Low level of covariance simulation

Xuelong Wang 2019-08-23

Contents

1	Motivation	1
2	setup	1
	2.1 Sample covariance matrix	1
	2.2 Simulation setup	8
3	Result	8
	3.1 1999	8
	3.2 2005	8

1 Motivation

Based on the investigation of the covariance matrix patter of the PCBs from 1999 - 2004, we found some patterns that appears among the covariance matrix of PCBs from different years. Besides, we also use the historical data to estimate the covariance matrix, then use the sample covariance matrix to decorrelate the PCBs for each year. For most years, the decorrelation procedure can reduce the correlation, e.g 1999-2001, but there are some years which the correlations still are high after decorrelation, e.g 2005-2006.

Since we are trying to borrow information of historical dataset, the decorrelated data will probably not be perfert uncorrelated. In other words, we will end up with data with low correlations among their coveriates. So the goal of this report is to see if the GCTA and EigenPrism method could work well under the low correlation setup.

2 setup

2.1 Sample covariance matrix

I use two different sample covariane matrices: 1999-2001 and 2007 -2008.

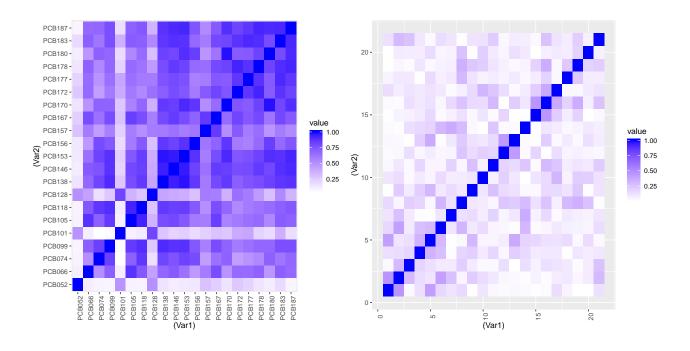


Figure 1: 1999-2000

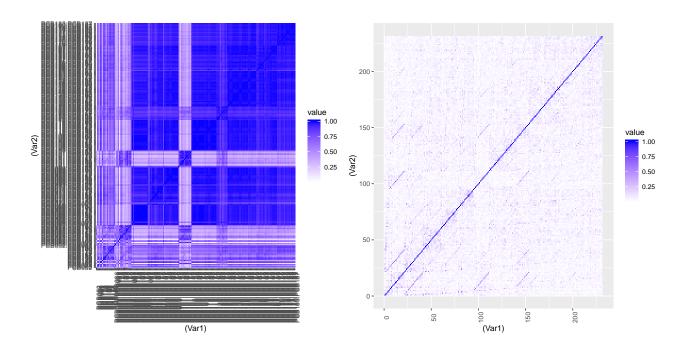
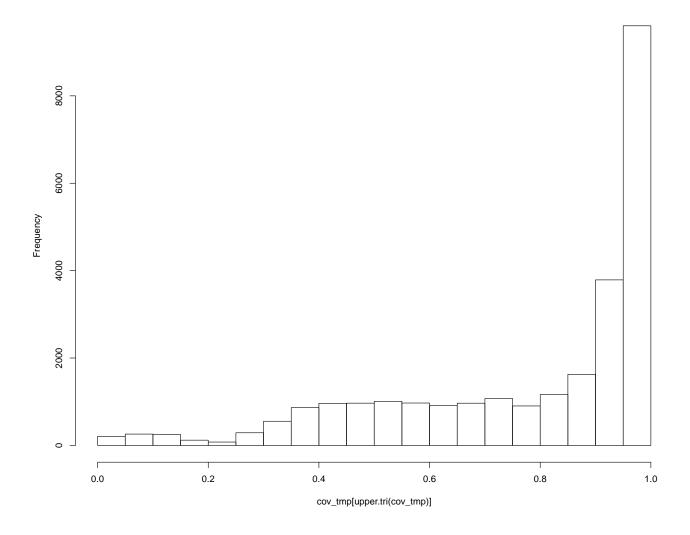
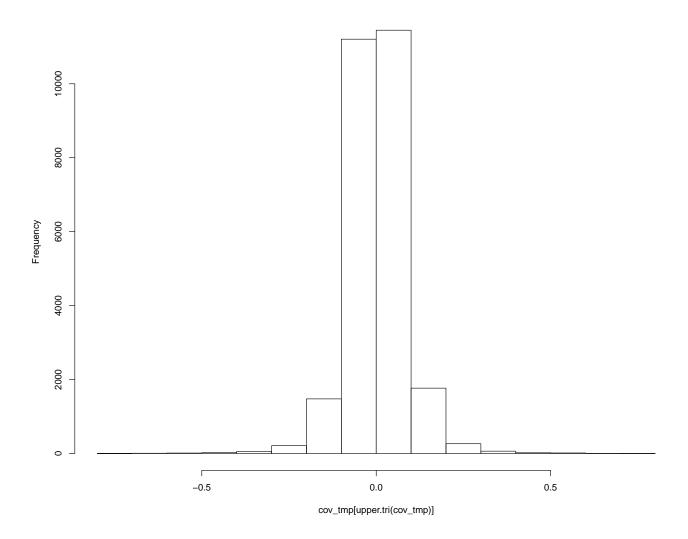


