MR-LDP: a two-sample Mendelian randomization for GWAS summary statistics accounting linkage disequilibrium and horizontal pleiotropy

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Introduction

This vignette provides an introduction to the MR.LDP package. R package MR.LDP implements MR-LDP, a two-sample Mendelian randomization for GWAS summary statistics accounting linkage disequilibrium and horizontal pleiotropy. The package can be installed with the following commands:

```
library(devtools);
install_github("QingChengO218/MR.LDP");
Load the package using the following command:
library(MR.LDP);
```

Fit MR-LDP using simulated data

We first generate genotype data using function genRawGeno:

```
library("mvtnorm");
## Warning: package 'mvtnorm' was built under R version 3.5.2
library("PDSCE");
## Warning: package 'PDSCE' was built under R version 3.5.2
set.seed(2019);
genRawGeno <- function(maf, L, M, rho, n){</pre>
  SIGMA = matrix(nrow=M,ncol=M)
  for (i in 1:M){
   for (j in 1:M){
      SIGMA[i,j] = rho^(abs(i-j));
  }
 nsnp = L*M;
  X = NULL;
  for ( l in 1:L ){
    index = (M*(1-1)+1): (M*1);
   AAprob = maf[index]^2.;
   Aaprob = 2*maf[index]*(1-maf[index]);
   quanti = matrix(c(1-Aaprob-AAprob, 1- AAprob),M,2);
   Xt = rmvnorm(n, mean=rep(0,M), sigma=SIGMA, method="chol")
   Xt2 = matrix(0,n,M);
   for (j in 1:M){
      cutoff = qnorm(quanti[j,]);
      Xt2[Xt[,j] < cutoff[1],j] = 0;
```

Estimate the covariance matrix using function *pdsoft*:

```
R0 = cor(G3);
R = pdsoft(R0, lam)$theta;
diag(R) = rep(1, p);
mask = kronecker(diag(L), matrix(1, M, M));
R = R*mask;
```

Generate the exposure data(y) and outcome data(z) with prespecified indirect(h_y^2) and direct(h_z^2) heritability based on

$$\mathbf{y} = \mathbf{G}_1 \gamma + \mathbf{U}_x \eta_x + \mathbf{e}_1, \quad \mathbf{z} = \beta_0 \mathbf{x} + \mathbf{G}_2 \alpha + \mathbf{U}_y \eta_y + \mathbf{e}_2,$$

```
h2z <- 0.05; h2y <- 0.1; b0 <- 0.1; q <- 50;
u = matrix(rnorm( (n1+n2) * q),ncol=q);

sigma2g <- 0.005;
gamma.nz = rnorm(m)*sqrt(sigma2g);
indx = sample(1:p,m);
gamma = numeric(p);
gamma[indx] = gamma.nz;

Su = matrix(c(1,0.8,0.8,1),nrow=2)
bu = rmvnorm(q,mean=rep(0,2), sigma = Su,method="chol")
by = bu[,1]; bz = bu[,2];
uby = u%*%by; ubz = u%*%bz;
uby = uby/sqrt(as.numeric(var(uby)/0.6));
ubz = ubz/sqrt(as.numeric(var(ubz)/0.2));

G12g = G12%*%gamma;
if(b0!=0){</pre>
```

```
h2ga = (h2y *(1 + b0^2))/(b0^2 * (1 - h2y));
  gamma0 = gamma/sqrt(as.numeric(var(G12g)/h2ga));
  G12g = G12\%*\%gamma0;
yall = G12g + uby + rnorm(n1+n2)*as.numeric(sqrt(1-var(uby)));
# The direct effects on Z
h2yb = var(b0*yall);
h2al = (h2z + h2z*h2yb)/(1 - h2z)
sigma2a <- 0.005;
if(h2z==0){
  alpha0 = rep(0, m);
  G12a = G12\%*\%alpha0;
}else{
  alno = floor(p*Alrate);
  alpha.nz <- rnorm(alno)*sqrt(sigma2a);</pre>
  # sparse setting for pleiotropy
  indxAL = sample(1:p,alno);
  alpha = numeric(p);
  alpha[indxAL] = alpha.nz;
  G12a = G12\%*\%alpha;
  alpha0 = alpha/sqrt(as.numeric(var(G12a)/(h2al)));
  G12a = G12\%*\%alpha0;
resz = ubz + rnorm(n1+n2)*as.numeric(sqrt(1-var(ubz)));
zall = b0*yall + G12a + resz;
H2a.res <- var(G12a)/var(zall);</pre>
H2g.res <- var(b0*G12g)/var(zall);</pre>
y = yall[1:n1];
z = zall[(n1+1):(n1+n2)];
```

We then conduct single-variant analysis to obtain the summary statistics.

```
gammahall = numeric(p); Gammahall = numeric(p);
sg2all = numeric(p); sG2all = numeric(p);
pval = numeric(p);
for (i in 1:p){
    fm = lm(y-1+G1[,i]);
    gammahall[i] = summary(fm)$coefficients[2,1];
    sg2all[i] = summary(fm)$coefficients[2,2]^2;
    pval[i] = summary(fm)$coefficients[2,4];

    fm = lm(z-1+G2[,i]);
    Gammahall[i] = summary(fm)$coefficients[2,1];
    sG2all[i] = summary(fm)$coefficients[2,2]^2;
}

index = 1:p
sig.indx = index
```

```
sg2 = sg2all[sig.indx];
sG2 = sG2all[sig.indx];
gammah = gammahall[sig.indx];
Gammah = Gammahall[sig.indx];
```

Initilize the parameters for MR-LDP algorithm.

```
epsStopLogLik <- 1e-7; maxIter <- 10000;
beta0 <- 0;
gamma <- rep(0, p);
alpha <- rep(0, p);
sgga2 <- 0.01;
sga12 <- 0.01;
model <- 2;</pre>
```

Fit MR-LDP w/ and w/o constraint that $\beta = 0$ as: