fRLR package: Fit Repeated Linear Regressions

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Contents

1	Introduction	2
2	An Example	2
3	Ideas	2
4	Method	2
5	Test	3
6	Computation Performance	6

1 Introduction

This R package aims to fit Repeated Linear Regressions in which there are some same terms.

2 An Example

Let's start with the simplest situation, we want to fit a set of regressions which only differ in one variable. Specifically, denote the response variable as y, and these regressions are as follows.

$$y \sim x_1 + cov_1 + cov_2 + \dots + cov_m$$

$$y \sim x_2 + cov_1 + cov_2 + \dots + cov_m$$

$$\cdot \sim \cdots$$

$$y \sim x_n + cov_1 + cov_2 + \dots + cov_m$$

where $cov_i, i = 1, ..., m$ are the same variables among these regressions.

3 Ideas

Intuitively, we can finish this task by using a simple loop.

However, it is not efficient in that situation. As we all know, in the linear regression, the main goal is to estimate the parameter β . And we have

$$\hat{\beta} = (X'X)^{-1}X'Y$$

where X is the design matrix and Y is the observation of response variable.

It is obvious that there are some same elements in the design matrix, and the larger m is, the more elements are the same. So I want to reduce the cost of computation by separating the same part in the design matrix.

4 Method

For the above example, the design matrix can be denoted as X = (x, cov). If we consider intercept, it also can be seen as the same variable among these regression, so it can be included in cov naturally. Then we have

$$(X'X)^{-1} = \begin{bmatrix} x'x & x'cov \\ cov'x & cov'cov \end{bmatrix} = \begin{bmatrix} a & v' \\ v & B \end{bmatrix}$$

Woodbury formula tells us

$$(A + UCV)^{-1} = A^{-1} - A^{-1}U(C^{-1} + VA^{-1}U)^{-1}VA^{-1}$$

Let

$$A = \left[\begin{array}{cc} a & O \\ O & B \end{array} \right], \ U = \left[\begin{array}{cc} 1 & 0 \\ O & v \end{array} \right], \ V = \left[\begin{array}{cc} 0 & v' \\ 1 & O \end{array} \right]$$

and $C = I_{2\times 2}$. Then we can apply woodbury formula,

$$(X'X)^{-1} = (A + UCV)^{-1} = A^{-1} - A^{-1}U(C^{-1} + VA^{-1}U)^{-1}VA^{-1}$$

where

$$A^{-1} = \left[\begin{array}{cc} a^{-1} & O \\ O & B^{-1} \end{array} \right]$$

We can do further calculations to simplify and obtain the following result

$$(X'X)^{-1} = \begin{bmatrix} 1/a + \frac{a}{a - v'B^{-1}v}v'B^{-1}v & -\frac{v'B^{-1}}{a - v'B^{-1}v} \\ -\frac{B^{-1}v}{a - v'B^{-1}v} & B^{-1} + \frac{-B^{-1}vv'B^{-1}}{a - v'B^{-1}v} \end{bmatrix}$$

Notice that matrix B is the same for all regression, the identical terms for each regression are just a and v, which are very easy to calculate. So theoretically, we can reduce the cost of computation significantly.

5 Test

Now test two simulation examples by using the functions in this package.

```
> ## use fRLR package
```

> library(fRLR)

```
[1] "fRLR" "stats" "graphics" "grDevices" "utils" "datasets"
```

[7] "methods" "base"

> set.seed(123)

NULL

> X = matrix(rnorm(50), 10, 5)

```
[,1] [,2] [,3] [,4] [,5]
```

- [1,] -0.56047565 1.2240818 -1.0678237 0.42646422 -0.69470698
- [2,] -0.23017749 0.3598138 -0.2179749 -0.29507148 -0.20791728
- [3,] 1.55870831 0.4007715 -1.0260044 0.89512566 -1.26539635
- [4,] 0.07050839 0.1106827 -0.7288912 0.87813349 2.16895597
- [5,] 0.12928774 -0.5558411 -0.6250393 0.82158108 1.20796200
- [6,] 1.71506499 1.7869131 -1.6866933 0.68864025 -1.12310858
- [7,] 0.46091621 0.4978505 0.8377870 0.55391765 -0.40288484
- [8,] -1.26506123 -1.9666172 0.1533731 -0.06191171 -0.46665535
- [9,] -0.68685285 0.7013559 -1.1381369 -0.30596266 0.77996512
- [10,] -0.44566197 -0.4727914 1.2538149 -0.38047100 -0.08336907

> Y = rnorm(10)

- [1] 0.25331851 -0.02854676 -0.04287046 1.36860228 -0.22577099 1.51647060
- [7] -1.54875280 0.58461375 0.12385424 0.21594157
- > COV = matrix(rnorm(40), 10, 4)