Figure 2: Combined main and interaction 1999-2000

correlation of main and inter



decorrelated correlation of main and inter



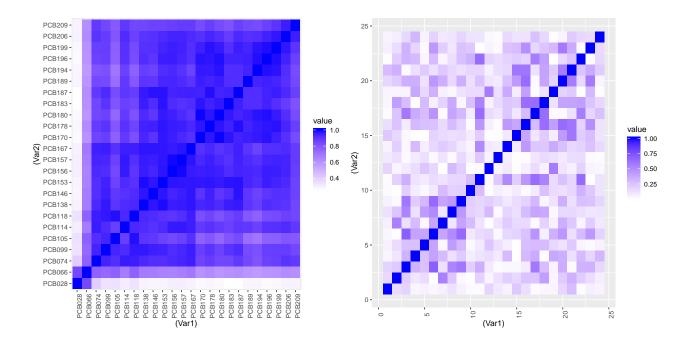


Figure 3: 2005-2006

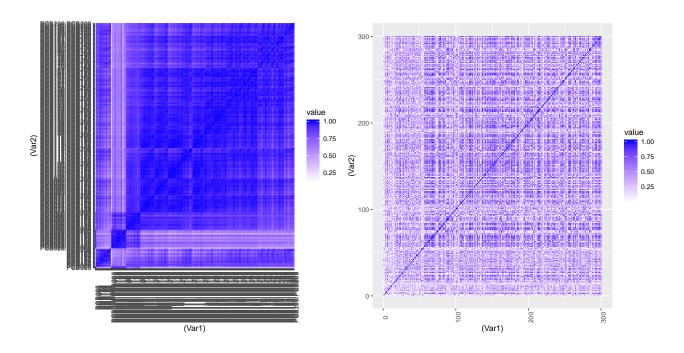
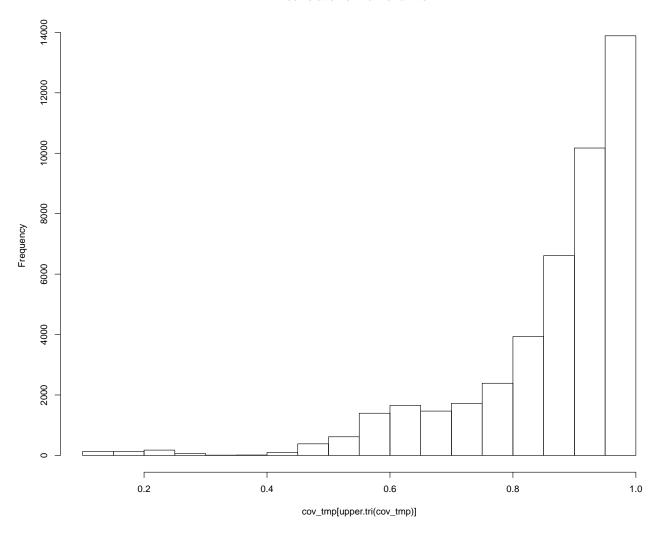
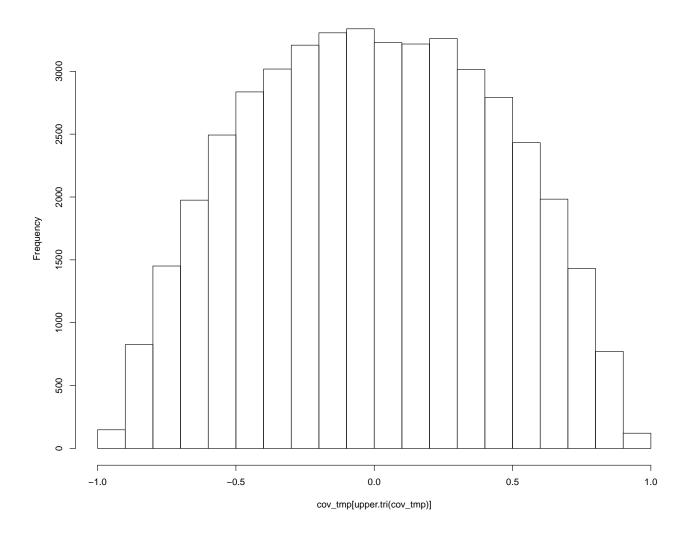


