

# Package ‘PoSI’

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**Type** Package

**Title** Valid Post-Selection Inference for Linear LS Regression

**Version** 1.1

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**Description** In linear LS regression, calculate for a given design matrix the multiplier  $K$  of coefficient standard errors such that the confidence intervals  $[b - K*SE(b), b + K*SE(b)]$  have a guaranteed coverage probability for all coefficient estimates  $b$  in any submodels after performing arbitrary model selection.

**Suggests** MASS

**License** GPL-3

**NeedsCompilation** no

**Repository** CRAN

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**Description**

In linear LS regression, calculate for a given regressor matrix the multiplier  $K$  of coefficient standard errors such that the confidence intervals  $[b - K*SE(b), b + K*SE(b)]$  have a guaranteed coverage probability for all coefficient estimates  $b$  in any submodels after performing arbitrary model selection.

**Details**

Package: PoSI  
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**References**

“Valid Post-Selection Inference,” Berk, R., Brown, L., Buja, A., Zhang, K., Zhao, L., The Annals of Statistics, 41 (2), 802–837~(2013).

**See Also**

`lm`, `link{model.matrix}`

**Examples**

```
data(Boston, package="MASS")
summary(PoSI(Boston[, -14]))
```

**Description**

Used in calculating multipliers  $K$  of standard errors in linear LS regression such that the confidence intervals

$$[b - K*SE(b), b + K*SE(b)]$$

have guaranteed coverage probabilities for all coefficient estimates  $b$  in any submodel arrived at after performing arbitrary model selection. The actual multipliers  $K$  are calculated by `summary`; `PoSI` returns an object of class "PoSI".

**Usage**

```
PoSI(X, modelSZ = 1:ncol(X), center = T, scale = T, verbose = 1,
      Nsim = 1000, bundleSZ = 100000, eps = 1e-08)
```

```
## S3 method for class 'PoSI'
summary(object, confidence = c(0.95, 0.99), alpha = NULL,
         df.err = NULL, eps.PoSI = 1e-06, digits = 3, ...)
```

**Arguments**

<code>X</code>	a regressor matrix as returned, for example, by the function <code>model.matrix</code> when applied to a linear model object from the function <code>lm</code> ; data frames are coerced to matrices
<code>modelSZ</code>	the model sizes to be included (default: <code>1:ncol(X)</code> ). This argument permits 'sparse PoSI' with, e.g., <code>modelSZ=1:5</code> when only models up to size 5 have been searched, or 'rich PoSI' with, e.g., <code>modelSZ=(ncol(X)-2):ncol(X)</code> when only the removal of up to two regressors has been tried.
<code>center</code>	whether to center the columns of $X$ (boolean, default: <code>TRUE</code> , in which case the intercept will be removed)
<code>scale</code>	whether to standardize the columns of $X$ (boolean, default: <code>TRUE</code> ; prevents problems from columns with vastly differing scales)
<code>verbose</code>	0: no printed reports during computations; 1: report bundle completion (default); 2: report each processed submodel (for debugging with small <code>ncol(X)</code> ).
<code>Nsim</code>	the number of tests being simulated (default: 1000). <code>PoSI</code> is partly simulation-based; increase <code>Nsim</code> for greater precision at the cost of increased run time.
<code>bundleSZ</code>	number of tests to be processed simultaneously (default: 100000). Larger bundles are computationally more efficient but require more memory.
<code>eps</code>	threshold below which singular values of $X$ will be considered to be zero (default: <code>1E-8</code> ). In cases of highly collinear columns in $X$ this threshold determines the effective dimension of the column space of $X$ .

object	an object of class "PoSI" as returned by the function PoSI
confidence	a numeric vector of values between 0 and 1 containing the confidence levels for which multipliers of standard error should be provided (default: c(.95, .99))
alpha	if specified, sets confidence = 1-alpha. (This argument is redundant with confidence; only one should be specified.)
df.err	error degrees of freedom for t-tests (default: NULL, performs z-tests)
eps.PoSI	precision to which standard error multipliers are computed (default: 1e-06)
digits	number of significant digits to which standard error multipliers are rounded (default: 3)
...	(other arguments)

### Details

Example of use of PoSI multipliers: In the Boston Housing data shown below, the 0.95 multiplier is 3.593. If after arbitrary variable selection we decide, for example, in favor of the submodel

```
summary(lm(medv ~ rm + nox + dis + ptratio + lstat, data=Boston))
```

the regressor *rm* (e.g.) has a coefficient estimate of 4.16 with a standard error of 0.41; hence the 0.95 PoSI confidence interval is found by

$$4.16 + c(-1,+1) * 3.593 * 0.41$$

which is (2.69, 5.63) after rounding. Similar intervals can be formed for any regressor in any submodel. The resulting confidence procedure has a 0.95 family-wise guarantee of containing the true coefficient even after arbitrary variable selection in any submodel one might arrive at.

The computational limitations of the PoSI method are in the exponential growth of the number of t/z-tests that are being computed:

(1) If  $p = \text{ncol}(X)$  and all submodels are being searched ( $\text{modelSZ}=1:p$ ), the number of tests is  $p * 2^{(p-1)}$ . Example:  $p=20$ ;  $\text{modelSZ}=1:20 \implies \# \text{ tests} = 10,485,760$

(2) If only models of sizes  $\text{modelSZ}=m$  are being searched, the number of tests is  $\text{sum}(m * \text{choose}(p, m))$ . Example:  $p=50$ ;  $m=1:5 \implies \# \text{ tests} = 11,576,300$

Thus limiting PoSI to small submodel sizes such as  $\text{modelSZ}=1:5$  ("sparse PoSI") puts larger  $p = \text{ncol}(X)$  within reach.

PoSI computations are partly simulation-based and require specification of a number  $N_{\text{sim}}$  of random unit vectors to be sampled in the column space of  $X$ . Large  $N_{\text{sim}}$  yields greater precision but requires more memory. The memory demands can be lowered by decreasing  $\text{bundleSZ}$  at the cost of some efficiency.  $\text{bundleSZ}$  determines how many tests are simultaneously processed.

### Value

PoSI returns an object of class "PoSI" whose only use is to be the first argument to the function `summary`.

`summary` returns a matrix containing in its first column the two-sided PoSI standard error multipliers  $K$  for the specified confidence levels or Type-I error probabilities. Additionally, in the second and third column, it returns standard error multipliers based on the Bonferroni and Scheffe methods which are more conservative than the PoSI method:  $\text{PoSI} < \text{Bonferroni} < \text{Scheffe}$  (sometimes  $\text{Bonferroni} > \text{Scheffe}$ ).

## References

"Valid Post-Selection Inference," by Berk, R., Brown, L., Buja, A., Zhang, K., Zhao, L., The Annals of Statistics, 41 (2), 802-837 (2013).

## Examples

```
## Not run:
# Boston Housing data from http://archive.ics.uci.edu/ml/datasets/Housing
data(Boston, package="MASS")
UL.Boston <- PoSI(Boston[, -14]) # 4.7 sec (**)
summary(UL.Boston)
##      K.PoSI K.Bonferroni K.Scheffe
## 95%  3.593         4.904     4.729
## 99%  4.072         5.211     5.262

## End(Not run)

# Just 1 predictor:
X.1 <- as.matrix(rnorm(100))
UL.max.1 <- PoSI(X.1)
summary(UL.max.1) # Assuming sigma is known
##      K.PoSI K.Bonferroni K.Scheffe
## 95%  1.960         1.960     1.960
## 99%  2.576         2.576     2.576
summary(UL.max.1, df.err=4) # sigma estimated with 4 dfs
##      K.PoSI K.Bonferroni K.Scheffe
## 95%  2.776         2.776     2.776
## 99%  4.604         4.604     4.604

# small N and automatic removal of intercept:
p <- 6; N <- 4
X.small <- cbind(1, matrix(rnorm(N*p), ncol=p))
UL.max.small <- PoSI(X.small, modelSZ=c(4,3,1), Nsim=1000, bundleSZ=5, verbose=2)
summary(UL.max.small, df.err=4)
##      K.PoSI K.Bonferroni K.Scheffe
## 95%  4.226         9.256     4.447
## 99%  6.731        13.988     7.077

## Not run:
# Orthogonal regressors:
p <- 10; N <- 10
X.orth <- qr.Q(qr(matrix(rnorm(p*N), ncol=p)))
UL.max.orth <- PoSI(X.orth, Nsim=10000) # 2.8 sec (**)
summary(UL.max.orth)
##      K.PoSI K.Bonferroni K.Scheffe
## 95%  3.448         4.422     4.113
## 99%  3.947         4.758     4.655

## End(Not run)
```

```

## Not run:
# Large p=50, small N=20, models up to size 4: 1.3min
p <- 50; N <- 20
X.p50.N20 <- matrix(rnorm(p*N), ncol=p)
UL.max.p50.N20 <- PoSI(X.p50.N20, Nsim=1000, bundleSZ=100000, modelSZ=1:4) # 1.3 min (*)
summary(UL.max.p50.N20)
##      K.PoSI K.Bonferroni K.Scheffe
## 95%  4.309      5.448      5.490
## 99%  4.769      5.728      6.016

## End(Not run)

## Not run:
# The following is modeled on a real data example:
p <- 84; N <- 2758
X.84 <- matrix(rnorm(p*N), ncol=p)
# --- (1) Rich submodels: sizes m=84 and m=83 with more simulations (10,000) for precision
UL.max.84 <- PoSI(X.84, Nsim=1000, bundleSZ=10000, modelSZ=c(p-1,p)) # 2 sec (*)
summary(UL.max.84)
##      K.PoSI K.Bonferroni K.Scheffe
## 95%  3.494      4.491     10.315
## 99%  3.936      4.823     10.819

## End(Not run)

## Not run:
# --- (2) Sparse submodels: p=84, model size m=4, in p=d=84 dimensions:
# WARNING: 17 minutes (*)
UL.max.84.4 <- PoSI(X.84, Nsim=1000, bundleSZ=100000, modelSZ=4)
summary(UL.max.84.4)
##      K.PoSI K.Bonferroni K.Scheffe
## 95%  3.553      5.804     10.315
## 99%  3.966      6.068     10.819
summary(UL.max.84.4, df.err=2758-84-1)
##      K.PoSI K.Bonferroni K.Scheffe
## 95%  3.557      5.823     10.338
## 99%  3.972      6.089     10.855

## End(Not run)

## Not run:
# Big experiment: full large PoSI for p=20
# WARNING: 13 minutes (*)
p <- 20; N <- 1000
X.p20 <- matrix(rnorm(N*p), ncol=p)
UL.max.p20 <- PoSI(X.p20, bundleSZ=100000)
summary(UL.max.p20)
##      K.PoSI K.Bonferroni K.Scheffe
## 95%  3.163      5.855      5.605
## 99%  3.626      6.117      6.129
summary(UL.max.p20, df.err=1000-21)
##      K.PoSI K.Bonferroni K.Scheffe

```

```

## 95% 3.171      5.908      5.624
## 99% 3.638      6.177      6.160

## End(Not run)

## Not run:
# Big experiment: sparse large PoSI with p=50 and m=1:5:
## WARNING: 22 minutes (*)
p <- 50; N <- 1000; m <- 1:5
X.p50 <- matrix(rnorm(N*p), ncol=p)
UL.max.p50.m5 <- PoSI(X.p50, bundleSZ=100000, modelSZ=m)
summary(UL.max.p50.m5)
##      K.PoSI K.Bonferroni K.Scheffe
## 95% 3.548      5.871      8.216
## 99% 4.041      6.133      8.727

## End(Not run)

## Not run:
# Exchangeable Designs:
# function to create exchangeable designs:
design.exch <- function(p,a) { (1-a)*diag(p) + a*matrix(1,p,p) }
# example:
p <- 12; a <- 0.5;
X.exch <- design.exch(p=p, a=a)
UL.exch <- PoSI(X.exch, verbose=0, modelSZ=1:p) # 2 sec (**)
summary(UL.exch)
##      K.PoSI K.Bonferroni K.Scheffe
## 95% 3.635      4.750      4.436
## 99% 4.129      5.066      4.972

## End(Not run)

# (*) Elapsed times were measured in R version 3.1.3, 32 bit,
#     on a processor Intel(R) Core(TM), 2.9 GHz, under Windows 7.
#     2015/04/16

# (**) Elapsed times were measured in R version 4.0.2, 64 bit,
#     on a processor Intel(R) Core(TM), 1.80 GHz, under Windows 10.
#     2020/10/26

```

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