

# PLSC 503 – Spring 2020

## Bootstrapping

January 30, 2020

**The population is to the sample as the sample is to the bootstrap sample.**

# Practical (Nonparametric) Bootstrapping

- Draw one bootstrap sample of size  $N$  **with replacement** from the original data,
- Estimate the parameter(s)  $\tilde{\theta}_{k \times 1}$ ,
- Repeat steps 1 and 2  $R$  times, to get  $\tilde{\theta}_r$ ,  $r \in \{1, 2, \dots, R\}$ , comprising elements  $\tilde{\theta}_{rk}$ ,
- Examine the empirical characteristics of the resulting distribution(s) of  $\tilde{\theta}_{rk}$ .

# Why Bootstrap?

- **It's intuitive.**
- **It's simple.**
- **It's robust.**

# Bootstrapping Simulation ( $N = 100$ )

```
N<-100
```

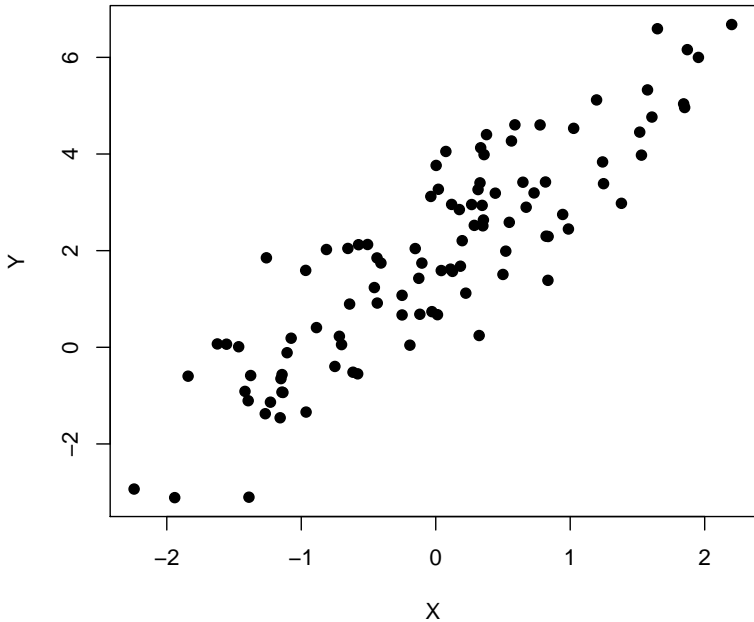
```
reps<-999
```

```
set.seed(7222009)
```

```
X<-rnorm(N)
```

```
Y<-2+2*X+rnorm(N)
```

# Bootstrapping Data



# Bootstrapping: “By Hand”

```
data<-data.frame(Y,X)
fitOLS<-lm(Y~X)
CI<-confint(fitOLS)

B0<-numeric(reps)
B1<-numeric(reps)

for (i in 1:reps) {
  temp<-data[sample(1:N,N,replace=TRUE),]
  temp.lm<-lm(Y~X,data=temp)
  B0[i]<-temp.lm$coefficients[1]
  B1[i]<-temp.lm$coefficients[2]
}

ByHandB0<-median(B0)
ByHandB1<-median(B1)
ByHandCI.B0<-quantile(B0,probs=c(0.025,0.975)) # <-- 95% c.i.s
ByHandCI.B1<-quantile(B1,probs=c(0.025,0.975))
```

# Bootstrapping Via boot

```
library(boot)

Bs<-function(formula, data, indices) { # <- regression function
  dat <- data[indices,]
  fit <- lm(formula, data=dat)
  return(coef(fit))
}

Boot.fit<-boot(data=data, statistic=Bs,
               R=reps, formula=Y~X)

BootB0<-median(Boot.fit$t[,1])
BootB1<-median(Boot.fit$t[,2])
BootCI.B0<-boot.ci(Boot.fit,type="basic",index=1)
BootCI.B1<-boot.ci(Boot.fit,type="basic",index=2)
```



