

Assignment 3

Question 1

Build a bias, standard deviation, and confidence interval estimator for the mean based on the bootstrap (use 10000 =nboot) and the jackknife –Build a simulator that draws n samples form a lognormal distribution (rlnorm) and builds both the central limit theorem based confidence interval, and compares it to the coverage rate for the 2 bootstrap and the normal based confidence interval (1000 simulation runs minimum)

Jackknife Resampling

In statistics, the jackknife is a resampling technique especially useful for variance and bias estimation. The jackknife predates other common resampling methods such as the bootstrap. The jackknife estimator of a parameter is found by systematically leaving out each observation from a dataset and calculating the estimate and then finding the average of these calculations.

```
In [1]: 1 Jackknife<-function(v1,statfunc=sd, alpha = 0.05)
        2 {
        3   n1<-length(v1)
        4   jackvec<-NULL
        5   mu0<-statfunc(v1)
        6   for(i in 1:n1){
        7     mua<-statfunc(v1[-i])
        8     jackvec<-c(jackvec, n1*(mu0)-(n1-1)*mua)
        9   }
       10   jackbias<-mean(jackvec)-mu0
       11   jacksd<-sd(jackvec)
       12   JLB<-mean(jackvec)-(jacksd/sqrt(n1))*qnorm(1-alpha/2)
       13   JUB<-mean(jackvec)+(jacksd/sqrt(n1))*qnorm(1-alpha/2)
       14   list(mu0=mu0,jackbias=jackbias,jacksd=jacksd, jackknife.confidence.interval
       15 }
```

```
In [2]: 1 Jackknife(1:1000, statfunc = mean)
```

\$mu0

500.5

\$jackbias

0

\$jacksd

288.819436095749

\$jackknife.confidence.interval

482.599114827485 518.400885172515

Bootstrap

In statistics, bootstrapping is any test or metric that relies on random sampling with replacement. Bootstrapping allows assigning measures of accuracy (defined in terms of bias, variance, confidence intervals, prediction error or some other such measure) to sample estimates.

```
In [3]: 1 my.bootstrappedci.ml<-function(vec0,nboot=10000,alpha=0.05)
2 {
3   #extract sample size, mean and standard deviation from the original data
4   n0<-length(vec0)
5   mean0<-mean(vec0)
6   sd0<-sqrt(var(vec0))
7   # create a vector to store the location of the bootstrap studentized deviat
8   bootvec<-NULL
9   bootbiasvec<-NULL
10  #create the bootstrap distribution using a for loop
11  for( i in 1:nboot){
12    vecb<-sample(vec0,replace=T)
13    #create mean and standard deviation to studentize
14    meanb<-mean(vecb)
15    sdb<-sqrt(var(vecb))
16    #note since resampling full vector we can use n0 for sample size of vecb
17    bootvec<-c(bootvec,(meanb-mean0)/(sdb/sqrt(n0)))
18    #Calculation the vector that stores the bias of each bootstrap sample
19    bootbiasvec <- c(bootbiasvec, meanb-mean0)
20  }
21
22  bootbias <- mean(bootbiasvec)
23  bootsd <- mean(bootvec) #***** verfiy this *****#
24  #Calculate lower and upper quantile of the bootstrap distribution
25  lq<-quantile(bootvec,alpha/2)
26  uq<-quantile(bootvec,1-alpha/2)
27  #incorporate into the bootstrap confidence interval (what algebra supports
28  LB<-mean0-(sd0/sqrt(n0))*uq[[1]]
29  UB<-mean0-(sd0/sqrt(n0))*lq[[1]]
30  #since I have the mean and standard deviation calculate the normal confiden
31  NLB<-mean0-(sd0/sqrt(n0))*qnorm(1-alpha/2)
32  NUB<-mean0+(sd0/sqrt(n0))*qnorm(1-alpha/2)
33  list(bootbias = bootbias, bootsd = bootsd, bootstrap.confidence.interval=c(
34  }
```

```
In [4]: 1 my.bootstrappedci.ml(1:1000)
```

