

# Sparse covariance estimation

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*2019-10-03*

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## 1 Motivation

After decorrelation with the information of the historical data, the correlation between the covariate is reduced. However, there are still some correlation coefficients are large. That may suggest that after using the historical data, the decorrelated data still is not uncorrelated. But the correlation structure becomes a sparse and symmetric. Therefore, we could apply another decorrelation to further reudce the non-zero correlation, so that we may have a better performance on the following variance estimation procedure.

## 2 Simulation

### 2.1 Simulation procedure

#### 2.1.1 Standardization will not change total variance

1. Standardize the X  $\tilde{Z}_m = (X - \mu)A_1$
2. Generate the interaction based on the  $\tilde{Z}_{int} = \tilde{Z}_m * \tilde{Z}_m$  without the square terms and set  $\tilde{Z}_t = (\tilde{Z}_m, \tilde{Z}_{int})$
3. Generate the Y based on the  $\tilde{Z}_t$
4. Estimate the  $Var(\tilde{Z}_t\beta_t)$  by  $Z = \tilde{Z}_tA_2$ , where  $A_2$  is for decorrelation

Note that the  $Var(\tilde{Z}_t\beta_t) = Var(Z\gamma)$ ,  $A_2 = \hat{\Sigma}_h^{-1/2}$  or  $A_2 = \hat{\Sigma}_h^{-1/2}\hat{\Sigma}_s^{-1/2}$

### 2.2 Decorrelation steps

### 2.3 two steps decorrelation

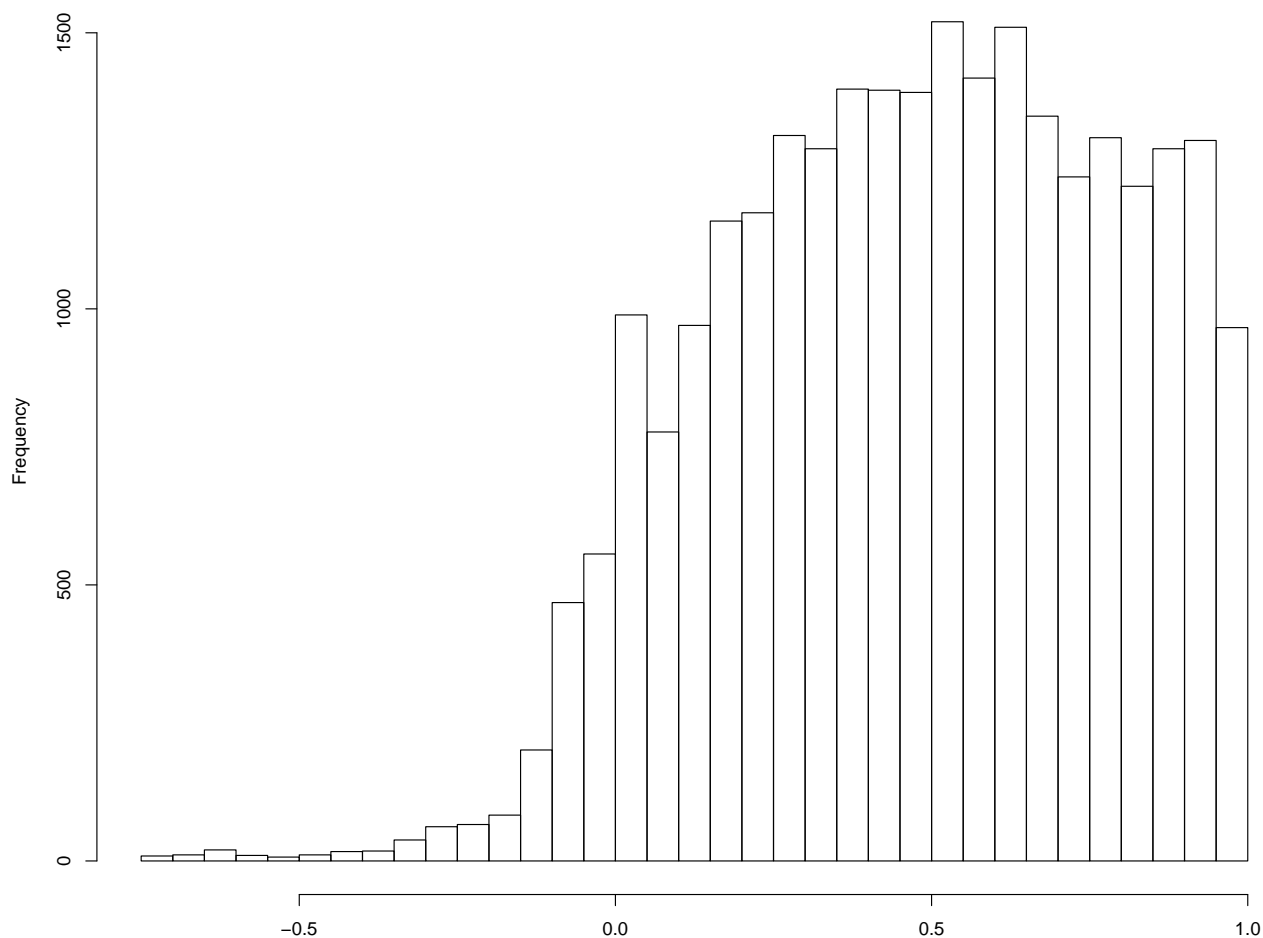
1. Decorrelation by covariance matrix estimated by historical data