# Bootstrapping Via simpleboot

```
library(simpleboot)
```

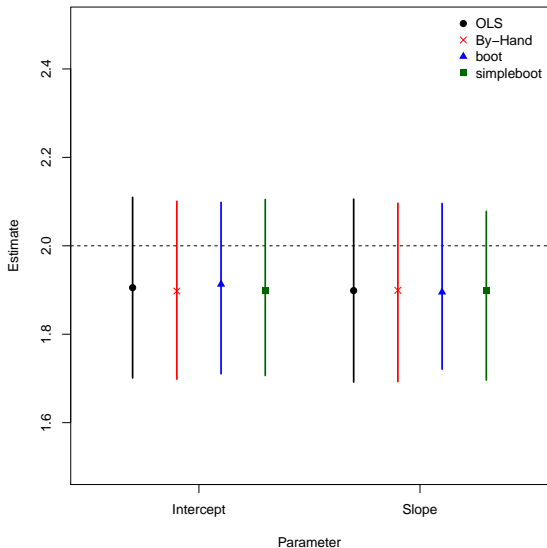
```
Simple<-lm.boot(fitOLS, reps)
```

```
SimpleB0<-perc(Simple, .50)[1]
```

```
SimpleB1<-perc(Simple, .50)[2]
```

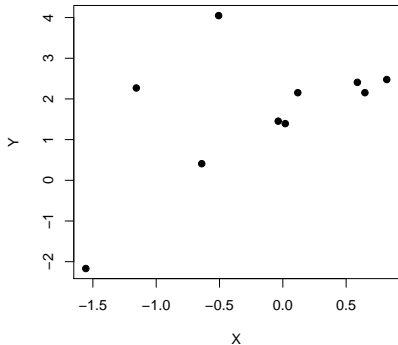
```
Simple.CIs<-perc(Simple, p=c(0.025, 0.975))
```

# Bootstrapping Results

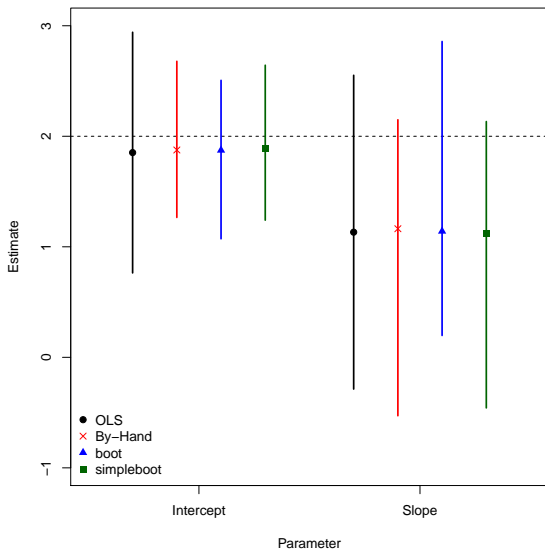


# Bootstrapping: Skewed Residuals ( $N = 10$ )

```
> N<-10  
> reps<-999  
>  
> set.seed(7222009)  
> X<-rnorm(N)  
> ustar<-rchisq(N,1) # <- skewed residuals  
> Y<-2+2*X+(ustar-mean(ustar))
```



# Skewed Residuals: Results



# Bootstrap SCOTUS Example

```
> library(RCurl)
> temp<-getURL("https://raw.githubusercontent.com/PrisonRodeo/PLSC503-2020-git/
master/Data/Justices.csv")
> Justices<-read.csv(text=temp, header=TRUE)
> rm(temp)
>
> summary(Justices)
```

	name	score	civrts	econs	Neditorials
Rehnquist:	2	Min. : -1.000	Min. : 19.80	Min. : 34.60	Min. : 2.000
Black	: 1	1st Qu.: -0.470	1st Qu.: 35.90	1st Qu.: 43.85	1st Qu.: 4.000
Blackmun	: 1	Median : 0.330	Median : 43.70	Median : 50.20	Median : 6.000
Brennan	: 1	Mean : 0.121	Mean : 51.42	Mean : 55.75	Mean : 8.742
Burger	: 1	3rd Qu.: 0.625	3rd Qu.: 75.55	3rd Qu.: 66.65	3rd Qu.: 11.500
Burton	: 1	Max. : 1.000	Max. : 88.90	Max. : 81.70	Max. : 47.000
(Other)	: 24				

