# Package 'SOPC'

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Type Package
Title The Sparse Online Principal Component Estimation Algorithm
Version 0.1.0
<b>Description</b> The sparse online principal component can not only process the online data set, but also obtain a sparse solution of the online data set. The philosophy of the package is described in Guo G. (2022) <doi:10.1007 s00180-022-01270-z="">.</doi:10.1007>
License MIT + file LICENSE
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RoxygenNote 7.2.3
Imports elasticnet, magrittr, stats
Suggests testthat (>= 3.0.0)
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Heart Heart failure

#### Description

Heart failure

## Usage

data("Heart")

#### **Format**

A data frame with 299 observations on the following 13 variables.

age a numeric vector
anaemia a numeric vector
creatinine\_phosphokinase a numeric vector
diabetes a numeric vector
ejection\_fraction a numeric vector
high\_blood\_pressure a numeric vector
platelets a numeric vector
serum\_creatinine a numeric vector
serum\_sodium a numeric vector
sex a numeric vector
smoking a numeric vector
time a numeric vector

#### **Details**

This dataset contains the medical records of 299 patients who had heart failure, collected during their follow-up period, where each patient profile has 13 clinical features.

#### Source

The Heart failure data set comes from the UCI database.

Hugging 3

#### References

Davide Chicco, Giuseppe Jurman. (2020). Machine learning can predict survival of patients with heart failure from serum creatinine and ejection fraction alone. BMC Medical Informatics and Decision Making.

#### **Examples**

```
data(Heart)
## maybe str(Heart) ; plot(Heart) ...
```

## Description

Hugging

The EMG Physical Action-Hugging data set.

#### Usage

```
data("Hugging")
```

#### **Format**

A data frame with 9752 observations on the following 8 variables.

Hugging

A a numeric vector

B a numeric vector

C a numeric vector

D a numeric vector

E a numeric vector

F a numeric vector

G a numeric vector

H a numeric vector

## Details

The data set is a body movement data set, including 10 normal and 10 aggressive body movements. The data frame with 9752 observations on the following 8 variables.

#### Source

The Hugging data set comes from the UCI database.

## References

Demir et al. (2019). Surface emg signals and deep transfer learning-based physical action classification. Neural Computing and Applications.

OPC OPC

#### **Examples**

```
data(Hugging)
## maybe str(Hugging) ; plot(Hugging) ...
```

IPC

The incremental principal component can handle online data sets with highly correlated.

## Description

The incremental principal component can handle online data sets with highly correlated.

#### Usage

```
IPC(data, m, eta)
```

## **Arguments**

data is a highly correlated online data set

m is the number of principal component

eta is the proportion of online data to total data

#### Value

Ai,Di

#### **Examples**

```
IPC(data=PSA,m=3,eta=0.8)
```

OPC

The online principal component method refers to the IPC method with the best performance among the IPC, the PPC and the SAPC methods.

## Description

The online principal component method refers to the IPC method with the best performance among the IPC, the PPC and the SAPC methods.

#### Usage

```
OPC(data, m, eta)
```

PC 5

## Arguments

data is a highly correlated online data set m is the number of principal component

eta is the proportion of online data to total data

#### Value

Ao,Do

## **Examples**

```
OPC(data=PSA,m=3,eta=0.8)
```

PC

The traditional principal component method. This method can estimate the eigen space of the data set.

## Description

The traditional principal component method. This method can estimate the eigen space of the data set.

## Usage

```
PC(data, m = m)
```

## Arguments

data is a highly correlated data set

m is the number of principal component

#### Value

Ahat, Dhat

## **Examples**

```
PC(data=PSA,m=3)
```

6 PSA

PPC	The perturbation principal component can handle online data sets
	with highly correlated.

## Description

The perturbation principal component can handle online data sets with highly correlated.

## Usage

```
PPC(data, m, eta)
```

## Arguments

data is a highly correlated online data set

m is the number of principal component

eta is the proportion of online data to total data

## Value

Ap,Dp

## **Examples**

```
PPC(data=PSA,m=3,eta=0.8)
```

PSA

Prostate Specific Antigen

## Description

The prostate specific antigen (PSA) data set.

## Usage

```
data("PSA")
```

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#### **Format**

```
lcavol a numeric vector
lweight a numeric vector
age a numeric vector
lbph a numeric vector
svi a numeric vector
lcp a numeric vector
gleason a numeric vector
pgg45 a numeric vector
lpsa a numeric vector
```

#### **Details**

The data set comes from the prostate specific antigen (PSA) data of 96 patients collected by Stanford University Medical Center. These patients all underwent radical prostatectomy.

#### Source

The Stanford University Medical Center.

#### References

NA

#### **Examples**

```
data(PSA)
## maybe str(PSA) ; plot(PSA) ...
```

SAPC

The stochastic approximation principal component can handle online data sets with highly correlated.

## Description

The stochastic approximation principal component can handle online data sets with highly correlated.

#### Usage

```
SAPC(data, m, eta)
```

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#### **Arguments**

data is a highly correlated online data set m is the number of principal component eta is the proportion of online data to total data

#### Value

Asa,Dsa

## **Examples**

```
SAPC(data=PSA,m=3,eta=0.8)
```

SOPC

The sparse online principal component can not only process online data sets, but also obtain a sparse solution of online data sets.

## Description

The sparse online principal component can not only process online data sets, but also obtain a sparse solution of online data sets.

## Usage

```
SOPC(data, m, gamma, eta)
```

#### **Arguments**

data is a highly correlated online data set is the number of principal component

gamma is a sparse parameter

is the proportion of online data to total data eta

#### Value

Aso, Dso

#### **Examples**

```
require(elasticnet)
SOPC(PSA, 3, 0.03, 0.6)
```

SPC 9

SPC	The sparse principal component can obtain sparse solutions of the eigenmatrix to better explain the relationship between principal com-
	ponents and original variables.

## Description

The sparse principal component can obtain sparse solutions of the eigenmatrix to better explain the relationship between principal components and original variables.

## Usage

```
SPC(data, m, gamma)
```

## Arguments

data is a highly correlated data set

m is the number of principal component

gamma is a sparse parameter

#### Value

As,Ds

## **Examples**

```
require(elasticnet)
SPC(data=PSA,m=3,gamma=0.03)
```

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