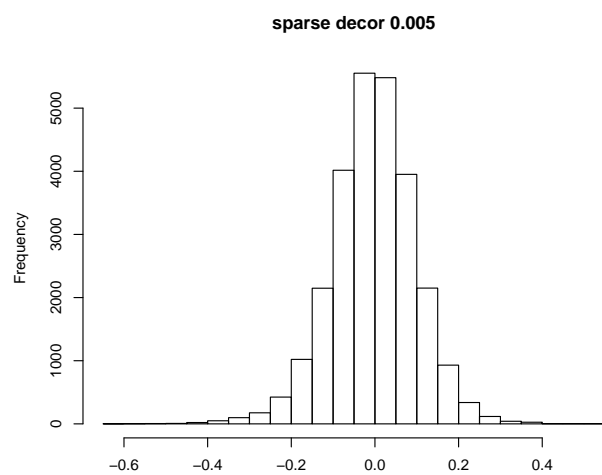
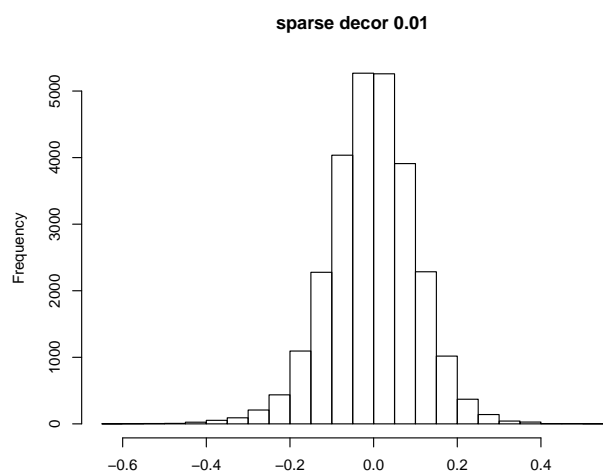
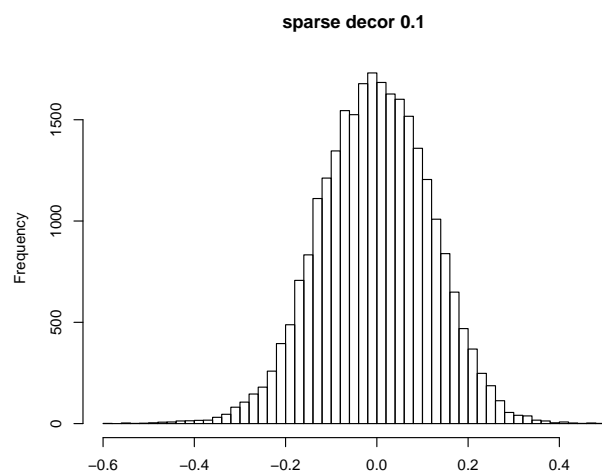
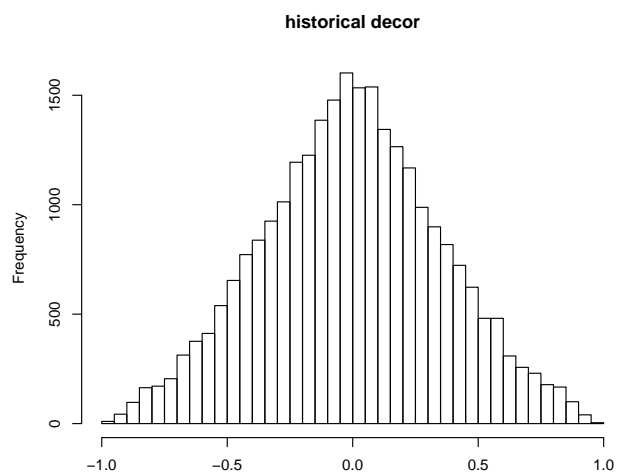
2. If after the step 1, the correlation is still large, then we may need a second decorrelation by sparse precision method

## 2.4 Dpglasso: The Graphical Lasso: New Insights and Alternatives

1. An Alternatives for Glasso
2. Glasso works on  $W$  the covariance matrix, but its alg cannot make sure the precision matrix  $\Theta$  is positive definite.
3. Dpglasso can provide both  $W$  and  $\Theta$  be positive definite

**Histogram of correlations of PCBs with sample size 150**





## 2.5 PCB

### 2.5.1 None

```

var_main_effect var_inter_effect cov_main_inter_effect var_total_effect
1:              8                2                0.62                11
  structure decor x_dist
1:          un FALSE   1999

      n MSE est_var est_mean NA_total      method
1: 100 206    112     21      3 EigenPrism
2: 100 153    108     18      0      GCTA
3: 150 304    112     25      0 EigenPrism
4: 150 278    149     23      0      GCTA
5: 231 276     83     25      0 EigenPrism
6: 231 217     86     23      0      GCTA
7: 500 NaN     NA     NaN    100 EigenPrism
8: 500 472    166     29      0      GCTA
9: 1000 NaN     NA     NaN    100 EigenPrism
10: 1000 495    113     31      0      GCTA

```

### 2.5.2 Hist

```

var_main_effect var_inter_effect cov_main_inter_effect var_total_effect
1:              8                2                0.62                11
  structure decor x_dist
1:          un  TRUE   1999

      n MSE est_var est_mean NA_total      method
1: 100  31     32     11      3 EigenPrism
2: 100  22     22     11      0      GCTA
3: 150  26     26     11      0 EigenPrism
4: 150  21     21     11      0      GCTA
5: 231  19     20     11      0 EigenPrism
6: 231  14     14     11      0      GCTA
7: 500 NaN     NA     NaN    100 EigenPrism
8: 500  31     31     12      0      GCTA
9: 1000 NaN     NA     NaN    100 EigenPrism
10: 1000  44     39     13      1      GCTA

```

### 2.5.3 Hist + sparse

```

var_main_effect var_inter_effect cov_main_inter_effect var_total_effect
1:              8                2                0.62                11
  structure decor x_dist
1:          un  TRUE   1999

      n MSE est_var est_mean NA_total      method
1: 100 14.6  14.68    11.4      0 EigenPrism
2: 100 14.0  14.11    11.2      0      GCTA
3: 150  8.6   7.91    10.4      0 EigenPrism
4: 150  6.9   6.78    10.8      0      GCTA
5: 231 11.6   7.42     9.2      0 EigenPrism
6: 231  5.2   4.37    10.3      0      GCTA

```

7:	500	NaN	NA	NaN	100	EigenPrism
8:	500	3.1	1.53	10.0	0	GCTA
9:	1000	NaN	NA	NaN	100	EigenPrism
10:	1000	2.4	0.99	10.1	1	GCTA

## 2.6 Chi

### 2.6.1 None

	var_main_effect	var_inter_effect	cov_main_inter_effect	var_total_effect	
1:	8		2	1.8	14
	structure	decor	x_dist		
1:	un	FALSE	chi		

	n	MSE	est_var	est_mean	NA_total	method
1:	100	108	67	20	3	EigenPrism
2:	100	77	68	17	0	GCTA
3:	200	213	90	25	7	EigenPrism
4:	200	189	109	23	0	GCTA
5:	500	NaN	NA	NaN	100	EigenPrism
6:	500	131	31	24	0	GCTA
7:	1000	NaN	NA	NaN	100	EigenPrism
8:	1000	134	20	24	0	GCTA

### 2.6.2 hist

	var_main_effect	var_inter_effect	cov_main_inter_effect	var_total_effect	
1:	8		2	1.8	14
	structure	decor	x_dist		
1:	un	TRUE	chi		

	n	MSE	est_var	est_mean	NA_total	method
1:	100	23.4	21.5	12	0	EigenPrism
2:	100	18.5	16.5	12	0	GCTA
3:	200	15.5	12.9	12	0	EigenPrism
4:	200	9.3	8.2	13	0	GCTA
5:	500	NaN	NA	NaN	100	EigenPrism
6:	500	4.1	2.8	13	0	GCTA
7:	1000	NaN	NA	NaN	100	EigenPrism
8:	1000	3.0	1.3	12	1	GCTA

### 2.6.3 hist + sparse

	var_main_effect	var_inter_effect	cov_main_inter_effect	var_total_effect	
1:	8		2	1.8	14
	structure	decor	x_dist		
1:	un	TRUE	chi		

	n	MSE	est_var	est_mean	NA_total	method
1:	100	27.7	27.6	14	0	EigenPrism
2:	100	26.9	27.1	14	0	GCTA
3:	200	12.4	10.7	12	0	EigenPrism
4:	200	8.9	8.8	13	0	GCTA

5:	500	NaN	NA	NaN	100	EigenPrism
6:	500	4.5	2.5	12	0	GCTA
7:	1000	NaN	NA	NaN	100	EigenPrism
8:	1000	4.1	1.8	12	0	GCTA

### 3 Mimic the histrocial covariance situation

Based on the previous simulation, we found that if the historical data is from extact the same distribution, then the sparse decorrelation may not be neccessary. That is after doing the second step of decorrelation the variance estimation does not get much improvement. So to mimic the situation situation we change the simulation so that there is historical covariance is not perfect.