$$[,1]$$
 $[,2]$ $[,3]$ $[,4]$

- [1,] 0.37963948 -0.4910312 0.005764186 0.9935039
- [2,] -0.50232345 -2.3091689 0.385280401 0.5483970
- [3,] -0.33320738 1.0057385 -0.370660032 0.2387317
- [4,] -1.01857538 -0.7092008 0.644376549 -0.6279061

```
[5,] -1.07179123 -0.6880086 -0.220486562 1.3606524
 [6,] 0.30352864 1.0255714 0.331781964 -0.6002596
 [7,] 0.44820978 -0.2847730 1.096839013 2.1873330
 [8,] 0.05300423 -1.2207177 0.435181491 1.5326106
 [9,] 0.92226747 0.1813035 -0.325931586 -0.2357004
[10,] 2.05008469 -0.1388914 1.148807618 -1.0264209
> frlr1(X, Y, COV)
  r r.p.value
1 2 0.2212869
2 4 0.6729983
3 0 0.4380128
4 3 0.9495018
5 1 0.7791076
> ## use simple loop
> res = matrix(nrow = 0, ncol = 2)
     [,1] [,2]
> for (i in 1:ncol(X))
  mat = cbind(X[,i], COV)
    df = as.data.frame(mat)
    model = lm(Y^{\sim}., data = df)
    tmp = c(i, summary(model)$coefficients[2, 4])
    res = rbind(res, tmp)
+ }
NULL
> res
    [,1]
              [,2]
tmp
       1 0.4380128
       2 0.7791076
tmp
tmp
       3 0.2212869
       4 0.9495018
tmp
tmp
       5 0.6729983
   As we can see in the above output, these p-values for the identical variable in each regression
are equal between two methods.
   Similarly, we can test another example
```

```
> library(fRLR)
[1] "fRLR"
                 "stats"
                             "graphics" "grDevices" "utils"
                                                                   "datasets"
[7] "methods"
                 "base"
> set.seed(123)
NULL
```

> X = matrix(rnorm(50), 10, 5)[,1][,2][,3] [,4][1,] -0.56047565 1.2240818 -1.0678237 0.42646422 -0.69470698 [2,] -0.23017749 0.3598138 -0.2179749 -0.29507148 -0.20791728 [3,] 1.55870831 0.4007715 -1.0260044 0.89512566 -1.26539635 [4,] 0.07050839 0.1106827 -0.7288912 0.87813349 2.16895597 [5,] 0.12928774 -0.5558411 -0.6250393 0.82158108 1.20796200 [6,] 1.71506499 1.7869131 -1.6866933 0.68864025 -1.12310858 [7,] 0.46091621 0.4978505 0.8377870 0.55391765 -0.40288484 [8,] -1.26506123 -1.9666172 0.1533731 -0.06191171 -0.46665535 [9,] -0.68685285 0.7013559 -1.1381369 -0.30596266 0.77996512 [10,] -0.44566197 -0.4727914 1.2538149 -0.38047100 -0.08336907 > Y = rnorm(10)[1] 0.25331851 -0.02854676 -0.04287046 1.36860228 -0.22577099 1.51647060 [7] -1.54875280 0.58461375 0.12385424 0.21594157 > COV = matrix(rnorm(40), 10, 4) [,1][,2] [,3] [,4][1,] 0.37963948 -0.4910312 0.005764186 0.9935039 [2,] -0.50232345 -2.3091689 0.385280401 0.5483970 [3,] -0.33320738 1.0057385 -0.370660032 0.2387317 [4,] -1.01857538 -0.7092008 0.644376549 -0.6279061 [5,] -1.07179123 -0.6880086 -0.220486562 1.3606524 [6,] 0.30352864 1.0255714 0.331781964 -0.6002596 [7,] 0.44820978 -0.2847730 1.096839013 2.1873330 [8,] 0.05300423 -1.2207177 0.435181491 1.5326106 [9,] 0.92226747 0.1813035 -0.325931586 -0.2357004 [10,] 2.05008469 -0.1388914 1.148807618 -1.0264209 > idx1 = c(1, 2, 3, 4, 1, 1, 1, 2, 2, 3)[1] 1 2 3 4 1 1 1 2 2 3 > idx2 = c(2, 3, 4, 5, 3, 4, 5, 4, 5, 5)[1] 2 3 4 5 3 4 5 4 5 5 > frlr2(X, idx1, idx2, Y, COV) r1 r2 r1.p.value r2.p.value 1 2 0.53021406 0.895719578 2 3 0.01812006 0.009833047 2 3 1 4 0.51074586 0.966484642 1 5 0.12479380 0.152802911 4 5 2 4 0.79302893 0.902402294

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2 5 0.73153760 0.663392258 3 5 0.32367303 0.877154122 4 5 0.91749181 0.712075464

1 3 0.33761507 0.210331456 10 3 4 0.29895922 0.963995969

Again, we obtain the same results by different methods.

6 Computation Performance

The main aim of this new method is to reduce the computation cost. Now let's compare its speed with the simple-loop method.

We can obtain the following time cost for $99 \times 100/2 = 4950$ linear regressions.

```
> library(fRLR)
> set.seed(123)
> n = 100
> X = matrix(rnorm(10*n), 10, n)
> Y = rnorm(10)
> COV = matrix(rnorm(40), 10, 4)
> #idx1 = c(1, 2, 3, 4, 1, 1, 1, 2, 2, 3)
> #idx2 = c(2, 3, 4, 5, 3, 4, 5, 4, 5, 5)
> id = combn(n, 2)
> idx1 = id[1, ]
> idx2 = id[2, ]
> system.time(frlr2(X, idx1, idx2, Y, COV))
   user system elapsed
                0.013
  0.056
        0.000
> simpleLoop <- function()</pre>
    res = matrix(nrow=0, ncol=4)
    for (i in 1:length(idx1))
      mat = cbind(X[, idx1[i]], X[,idx2[i]], COV)
      df = as.data.frame(mat)
      model = lm(Y^{-}., data = df)
      tmp = c(idx1[i], idx2[i], summary(model)$coefficients[2,4], summary(model)$coefficients[3
      res = rbind(res, tmp)
    }
+ }
> system.time(simpleLoop())
```

user system elapsed 5.420 0.000 5.421