## Package 'TSGSIS'

July 21, 2025

**Description**To provide a high dimensional grouped variable selection approach for detection of whole-

genome SNP effects and SNP-SNP interactions, as described in Fang et al. (2017, under review).
Version 0.1
Author Yao-Hwei Fang, Jie-Huei Wang, and Chao A. Hsiung
Maintainer Yao-Hwei Fang <yhfang@nhri.org.tw></yhfang@nhri.org.tw>
Date 2017-04-18
<b>Depends</b> R (>= 3.2.3), glmnet, MASS, stats
License GPL (>= 2)
Encoding UTF-8
LazyData true
Repository CRAN
RoxygenNote 6.0.1
NeedsCompilation no

**Date/Publication** 2017-04-18 06:43:40 UTC

Title Two Stage-Grouped Sure Independence Screening

## **Contents**

	5U5I5
Index	5
TSGSI	Two Stage-Grouped Sure Independence Screening

## Description

The package is a beta version that provides a high-dimensional grouped variable selection approach for detection of whole-genome SNP effects and SNP-SNP interactions, as described in Fang et al. (2017, under review). The proposed TSGSIS is developed to study interactions that may not have marginal effects.

2 TSGSIS

#### Usage

```
TSGSIS(XA, Y, Gene_list, ntest, lambda, Method)
```

#### **Arguments**

XA The  $N \times P$  matrix of XA. There are N individuals and P variables in matrix,

with one individual in each row and one genotype in each column.

Y The  $N \times 1$  matrix of Y. It can be real number or binary outcome.

Gene\_list The  $a \times d$  matrix of the Gene\_list. a is the maximal number of gene size in the

Gene\_list which other values are denoted by 0. d is the number of genes.

ntest The ntest (< N) is the number of testing data for evaluation of MSE.

lambda The lambda is the parameter of Lasso regression.

Method "Reg" for quantitative trait modeling, "LR" for disease trait modeling.

#### Value

Returns a result of screening

result First element of the result is the MSE of testing data, the rest elements are the

important SNP effects and SNP-SNP interactions after TSGSIS modeling.

#### Note

The missing value (NA) in the XA and Y is not allowed in this beta version.

#### References

Yao-Hwei Fang, Jie-Huei Wang and Chao A. Hsiung (2017). TSGSIS: A High-dimensional Grouped Variable Selection Approach for Detection of Whole-genome SNP-SNP Interactions. (Under revision in Bioinformatics)

### **Examples**

```
#We investigate the performance of TS-GSIS under model 1 with intra-gene correlation rho = 0.2,
#trait dispersion sigma^2 = 1, effect size k = 3 and homogeneous MAF.
#Given 100 SNPs with gene size d = 10, 500 unrelated individuals are simulated.
#(Please refer to the Figure 3 of the reference)

library(glmnet)
library(MASS)

set.seed(1)# Set seed
#Parameter setting
ntotal = 500
p = 100
n.pred = 10 #Gene sizes
rho = 0.2 #Intra-gene correlation in block
k = 3 #Effect size
vari = 1 #Sigma2
```

TSGSIS 3

```
lambda = 0.5 #For lasso parameter
ntest = 150 #For evaluation
Method="Reg"#For quantitative trait
#Heterogeneous MAF: randomly set to 0.35, 0.2 or 0.1 with equal likelihood.
MAF = matrix(0,2,3)
MAF[,1] = c(0.1225,0.5775)
MAF[,2] = c(0.04,0.36)
MAF[,3] = c(0.01,0.19)
#Trait Y
modelY = "k*XA[,1] - k*(sqrt(rho))*XA[,5] + k*XA[,31]*XA[,5] + rnorm(ntotal,0,vari)"
PAS1 = function(z){ g = paste("A",z,sep = "")
return(g)
}#Define colname fun.
norm = function(a) (a-mean(a))/sd(a) #Define standardization fun.
#The codes of simulated data for quantitative trait are listed in the following. We use myrnorm
#function to simulate the genotype data. Y is continuous with normal distribution, all errors are
\#assumed to be normally distributed with a mean of zero and a variance of one (vari = 1).
out = array(0, dim=c(n.pred)) #For LOOCV
corrmat = diag(rep(1-rho, n.pred)) + matrix(rho, n.pred, n.pred) #Create covariance matrix with rho
corrmat[,5] = sqrt(rho)
corrmat[5,] = sqrt(rho)
corrmat[5,5] = 1
L = array(0, dim=c(n.pred, n.pred, (p/n.pred)))
L[,,1] = corrmat
for(i in 2:(p/n.pred)){
L[,,i] = diag(rep(1-rho, n.pred)) + matrix(rho, n.pred, n.pred)
temp = "bdiag(L[,,1]"
for (i in 2:(p/n.pred)){
temp = paste(temp,",","L[,,",i,"]", sep="")
temp = paste(temp,")", sep="")
corrmat2 = eval(parse(text=temp))
beta0 = matrix(0,p,1) #Simulate genotype
X = matrix(0,ntotal,p)
X = mvrnorm(ntotal, beta0, corrmat2 , tol=1e-8, empirical=FALSE)
XA = data.frame(X); colnames(XA) <- c(sapply(1:p,PAS1))</pre>
C1 = matrix(0,1,p)
C2 = matrix(0,1,p)
tempMAF = sample(3,1)
for (i in 1:p){
C2[1,i] = quantile(X[,i], MAF[1,tempMAF])
C1[1,i] = quantile(X[,i], MAF[2,tempMAF])
XA[X[,i] > C1[,i],i] = 1
XA[X[,i] \le C1[,i] & X[,i] >= C2[,i],i] = 0
XA[X[,i] < C2[,i],i] = -1
XA = apply(XA, 2, norm) #Standardization
Y = eval(parse(text=modelY)) #Simulate gaussian response
```

TSGSIS TSGSIS

temp = 1:p
Gene\_list = matrix(temp,nrow=n.pred) #Create Gene-based SNP set
#Run TSGSIS fun. with XA, Y, Gene\_list, ntest (for predicted model), lambda of lasso regression,
#Method types: "Reg" for quantitative trait; "LR" for disease trait.
Screen\_result = TSGSIS(XA, Y, Gene\_list, ntest, lambda, Method)

# **Index**

TSGSIS, 1