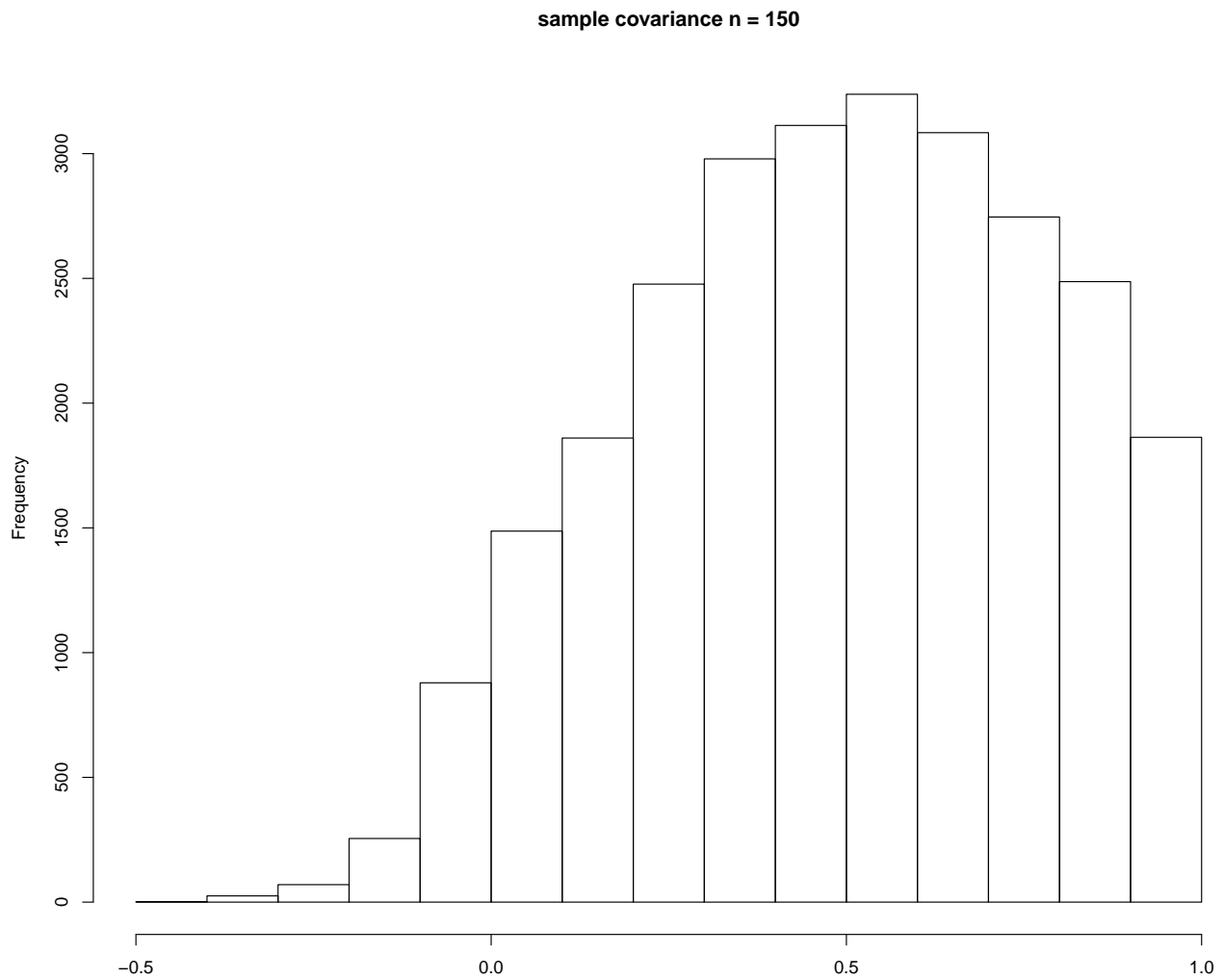
#### 3.1 Simulation setup

- $p = 21$
- $X \sim \chi_1^2$
- $Cor(X)$  is the sample covariance of subset of standardized PCB data with  $n = 150$

- $X_h = XB$ , where  $B = \begin{bmatrix} 1 & 1 & 1 & 1 & 1 \dots \\ 0 & 1 & 1 & 1 & 1 \dots \\ 0 & & 1 & 1 & 1 \dots \\ 0 & & & 1 & 1 \dots \\ 0 & & & & 1 \dots \end{bmatrix}$ . So that the  $X_h$  is a column transfromation of  $X$ , therefore the its covariance is different from the true value.

## 3.2 Decorrelation result

### 3.2.1 $X_h = X$



Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
-0.42	0.29	0.50	0.49	0.72	1.00

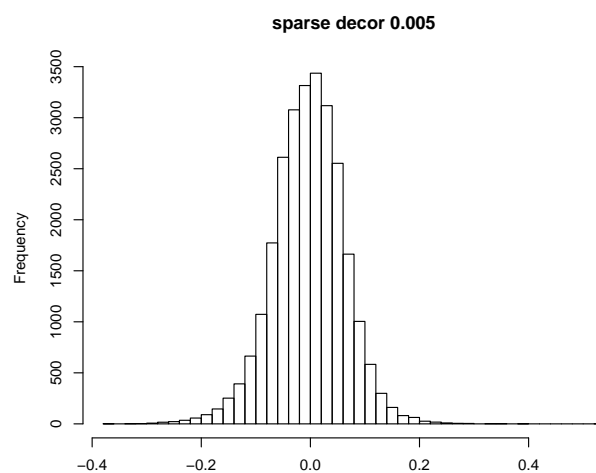
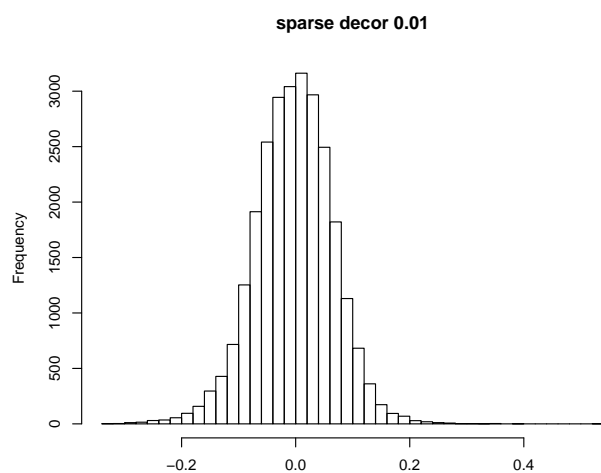
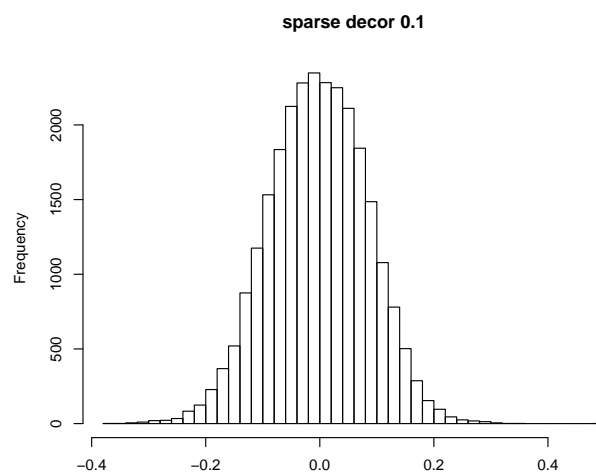
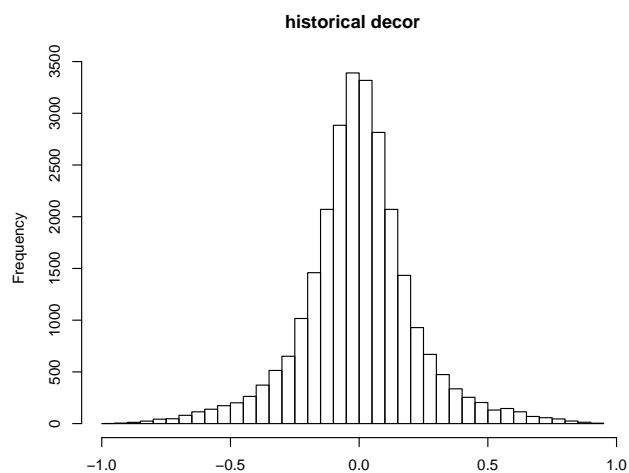
Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
-0.96	-0.11	0.00	0.00	0.11	0.94

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
-0.37	-0.06	0.00	0.00	0.06	0.48