	eratio	scoresq	lnNedit
Min.	: 0.5000	Min. : 0.0000	Min. : 0.6931
1st Qu.:	0.7083	1st Qu.: 0.1936	1st Qu.: 1.3863
Median :	1.0000	Median : 0.2500	Median : 1.7918
Mean :	2.0242	Mean : 0.4599	Mean : 1.8441
3rd Qu.:	2.5000	3rd Qu.: 0.8281	3rd Qu.: 2.4414
Max. :	11.7500	Max. : 1.0000	Max. : 3.8501

# Bootstrap SCOTUS Example

```
> JOLS<-with(Justices, lm(civrts~score))
> JOLShats<-predict(JOLS,interval="confidence")
> summary(JOLS)
```

Call:

```
lm(formula = civrts ~ score)
```

Residuals:

Min	1Q	Median	3Q	Max
-29.954	-8.088	-2.120	9.396	29.680

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	48.810	2.852	17.113	< 2e-16 ***
score	21.544	4.206	5.122	1.81e-05 ***

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Residual standard error: 15.63 on 29 degrees of freedom  
Multiple R-squared: 0.475, Adjusted R-squared: 0.4569  
F-statistic: 26.24 on 1 and 29 DF, p-value: 1.806e-05

# Bootstrap SCOTUS Example

```
> JBoot <- lm.boot(JOLS, reps)
> summary(JBoot)
```

BOOTSTRAP OF LINEAR MODEL (method = rows)

Original Model Fit

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Call:

```
lm(formula = civrts ~ score)
```

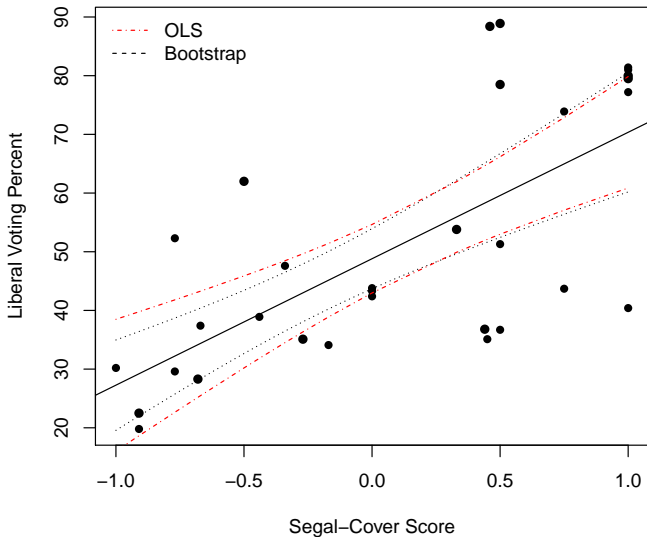
Coefficients:

(Intercept)	score
48.81	21.54

Bootstrap SD's:

(Intercept)	score
2.561338	3.709290

# Conventional and Bootstrap CIs





# Bootstrapping Miscellanea

In general, use bootstraps when:

- Samples are small
- Residuals are “strange”
- Standard errors are otherwise hard to derive / estimate.

References, practical and otherwise:

- Carpenter, James, and John Bithell. 2000. “Bootstrap Confidence Intervals: When, Which, What? A Practical Guide for Medical Statisticians.” *Statistics in Medicine* 19:1141-1164.
- Chernick, Michael R., and Robert A. LaBudde. 2011. *An Introduction to Bootstrap Methods with Applications to R*. New York: Wiley.
- Davison, A.C., and D.V. Hinkley. 1997. *Bootstrap Methods and their Application*. New York: Cambridge University Press.
- Efron, Bradley, and R.J. Tibshirani. 1993. *An Introduction to the Bootstrap*. London: Chapman and Hall.