\$bootbias

-0.0665186000000034

\$bootsd

-0.00701678839115286

\$bootstrap.confidence.interval

482.311914886103 518.397600215478

\$normal.confidence.interval

482.599114827485 518.400885172515

Compare the coverage rates for the bootstrap confidence interval, and the central limit theorem based confidence interval. For sample sizes 10, 30, and 100 alpha=0.05 (95% confidence)

```
In [5]: 1 simulation <- function(mu.val=3, n=30, nsim=1000)
2 {
3   #create coverage indicator vectors for bootstrap and normal
4   cvec.boot<-NULL
5   cvec.norm<-NULL
6   cvec.jack<-NULL
7   #calculate real mean
8   mulnorm<-(exp(mu.val+1/2))
9   #run simulation
10  for(i in 1:nsim){
11    if((i/100)==floor(i/100)){
12      print(i)
13      #let me know computer hasnt died
14    }
15    #sample the simulation vector
16    vec.sample<-rlnorm(n,mu.val)
17    #bootstrap it
18    boot.list<-my.bootstrpci.ml(vec.sample)
19    #jackknife it
20    jack.list <- Jackknife(vec.sample, statfunc=mean, alpha = 0.05)
21    #fetch confidence intervals
22    boot.conf<-boot.list$bootstrap.confidence.interval
23    jack.conf<-jack.list$jackknife.confidence.interval
24    norm.conf<-boot.list$normal.confidence.interval
25
26    #calculate if confidence intervals include mu
27    #count up the coverage by the bootstrap interval
28    cvec.boot<-c(cvec.boot,(boot.conf[1]<mulnorm)*(boot.conf[2]>mulnorm))
29    #count up the coverage by the jackknife interval
30    cvec.jack<-c(cvec.jack,(jack.conf[1]<mulnorm)*(jack.conf[2]>mulnorm))
31    #count up the coverage by the normal theory interval
32    cvec.norm<-c(cvec.norm,(norm.conf[1]<mulnorm)*(norm.conf[2]>mulnorm))
33  }
34  #calculate and output coverage probability estimates
35  list(boot.coverage=(sum(cvec.boot)/nsim), jack.coverage=(sum(cvec.jack)/nsi
36 }
```

```
In [6]: 1 simulation(mu.val = 4, n = 10, nsim = 1000)
```

```
[1] 100  
[1] 200  
[1] 300  
[1] 400  
[1] 500  
[1] 600  
[1] 700  
[1] 800  
[1] 900  
[1] 1000
```

\$boot.coverage

0.895

\$jack.coverage

0.803

\$norm.coverage

0.803

```
In [7]: 1 simulation(mu.val = 4, n = 30, nsim = 1000)
```

```
[1] 100  
[1] 200  
[1] 300  
[1] 400  
[1] 500  
[1] 600  
[1] 700  
[1] 800  
[1] 900  
[1] 1000
```

\$boot.coverage

0.916

\$jack.coverage

0.849

\$norm.coverage

0.849

```
In [8]: 1 simulation(mu.val = 4, n = 100, nsim = 1000)
```

```
[1] 100
[1] 200
[1] 300
[1] 400
[1] 500
[1] 600
[1] 700
[1] 800
[1] 900
[1] 1000
```

\$boot.coverage

0.939

\$jack.coverage

0.918

\$norm.coverage

0.918

For the standard deviation of the normal distribution, estimate the bias of the the sample standard deviation when dividing by n , compare the bootstrap and the jackknife (1000 simulations).

```
In [9]: 1 Jackknife_sd<-function(v1){
2       n1<-length(v1)
3       jackvec<-NULL
4       mu0<-sd(v1)/n1
5       for(i in 1:n1){
6         mua<-sd(v1[-i])/(n1-1)
7         jackvec<-c(jackvec, n1*(mu0)-(n1-1)*mua)
8       }
9       jackbias<-mean(jackvec)-mu0
10      return (jackbias)
11    }
```

```

In [10]: 1 bootstrap_sd<-function(vec0,nboot=10000){
2         #extract sample size, mean and standard deviation from the original dat
3         n<-length(vec0)
4         mean0<-sd(vec0)/n
5         bootvec<-NULL
6         bootbiasvec<-NULL
7         #create the bootstrap distribution using a for loop
8         for( i in 1:nboot){
9             vecb<-sample(vec0,replace=T)
10            #create mean and standard deviation to studentize
11            meanb<-sd(vecb)/n
12            #note since resampling full vector we can use n0 for sample size of v
13            bootvec<-c(bootvec,meanb)
14            #Calculation the vector that stores the bias of each bootstap sample
15            bootbiasvec <- c(bootbiasvec, meanb-mean0)
16            }
17            return(mean(bootbiasvec))
18
19        }

```

```

In [11]: 1 simulation_q4 <- function(mu=3, sd= 2, n=30 , nsim=4)
2         {
3             #create coverage indicator vectors for bootstrap and normal
4             bvec.boot<-NULL
5             bvec.jack<-NULL
6
7             #run simulation
8             for(i in 1:nsim){
9                 if((i/100)==floor(i/100)){
10                    print(i)
11                    #let me know computer hasnt died
12                    }
13                    #sample the simulation vector
14                    vec.sample<-rnorm(n,mean = mu, sd = sd)
15                    #bootstrap bias
16                    bvec.boot<- c(bvec.boot, bootstrap_sd(vec.sample))
17                    #jackknife bias
18                    bvec.jack <- c(bvec.jack, Jackknife_sd(vec.sample))
19                    }
20                #return
21                list(boot_bias = bvec.boot, jack_bias = bvec.jack)
22
23            }

```

```
In [12]: 1 Output_4 <- simulation_q4(mu=3, sd= 2, n=30 , nsim=1000)
```

```
[1] 100  
[1] 200  
[1] 300  
[1] 400  
[1] 500  
[1] 600  
[1] 700  
[1] 800  
[1] 900  
[1] 1000
```