corresponding to PE method.

Usage

\[
\text{KPE}(X, \text{kmax}, c = 0)
\]

Arguments

- **X**: Input an array with \( T \times p_1 \times p_2 \), where \( T \) is the sample size, \( p_1 \) is the row dimension of each matrix observation and \( p_2 \) is the column dimension of each matrix observation.
- **kmax**: The user-supplied maximum factor numbers. Here it means the upper bound of the number of row factors and column factors.
- **c**: A constant to avoid vanishing denominators. The default is 0.

Details

The function \text{KPE} uses the eigenvalue-ratio idea to estimate the number of factors. First, obtain the initial estimators \( \hat{R} \) and \( \hat{C} \). Second, define

\[
\hat{Y}_t = \frac{1}{p_2} X_t \hat{C}_t, \quad \hat{Z}_t = \frac{1}{p_1} X_t^\top \hat{R}_t,
\]

and

\[
\hat{M}_1 = \frac{1}{T p_1} \hat{Y}_t \hat{Y}_t^\top, \quad \hat{M}_2 = \frac{1}{T p_2} \sum_{t=1}^{T} \hat{Z}_t \hat{Z}_t^\top,
\]

the number of factors \( k_1 \) is estimated by

\[
\hat{k}_1 = \arg \max_{j \leq k_{\text{max}}} \frac{\lambda_j(\hat{M}_1)}{\lambda_{j+1}(\hat{M}_1)},
\]

where \( k_{\text{max}} \) is a predetermined upper bound for \( k_1 \). The estimation of \( k_2 \) is defined similarly with respect to \( \hat{M}_2 \). For details, see Yu et al. (2022).

Value

- **\( k_1 \)**: The estimated row factor number.
- **\( k_2 \)**: The estimated column factor number.
MHFA

Author(s)
Yong He, Changwei Zhao, Ran Zhao.

References

Examples
```r
set.seed(11111)
T=20;p1=20;p2=20;k1=3;k2=3
R=matrix(runif(p1*k1,min=-1,max=1),p1,k1)
C=matrix(runif(p2*k2,min=-1,max=1),p2,k2)
X=array(0,c(T,p1,p2))
Y=X;E=Y
F=array(0,c(T,k1,k2))
for(t in 1:T){
  F[,]=matrix(rnorm(k1*k2),k1,k2)
  E[,]=matrix(rnorm(p1*p2),p1,p2)
  Y[,]=R%*%F[,]%*%t(C)
}
X=Y+E
KPE(X, 8, c = 0)
```

MHFA

Matrix Huber Factor Analysis

Description
This function is to fit the matrix factor models via the Huber loss. We propose two algorithms to do robust factor analysis. One is based on minimizing the Huber loss of the idiosyncratic error’s Frobenius norm, which leads to a weighted iterative projection approach to compute and learn the parameters and thereby named as Robust-Matrix-Factor-Analysis (RMFA). The other one is based on minimizing the element-wise Huber loss, which can be solved by an iterative Huber regression algorithm (IHR).

Usage
```
MHFA(X, W1=NULL, W2=NULL, m1, m2, method, max_iter = 100, ep = 1e-04)
```

Arguments
| X     | Input an array with $T \times p_1 \times p_2$, where $T$ is the sample size, $p_1$ is the row dimension of each matrix observation and $p_2$ is the column dimension of each matrix observation. |
Only if method="E", the initial value of row loadings matrix. The default is NULL, which is randomly chosen and all entries from a standard normal distribution.

Only if method="E", the initial value of column loadings matrix. The default is NULL, which is randomly chosen and all entries from a standard normal distribution.

A positive integer indicating the row factor numbers.

A positive integer indicating the column factor numbers.

Character string, specifying the type of the estimation method to be used.

"p", indicates minimizing the Huber loss of the idiosyncratic error’s Frobenius norm. (RMFA)

"E", indicates minimizing the elementwise Huber loss. (IHR)

Only if method="E", the maximum number of iterations in the iterative Huber regression algorithm. The default is 100.

Only if method="E", the stopping criterion parameter in the iterative Huber regression algorithm. The default is $10^{-4} \times T^{1/p_1} p_2$.

For the matrix factor models, He et al. (2021) propose a weighted iterative projection approach to compute and learn the parameters by minimizing the Huber loss function of the idiosyncratic error’s Frobenius norm. In details, for observations $X_t, t = 1, 2, \cdots, T$, define

$$M_{w}^c = \frac{1}{Tp_2} \sum_{t=1}^{T} w_t X_t C C^\top X_t^\top, M_{w}^r = \frac{1}{Tp_1} \sum_{t=1}^{T} w_t X_t^\top R R^\top X_t.$$  

The estimators of loading matrices $\hat{R}$ and $\hat{C}$ are calculated by $\sqrt{p_1}$ times the leading $k_1$ eigenvectors of $M_{w}^c$ and $\sqrt{p_2}$ times the leading $k_2$ eigenvectors of $M_{w}^r$. And

$$\hat{F}_t = \frac{1}{p_1 p_2} \hat{R}^\top X_t \hat{C}. $$

For details, see He et al. (2023).

