

# PLSC 503 – Spring 2017

## Bootstrapping

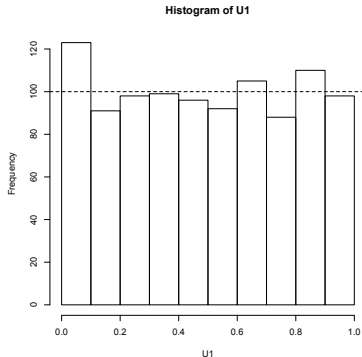
February 2, 2017

# What We'll Do Today

- Review “Homework Zero”
- Bootstrapping

Generate 1000 i.i.d.  $u_j \sim U(0, 1)$

```
seed<-07222009  
set.seed(seed)  
U1<-runif(1000)  
hist(U1)  
abline(h=100,lty=2)  
# etc.
```



Repeat 999 more times, saving each set of draws

```
listU<-paste("U",1:1000,sep="")  
U<-sapply(listU, function(U) U<-runif(1000))
```

# or

```
U<-data.frame(matrix(nrow=1000,ncol=1000))  
colnames(U)<-paste("U",1:1000,sep="")  
for (i in 1:1000) {  
  U[,i]<-runif(1000)  
}
```

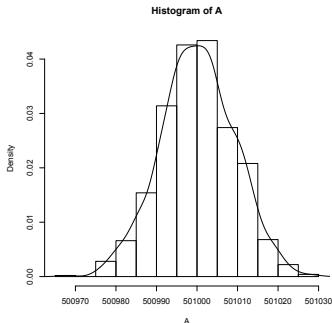
Create  $V_i$  by adding the integer corresponding to the order of the observation to the value of  $u_{ij}$ .

```
Seq<-seq(1,1000,1)  
V<-U+Seq
```

Generate an object  $A$ ...where the  $i$ th entry is

$$A_i = \sum_{j=1}^{1000} V_{ij})$$

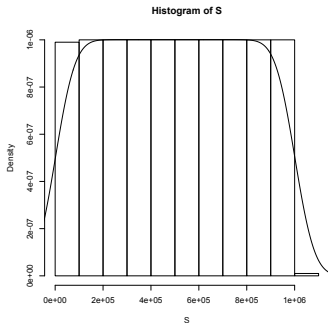
```
A<-numeric(1000)
for(i in 1:1000) {
  A[i]<-sum(V[,i]) }
hist(A,freq=FALSE)
lines(density(A))
```



Create a second object  $S$ ...where the  $j$ th entry is

$$S_j = \sum_{i=1}^{1000} V_{ij}.$$

```
S<-numeric(1000)
for(i in 1:1000) {
  S[i]<-sum(V[i,]) }
hist(S,freq=FALSE)
lines(density(S))
```



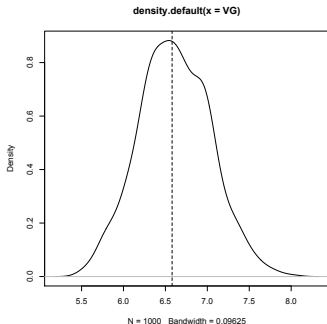
Transform your 1000 bundles of  $U(0, 1)$  draws into 1000 bundles  $G_{ij}$  of draws from a Gumbel(1,2) distribution.

```
G <- 1-2*(log(-log(U)))
```



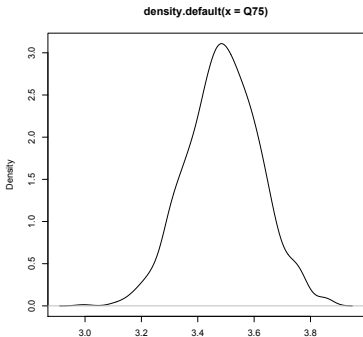
# Plot the empirical variances of $G...$

```
VG<-numeric(1000)
for(i in 1:1000) {
  VG[i]<-var(G[,i]) }
plot(density(VG))
abline(v=((3.14159265^2) / 6) * 4,lty=2)
```



# Plot the density of the values of the 75th percentiles...

```
Q75<-numeric(1000)
for(i in 1:1000) {
  Q75[i]<-quantile(G[,i], .75)
}
plot(density(Q75))
```

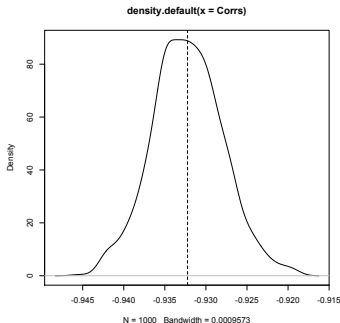


Generate 1000 draws  $Y_{ij} = -2G_{ij} + \epsilon_{ij}$ ,  
 $\epsilon_{ij} \sim N(0, 4)$ .

```
Y<-(-2*G)+(rnorm(1000,mean=0,sd=2))
```

# Plot...the distribution of the 1000 Pearson correlations between $Y$ and $G$

```
Corrs<-numeric(1000)
for(i in 1:1000){
  Corrs[i]<-cor(G[,i],Y[,i])
}
plot(density(Corrs))
abline(v=mean(Corrs),lty=2)
```



# Bootstrapping

**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.**



# Bootstrap Example

```
> Justices<-read.csv("Justices.csv")
> attach(Justices)
> summary(Justices)
```

name	score	civrts	econs
Length:31	Min. : -1.0000	Min. : 19.80	Min. : 34.60
Class :character	1st Qu.: -0.4700	1st Qu.: 35.90	1st Qu.: 43.85
Mode :character	Median : 0.3300	Median : 43.70	Median : 50.20
	Mean : 0.1210	Mean : 51.42	Mean : 55.75
	3rd Qu.: 0.6250	3rd Qu.: 75.55	3rd Qu.: 66.65
	Max. : 1.0000	Max. : 88.90	Max. : 81.70