Figure 4: Combined main and interaction 2005-2006

correlation of main and inter



decorrelated correlation of main and inter



2.2 Simulation setup

- 1. p = 231 for 1999 or 300 for 2005
- 2. $n \in \{100, 150, p\}$
- 3. the simulated covariates will follow Normal or Chi with $\mathrm{df}=1$
- 4. Variance estimation method will be GCTA and EigenPrism method
- 5. Iteration time is 100

3 Result

3.1 1999

	n	MSE	est_var	est_mean	method	target	<pre>var_main_effect</pre>	decor
1:	100	19.6	18.9	10.9	${\tt EigenPrism}$	main	10	FALSE
2:	150	8.7	8.7	10.2	${\tt EigenPrism}$	main	10	FALSE
3:	231	5.5	5.5	10.1	${\tt EigenPrism}$	main	10	FALSE
4:	100	21.3	21.4	10.3	GCTA	main	10	FALSE
5:	150	9.3	9.4	10.1	GCTA	main	10	FALSE
6:	231	5.0	5.1	10.0	GCTA	main	10	FALSE
7:	100	20.6	20.6	10.4	${\tt EigenPrism}$	main	10	FALSE
8:	150	10.4	10.4	9.7	${\tt EigenPrism}$	main	10	FALSE
9:	231	5.3	5.2	10.4	${\tt EigenPrism}$	main	10	FALSE
10:	100	20.7	21.0	10.0	GCTA	main	10	FALSE
11:	150	10.9	10.6	9.4	GCTA	main	10	FALSE
12:	231	4.8	4.7	10.4	GCTA	main	10	FALSE
	x_d:	ist						
1:	(chi						
2:	(chi						
3:	(chi						
4:	(chi						
5:	(chi						
6:	(chi						
7:	norr	nal						
8:	norr	nal						
9:	norr	nal						
10:	norr	nal						

3.2 2005

11: normal
12: normal

	n	MSE	${\tt est_var}$	${\tt est_mean}$	method	target	${\tt var_main_effect}$	decor
1:	100	16.4	15.8	10.9	EigenPrism	main	10	FALSE
2:	150	13.3	11.6	11.3	EigenPrism	main	10	FALSE
3:	300	4.5	4.6	9.9	EigenPrism	main	10	FALSE
4:	100	12.3	11.2	11.1	GCTA	main	10	FALSE
5:	150	11.0	7.7	11.8	GCTA	main	10	FALSE.

8: 150 11.4 10.6 11.0 Ei	GCTA main igenPrism main igenPrism main	10 FALSE 10 FALSE
8: 150 11.4 10.6 11.0 Ei	•	
	igenPrism main	
9: 300 6.7 6.7 10.3 Ei		10 FALSE
0. 000 0., 0., 10.0 H	igenPrism main	10 FALSE
10: 100 12.1 10.2 11.4	GCTA main	10 FALSE
11: 150 9.4 7.2 11.5	GCTA main	10 FALSE
12: 300 4.4 3.4 11.0	GCTA main	10 FALSE
x_dist		
1: chi		
2: chi		
3: chi		
4: chi		
5: chi		
6: chi		
7: normal		
8: normal		
9: normal		
10: normal		
11: normal		

12: normal