The other one is based on minimizing the element-wise Huber loss. Define

$$M_{i,Tp_2}(r, F_t, C) = \frac{1}{Tp_2} \sum_{t=1}^{T} \sum_{j=1}^{p_2} H_\tau (x_{t,ij} - r_i F_t c_j),$$

$$M_{i,Tp_1}(R, F_t, c) = \frac{1}{Tp_1} \sum_{t=1}^{T} \sum_{i=1}^{p_1} H_\tau (x_{t,ij} - r_i F_t c_j),$$

$$M_{t,p_1 p_2}(R, vec(F), C) = \frac{1}{p_1 p_2} \sum_{i=1}^{p_1} \sum_{j=1}^{p_2} H_\tau (x_{t,ij} - (c_j \otimes r_i)^\top vec(F)).$$

This can be seen as Huber regression as each time optimizing one argument while keeping the other two fixed.
Value

The return value is a list. In this list, it contains the following:

- **F** The estimated factor matrix of dimension $T \times m_1 \times m_2$.
- **R** The estimated row loading matrix of dimension $p_1 \times m_1$, satisfying $R^T R = p_1 I_{m_1}$.
- **C** The estimated column loading matrix of dimension $p_2 \times m_2$, satisfying $C^T C = p_2 I_{m_2}$.

Author(s)

Yong He, Changwei Zhao, Ran Zhao.

References


Examples

```r
set.seed(11111)
T=20;p1=20;p2=20;k1=3;k2=3
R=matrix(runif(p1*k1,min=-1,max=1),p1,k1)
C=matrix(runif(p2*k2,min=-1,max=1),p2,k2)
X=array(0,c(T,p1,p2))
Y=X;E=Y
F=array(0,c(T,k1,k2))
for(t in 1:T){
  F[t,]=matrix(rnorm(k1*k2),k1,k2)
  E[t,]=matrix(rnorm(p1*p2),p1,p2)
  Y[t,]=R%*%F[t,]%*%t(C)
}
X=Y+E

#Estimate the factor matrices and loadings by RMFA
fit1=MHFA(X, m1=3, m2=3, method="P")
Rhat1=fit1$R
Chat1=fit1$C
Fhat1=fit1$F

#Estimate the factor matrices and loadings by IHR
fit2=MHFA(X, W1=NULL, W2=NULL, 3, 3, "E")
Rhat2=fit2$R
Chat2=fit2$C
Fhat2=fit2$F

#Estimate the common component by RMFA
CC1=array(0,c(T,p1,p2))
```
for (t in 1:T){
  CC1[t,,]=Rhat1%*%Fhat1[t,,]%*%t(Chat1)
}
CC1

#Estimate the common component by IHR
CC2=array(0,c(T,p1,p2))
for (t in 1:T){
  CC2[t,,]=Rhat2%*%Fhat2[t,,]%*%t(Chat2)
}
CC2

PE

Projected Estimation for Large-Dimensional Matrix Factor Models

Description

This function is to fit the matrix factor model via the PE method by projecting the observation matrix onto the row or column factor space.

Usage

PE(X, m1, m2)

Arguments

X Input an array with $T \times p_1 \times p_2$, where $T$ is the sample size, $p_1$ is the the row dimension of each matrix observation and $p_2$ is the the column dimension of each matrix observation.
m1 A positive integer indicating the row factor numbers.
m2 A positive integer indicating the column factor numbers.

Details

For the matrix factor models, Yu et al. (2022) propose a projection estimation method to estimate the model parameters. In details, for observations $X_t, t = 1, 2, \cdots, T$, the data matrix is projected to a lower dimensional space by setting

$$Y_t = \frac{1}{p_2} X_t C.$$ 

Given $Y_t$, define

$$M_1 = \frac{1}{T p_1} \sum_{t=1}^{T} Y_t Y_t^T,$$

and then the row factor loading matrix $R$ can be estimated by $\sqrt{p_1}$ times the leading $k_1$ eigenvectors of $M_1$. However, the projection matrix $C$ is unavailable in practice. A natural solution is to replace it with a consistent initial estimator. The column factor loading matrix $C$ can be similarly estimated by projecting $X_t$ onto the space of $C$ with $R$. See Yu et al. (2022) for the detailed algorithm.
**Value**

The return value is a list. In this list, it contains the following:

- **F**  
  The estimated factor matrix of dimension $T \times m_1 \times m_2$.

- **R**  
  The estimated row loading matrix of dimension $p_1 \times m_1$, satisfying $R^T R = p_1 I_{m_1}$.

- **C**  
  The estimated column loading matrix of dimension $p_2 \times m_2$, satisfying $C^T C = p_2 I_{m_2}$.

**Author(s)**

Yong He, Changwei Zhao, Ran Zhao.

**References**


**Examples**

```r
set.seed(11111)
T=20;p1=20;p2=20;k1=3;k2=3
R=matrix(runif(p1*k1,min=-1,max=1),p1,k1)
C=matrix(runif(p2*k2,min=-1,max=1),p2,k2)
X=array(0,c(T,p1,p2))
Y=X;E=Y
F=array(0,c(T,k1,k2))
for(t in 1:T){
  F[t,,]=matrix(rnorm(k1*k2),k1,k2)
  E[t,,]=matrix(rnorm(p1*p2),p1,p2)
  Y[t,,]=R%*%F[t,,]%*%t(C)
}
X=Y+E

#Estimate the factor matrices and loadings
fit=PE(X, k1, k2)
Rhat=fit$R
Chat=fit$C
Fhat=fit$F

#Estimate the common component
CC=array(0,c(T,p1,p2))
for (t in 1:T){
  CC[t,,]=Rhat%*%Fhat[t,,]%*%t(Chat)
}
CC
```
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