Neditorials	eratio	scoresq	lnNedit
Min. : 2.000	Min. : 0.5000	Min. : 0.0000	Min. : 0.6931
1st Qu.: 4.000	1st Qu.: 0.7083	1st Qu.: 0.1936	1st Qu.: 1.3863
Median : 6.000	Median : 1.0000	Median : 0.2500	Median : 1.7918
Mean : 8.742	Mean : 2.0242	Mean : 0.4599	Mean : 1.8442
3rd Qu.: 11.500	3rd Qu.: 2.5000	3rd Qu.: 0.8281	3rd Qu.: 2.4414
Max. : 47.000	Max. : 11.7500	Max. : 1.0000	Max. : 3.8501

# Bootstrap Example

```
> OLSfit<-with(Justices, lm(civrts~score))  
> summary(OLSfit)
```

Call:

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

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 ***

---

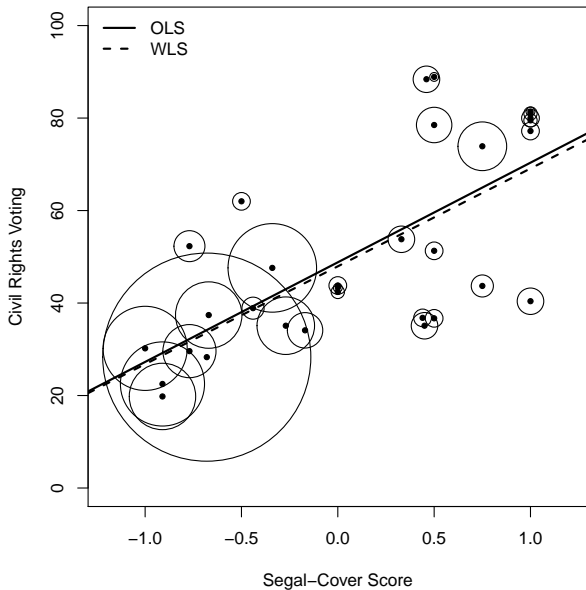
Signif. codes: 0 \*\*\* 0.001 \*\* 0.01 \* 0.05 . 0.1 1

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

Figure: Plot of civrts Against score, Weighted by Neditorials



# Bootstrapping: “By Hand”

```
N<-100
reps<-999

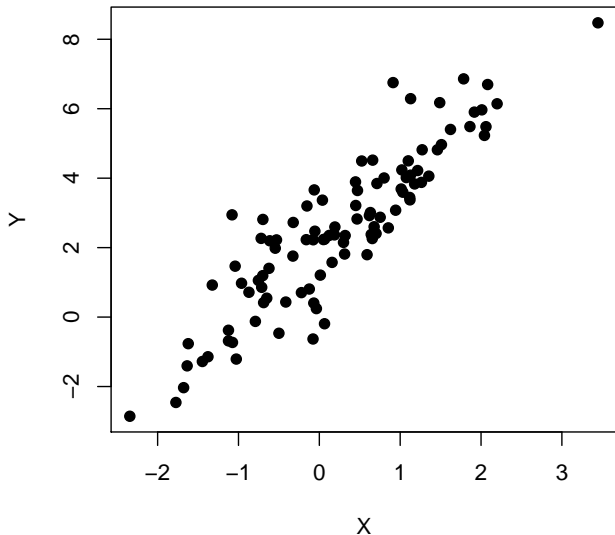
set.seed(1337)
X<-rnorm(N)
Y<-2+2*X+rnorm(N)
data<-data.frame(Y,X)
fitOLS<-lm(Y~X)
CI<-confint(fitOLS)

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 “By Hand”



# 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)
```

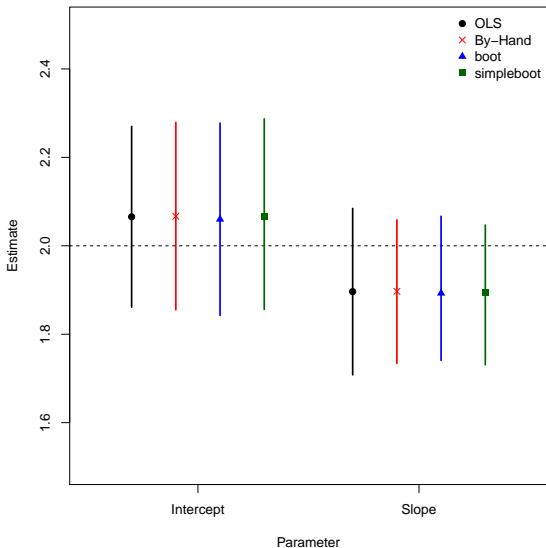
```
Simple<-lm.boot(fitOLS, reps)
```

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

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

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

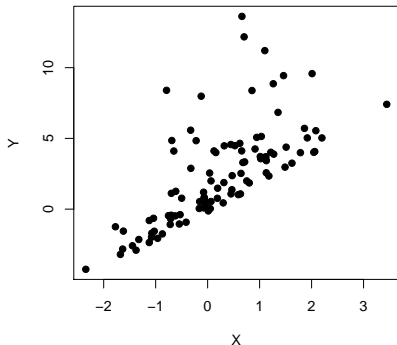
# Bootstrapping Results





# Bootstrapping: Skewed Residuals

```
N<-100  
reps<-999  
  
set.seed(1337)  
X<-rnorm(N)  
ustar<-rchisq(N,2) # <- skewed u.s  
Y<-2+2*X+(ustar-mean(ustar))  
data<-data.frame(Y,X)  
fitOLS<-lm(Y~X)  
CI<-confint(fitOLS)
```



# Skewed Residuals: Results

