## **EXERCISE 3**

## WEIYU LI

1. Consider the scor dataset in the package bootstrap, which is an  $88 \times 5$  matrix. Denote its covariance matrix as  $\Sigma$ , and its eigenvalues  $\lambda_1 > \ldots > \lambda_5 > 0$ . Then

$$\theta = \frac{\lambda_1}{\sum_{i=1}^5 \lambda_i}$$

represents the explained proportion of variance by the first principal component. Denote  $\hat{\lambda}_1 > \ldots > \hat{\lambda}_5$  the eigenvalues of the sample covariance matrix  $\hat{\Sigma}$ .

(1) Use Bootstrap and Jackknife to estimate the bias and standard error of the estimation of  $\theta$ , that is,

$$\hat{\theta} = \frac{\hat{\lambda}_1}{\sum_{i=1}^5 \hat{\lambda}_i}.$$

Here's an example of the R code:

```
set.seed(0)
install.packages('boot')
library(boot)
lambda_hat <- eigen(cov(scor))$values</pre>
theta_hat <- lambda_hat[1] / sum(lambda_hat)</pre>
B <- 200 # number of bootstrap samples
n <- nrow(scor) # number of rows (data size)</pre>
# Bootstrap
func <- function(dat, index){</pre>
# input: dat, data; index, a vector of the bootstrap index
# output: theta, the estimated theta using the bootstrap sample
  x <- dat[index,]
  lambda <- eigen(cov(x))$values</pre>
  theta <- lambda[1] / sum(lambda)
 return(theta)
}
bootstrap_result <- boot(</pre>
  data = cbind(scor$mec, scor$vec, scor$alg, scor$ana, scor$sta),
  statistic = func, R = B)
```

Date: 2019/09/30. liweiyu@mail.ustc.edu.cn. 2 WEIYU LI

theta\_b <- bootstrap\_result\$t</pre>

```
bias_boot <- mean(theta_b) - theta_hat</pre>
   # the estimated bias of theta_hat, using bootstrap
   se_boot <- sqrt(var(theta_b))</pre>
   # the estimated standard error (se) of theta_hat, using bootstrap
   # Jackknife
   theta_j <- rep(0, n)
   for (i in 1:n) {
     x <- scor [-i,]
     lambda <- eigen(cov(x))$values</pre>
     theta_j[i] <- lambda[1] / sum(lambda)</pre>
     # the i-th entry of theta_j is the i-th "leave-one-out" estimation of theta
   bias_jack <- (n - 1) * (mean(theta_j) - theta_hat)</pre>
   # the estimated bias of theta_hat, using jackknife
   se_jack \leftarrow (n - 1) * sqrt(var(theta_j) / n)
   # the estimated se of theta_hat, using jackknife
   # print the answers
   bias_boot
   se_boot
   bias_jack
   se_jack
   This example gives the result:
                       Method
                                    Bias
                                                 SE
                      Bootstrap | 0.005884122 |
                                              0.0469498
                      Jackknife | 0.001069139 | 0.04955231
                                                                         (2) Compute the 95% percentile confidence interval and BCa confidence
   interval of \theta, using the Bootstrap samples in (1). The R code is: (contin-
   ued)
   boot.ci(bootstrap_result, conf = 0.95, type = c('perc', 'bca'))
   whose output is
   BOOTSTRAP CONFIDENCE INTERVAL CALCULATIONS
```

```
Compute the 95% percentile confidence interval and BCa confidence interval of θ, using the Bootstrap samples in (1). The R code is: (continued)

boot.ci(bootstrap_result, conf = 0.95, type = c('perc', 'bca'))

whose output is

BOOTSTRAP CONFIDENCE INTERVAL CALCULATIONS

Based on 200 bootstrap replicates

CALL:

boot.ci(boot.out = bootstrap_result, conf = 0.95, type = c("perc", "bca"))

Intervals:

Level Percentile BCa

95% (0.5352, 0.7016) (0.5256, 0.7004)
```

EXERCISE 3 3

Calculations and Intervals on Original Scale Some percentile intervals may be unstable Some BCa intervals may be unstable

2. Let  $X_1, \ldots, X_n$  be different sample values,  $X_1^*, \ldots, X_n^*$  is a Bootstrap sampling and let  $\bar{X}^* = \frac{1}{n} \sum_i X_i^*$ . Compute  $E\left(\bar{X}^*|X_1, \ldots, X_n\right)$ ,  $Var\left(\bar{X}^*|X_1, \ldots, X_n\right)$ ,  $E\left(\bar{X}^*\right)$  and  $Var\left(\bar{X}^*\right)$ .

Solve. Notice that  $X_1^*, \ldots, X_n^* \stackrel{i.i.d.}{\sim} Unif\{X_1, \ldots, X_n\}$ , then

$$E(X_1^*|X_1, ..., X_n) = \frac{1}{n} \sum_i X_i := \bar{X},$$
  
$$E(X_1^{*2}|X_1, ..., X_n) = \frac{1}{n} \sum_i X_i^2 := \overline{X^2}.$$

Thus,

(1) 
$$E\left(\bar{X}^*|X_1,\dots,X_n\right) = \frac{1}{n}\sum_{i}E\left(X_i^*|X_1,\dots,X_n\right) = \bar{X},$$

(2) 
$$Var\left(\bar{X}^*|X_1,\ldots,X_n\right) = \frac{1}{n}\left[\overline{X^2} - (\bar{X})^2\right],$$

and taking expectations on  $X_1, \ldots, X_n$  gives that

(3) 
$$E\left(\bar{X}^*\right) = E\left[E\left(\bar{X}^*|X_1,\dots,X_n\right)\right] = E\left(\bar{X}\right) = EX,$$

(4) 
$$Var\left(\bar{X}^*\right) = Var\left[E\left(\bar{X}^*|X_1,\dots,X_n\right)\right] + E\left[Var\left(\bar{X}^*|X_1,\dots,X_n\right)\right]$$
$$= \frac{1}{n}Var(X) + \frac{1}{n}\frac{n-1}{n}Var(X) = \frac{2n-1}{n^2}Var(X),$$

where  $X_1, \ldots, X_n \sim X$ , *i.i.d.*.