

# Package: LIC (via r-universe)

November 4, 2024

**Title** The LIC Criterion for Optimal Subset Selection

**Version** 0.0.2

**Description** The LIC criterion is to determine the most informative subsets so that the subset can retain most of the information contained in the complete data. The philosophy of the package is described in Guo G. (2022)  [<doi:10.1080/02664763.2022.2053949>](https://doi.org/10.1080/02664763.2022.2053949).

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**Imports** stats

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**NeedsCompilation** no

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**Repository** <https://guangbaog.r-universe.dev>

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airfoil	<i>Airfoil self-noise</i>
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### Description

The Airfoil self-noise data set

### Usage

```
data("airfoil")
```

### Format

A data frame with 1503 observations on the following 6 variables.

V1 a numeric vector

V2 a numeric vector

V3 a numeric vector

V4 a numeric vector

V5 a numeric vector

V6 a numeric vector

### Details

The data set contains 1503 data points, including the 6 variables. Among them, the scaled sound pressure level is the dependent variable and the other five are independent variables.

### Source

The Airfoil Self-Noise data set is from the NASA data set in UCI database.

### References

T.F. Brooks, D.S. Pope, and A.M. Marcolini. Airfoil self-noise and prediction. Technical report, NASA RP-1218, July 1989.

### Examples

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

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estate	<i>Real estate valuation</i>
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**Description**

The real estate valuation data set.

**Usage**

```
data("estate")
```

**Format**

A data frame with 414 observations on the following 8 variables.

No a numeric vector

X1.transaction.date a numeric vector

X2.house.age a numeric vector

X3.distance.to.the.nearest.MRT.station a numeric vector

X4.number.of.convenience.stores a numeric vector

X5.latitude a numeric vector

X6.longitude a numeric vector

Y.house.price.of.unit.area a numeric vector

**Details**

Real estate valuation data set contains information about 414 real estate prices of 5 independent variables. The dependent variable is the price per unit area.

**Source**

The data set is from Xindian District, New Taipei City, Taiwan.

**References**

Yeh, I. C., & Hsu, T. K. (2018). Building real estate valuation models with comparative approach through case-based reasoning. *Applied Soft Computing*, 65, 260-271.

**Examples**

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

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`gt2015`*Gas turbine NOx emission*

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**Description**

The gas turbine NOx emission data set.

**Usage**

```
data("gt2015")
```

**Format**

A data frame with 7384 observations on the following 11 variables.

AT a numeric vector

AP a numeric vector

AH a numeric vector

AFDP a numeric vector

GTEP a numeric vector

TIT a numeric vector

TAT a numeric vector

TEY a numeric vector

CDP a numeric vector

CO a numeric vector

NOX a numeric vector

**Details**

To predict nitrogen oxide emissions, we use the gas turbine NOx emission data set in UCI database, which contains 36,733 instances of 11,733 sensor measurements. The pollutant emission factors of gas turbines include 9 variables. We select 7,200 data points in 2015.

**Source**

The gas turbine NOx emission data set is from UCI database.

**References**

NA

**Examples**

```
data(gt2015)
## maybe str(gt2015) ; plot(gt2015) ...
```

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LIC	<i>The LIC criterion is to determine the most informative subsets so that the subset can retain most of the information contained in the complete data.</i>
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### Description

The LIC criterion is to determine the most informative subsets so that the subset can retain most of the information contained in the complete data.

### Usage

```
LIC(X, Y, alpha, K, nk)
```

### Arguments

X	is a design matrix
Y	is a random response vector of observed values
alpha	is the significance level
K	is the number of subsets
nk	is the sample size of subsets

### Value

```
MUopt,Bopt,MAEMUopt,MSEMUopt,opt,Yopt
```

### Examples

```
set.seed(12)
X=matrix(data=sample(1:3,1200*5, replace = TRUE) ,nrow=1200,ncol=5)
b=sample(1:3,5, replace = TRUE)
e= rnorm(1200, 0, 1)
Y=X%*%b+e
alpha=0.05
K=10
nk=1200/K
LIC(X,Y,alpha,K,nk)
```

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Opt1	<i>The Opt1 chooses the optimal index subset based on minimized interval length.</i>
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### Description

The Opt1 chooses the optimal index subset based on minimized interval length.

### Usage

```
Opt1(X, Y, alpha, K, nk)
```

### Arguments

X	is a design matrix
Y	is a random response vector of observed values
alpha	is the significance level
K	is the number of subsets
nk	is the sample size of subsets

### Value

MUopt1,Bopt1,MAEMUopt1,MSEMUopt1,opt1,Yopt1

### Examples

```
set.seed(12)
X=matrix(data=sample(1:3,1200*5, replace = TRUE) ,nrow=1200,ncol=5)
b=sample(1:3,5, replace = TRUE)
e= rnorm(1200, 0, 1)
Y=X%*%b+e
alpha=0.05
K=10
nk=1200/K
Opt1(X,Y,alpha,K,nk)
```

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Opt2	<i>The Opt2 chooses the optimal index subset based on maximized information sub-matrix.</i>
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### Description

The Opt2 chooses the optimal index subset based on maximized information sub-matrix.

**Usage**

```
Opt2(X, Y, alpha, K, nk)
```

**Arguments**

X	is a design matrix
Y	is a random response vector of observed values
alpha	is the significance level
K	is the number of subsets
nk	is the sample size of subsets

**Value**

```
MUopt2,Bopt2,MAEMUopt2,MSEMUopt2,opt2,Yopt2
```

**Examples**

```
set.seed(12)
X=matrix(data=sample(1:3,1200*5, replace = TRUE) ,nrow=1200,ncol=5)
b=sample(1:3,5, replace = TRUE)
e= rnorm(1200, 0, 1)
Y=X%*%b+e
alpha=0.05
K=10
nk=1200/K
Opt2(X,Y,alpha,K,nk)
```

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OSA	<i>The OSA gives a simple average estimatoris by averaging all these least squares estimators.</i>
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**Description**

The OSA gives a simple average estimatoris by averaging all these least squares estimators.

**Usage**

```
OSA(X, Y, alpha, K, nk)
```

**Arguments**

X	is a design matrix
Y	is a random response vector of observed values
alpha	is the significance level
K	is the number of subsets
nk	is the sample size of subsets

**Value**

MUA,BetaA,MAEMUA,MSEMUA

**Examples**

```
set.seed(12)
X=matrix(data=sample(1:3,1200*5, replace = TRUE) ,nrow=1200,ncol=5)
b=sample(1:3,5, replace = TRUE)
e= rnorm(1200, 0, 1)
Y=X%*%b+e
alpha=0.05
K=10
nk=1200/K
OSA(X,Y,alpha,K,nk)
```

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OSM

*The OSM is a median processing method for the central processor.*

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**Description**

The OSM is a median processing method for the central processor.

**Usage**

OSM(X, Y, alpha, K, nk)

**Arguments**

X	is a design matrix
Y	is a random response vector of observed values
alpha	is the significance level
K	is the number of subsets
nk	is the sample size of subsets

**Value**

MUM,BetaM,MAEMUM,MSEMUM

**Examples**

```
set.seed(12)
X=matrix(data=sample(1:3,1200*5, replace = TRUE) ,nrow=1200,ncol=5)
b=sample(1:3,5, replace = TRUE)
e= rnorm(1200, 0, 1)
Y=X%*%b+e
alpha=0.05
K=10
nk=1200/K
OSA(X,Y,alpha,K,nk)
```



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