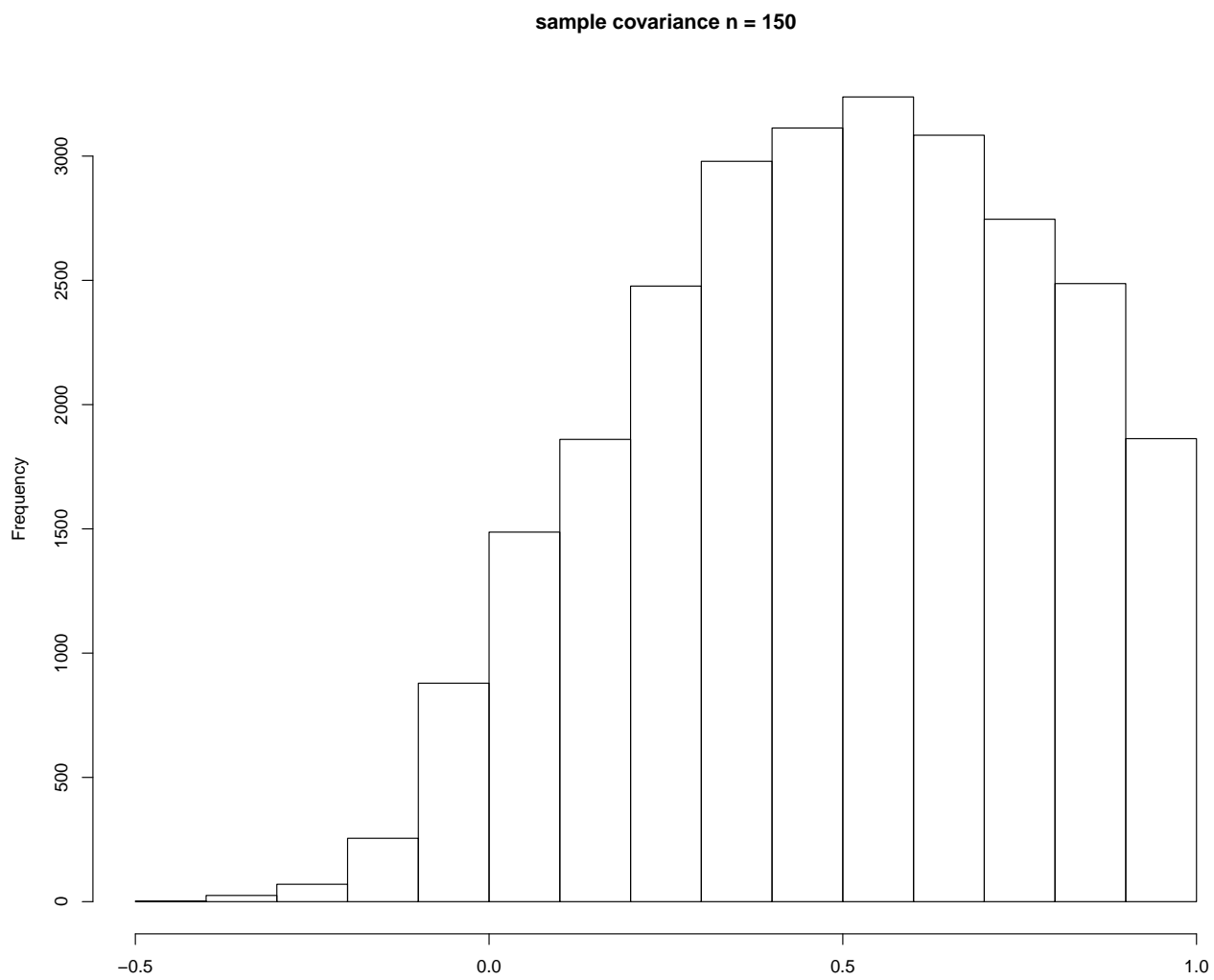
Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
-0.33	-0.05	0.00	0.00	0.04	0.54



Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
-0.37	-0.04	0.00	0.00	0.04	0.53



### 3.2.2 $X_h = XB, t = 8$



Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
-0.42	0.29	0.50	0.49	0.72	1.00

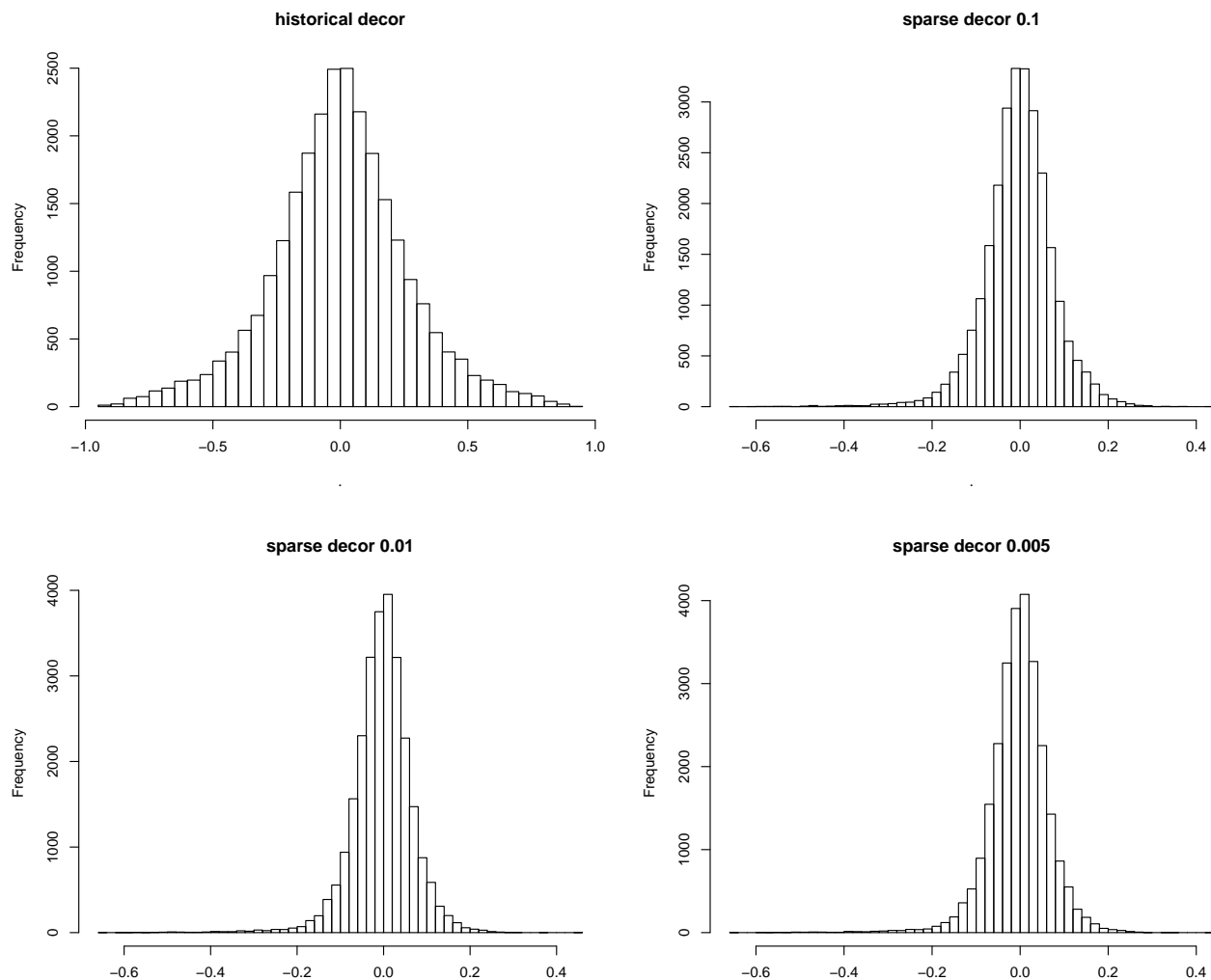
Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
-0.93	-0.15	0.00	0.00	0.15	0.91

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
-0.65	-0.04	0.00	0.00	0.04	0.42

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
-0.64	-0.04	0.00	0.00	0.04	0.44



Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
-0.64	-0.04	0.00	0.00	0.03	0.44

### 3.3 Simulation result on the variance estimation process

#### 3.3.1 None

	var_main_effect	var_inter_effect	cov_main_inter_effect	var_total_effect	
1:	8	2	1.8	14	

	structure	decor	x_dist	
1:	un	FALSE	chi	

	n	MSE	est_var	est_mean	NA_total	method
1:	100	108	67	20	3	EigenPrism
2:	100	77	68	17	0	GCTA
3:	200	213	90	25	7	EigenPrism
4:	200	189	109	23	0	GCTA
5:	500	NaN	NA	NaN	100	EigenPrism
6:	500	131	31	24	0	GCTA
7:	1000	NaN	NA	NaN	100	EigenPrism

8: 1000 134 20 24 0 GCTA

### 3.3.2 Hist

```

var_main_effect var_inter_effect cov_main_inter_effect var_total_effect
1:              8                2                1.8                14
structure decor x_dist
1:          un TRUE      chi

      n MSE est_var est_mean NA_total      method
1: 100 32  27.3    11      0 EigenPrism
2: 100 25  18.1    11      0      GCTA
3: 200 29  22.8    11      0 EigenPrism
4: 200 19  13.4    11      0      GCTA
5: 500 NaN   NA    NaN    100 EigenPrism
6: 500 14   3.5    10      0      GCTA
7: 1000 NaN   NA    NaN    100 EigenPrism
8: 1000 15   2.9    10      0      GCTA

```

### 3.3.3 Hist + Sparse(0.1)

```

var_main_effect var_inter_effect cov_main_inter_effect var_total_effect
1:              8                2                1.8                14
structure decor x_dist
1:          un TRUE      chi

      n MSE est_var est_mean NA_total      method
1: 100 19.8  20.0    14      0 EigenPrism
2: 100 22.0  22.0    13      0      GCTA
3: 200 13.6   8.5    11      0 EigenPrism
4: 200 7.7   6.9    13      0      GCTA
5: 500 NaN   NA    NaN    100 EigenPrism
6: 500 6.0   1.5    12      0      GCTA
7: 1000 NaN   NA    NaN    100 EigenPrism
8: 1000 10.1  0.9    11      1      GCTA

```

### 3.3.4 Hist + Sparse(0.01)

```

var_main_effect var_inter_effect cov_main_inter_effect var_total_effect
1:              8                2                1.8                14
structure decor x_dist
1:          un TRUE      chi

      n MSE est_var est_mean NA_total      method
1: 100 39.5  39.37    14      0 EigenPrism
2: 100 22.5  22.69    13      0      GCTA
3: 200 13.7   8.43    11      0 EigenPrism
4: 200 7.5   6.19    13      0      GCTA
5: 500 NaN   NA    NaN    100 EigenPrism
6: 500 7.5   1.43    11      0      GCTA
7: 1000 NaN   NA    NaN    100 EigenPrism
8: 1000 10.6  0.93    11      1      GCTA

```

### 3.3.5 Hist + Sparse(0.001)

```

var_main_effect var_inter_effect cov_main_inter_effect var_total_effect
1:              8                2                1.8                14
structure decor x_dist
1:          un  TRUE    chi

      n  MSE est_var est_mean NA_total    method
1: 100 74.2  67.14     16      0 EigenPrism
2: 100 32.0  32.36     14      0      GCTA
3: 200 12.5   8.37     12      0 EigenPrism
4: 200  7.4   6.25     13      0      GCTA
5: 500  NaN    NA     NaN    100 EigenPrism
6: 500  7.7   1.43     11      0      GCTA
7: 1000 NaN    NA     NaN    100 EigenPrism
8: 1000 10.4   0.96     11      0      GCTA

```

### 3.3.6 Perfect Hist

```

var_main_effect var_inter_effect cov_main_inter_effect var_total_effect
1:              8                2                1.8                14
structure decor x_dist
1:          un  TRUE    chi

      n  MSE est_var est_mean NA_total    method
1: 100 23.4  21.5     12      0 EigenPrism
2: 100 18.5  16.5     12      0      GCTA
3: 200 15.5  12.9     12      0 EigenPrism
4: 200  9.3   8.2     13      0      GCTA
5: 500  NaN    NA     NaN    100 EigenPrism
6: 500  4.1   2.8     13      0      GCTA
7: 1000 NaN    NA     NaN    100 EigenPrism
8: 1000 3.0   1.3     12      1      GCTA

```

### 3.3.7 Perfect Hist + Sparse(0.1)

```

var_main_effect var_inter_effect cov_main_inter_effect var_total_effect
1:              8                2                1.8                14
structure decor x_dist
1:          un  TRUE    chi

      n  MSE est_var est_mean NA_total    method
1: 100 27.7  27.6     14      0 EigenPrism
2: 100 26.9  27.1     14      0      GCTA
3: 200 12.4  10.7     12      0 EigenPrism
4: 200  8.9   8.8     13      0      GCTA
5: 500  NaN    NA     NaN    100 EigenPrism
6: 500  4.5   2.5     12      0      GCTA
7: 1000 NaN    NA     NaN    100 EigenPrism
8: 1000 4.1   1.8     12      0      GCTA

```

### 3.3.8 Perfect Hist + Sparse(0.01)

```

var_main_effect var_inter_effect cov_main_inter_effect var_total_effect
1:              8                2                1.8                14
structure decor x_dist
1:          un  TRUE    chi

      n  MSE est_var est_mean NA_total    method
1: 100 59.9   54.4     11      3 EigenPrism
2: 100 60.5   59.7     13      0      GCTA
3: 200 13.6   13.0     15      0 EigenPrism
4: 200 12.4   12.4     14      0      GCTA
5: 500  NaN    NA     NaN    100 EigenPrism
6: 500  3.6    3.1     13      0      GCTA
7: 1000 NaN    NA     NaN    100 EigenPrism
8: 1000 2.9    2.1     13      0      GCTA

```

### 3.3.9 Perfect Hist + Sparse(0.001)

```

var_main_effect var_inter_effect cov_main_inter_effect var_total_effect
1:              8                2                1.8                14
structure decor x_dist
1:          un  TRUE    chi

      n  MSE est_var est_mean NA_total    method
1: 100 148.2  146.6     15      0 EigenPrism
2: 100  76.4   76.7     13      0      GCTA
3: 200  32.2   27.3     16      3 EigenPrism
4: 200  12.5   12.4     14      0      GCTA
5: 500   NaN    NA     NaN    100 EigenPrism
6: 500   3.8    3.1     13      0      GCTA
7: 1000  NaN    NA     NaN    100 EigenPrism
8: 1000   2.7    2.4     13      0      GCTA

```