

# 16) Bootstrap

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Tables, Graphics, and Figures from  
**An Introduction to Statistical Learning**

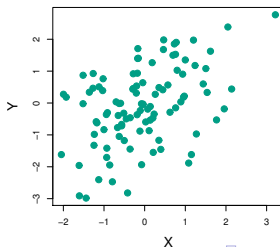
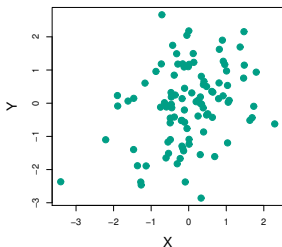
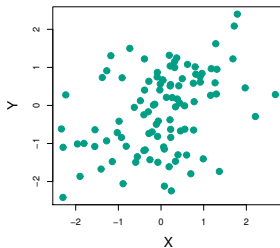
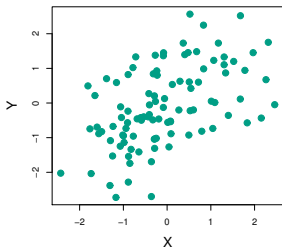
James et al. (2017): Chapters: 5.2, 5.3.4

$$\text{Var}[\alpha X + (1 - \alpha) Y]$$

$$\alpha = \frac{\sigma_Y^2 - \sigma_{XY}}{\sigma_X^2 + \sigma_Y^2 - 2\sigma_{XY}}$$

$$\hat{\alpha} \in [53\% \text{ to } 65\%]$$

57.6%, 53.2%, 65.7%, and 65.1%



## 1000 Estimates for $\alpha$

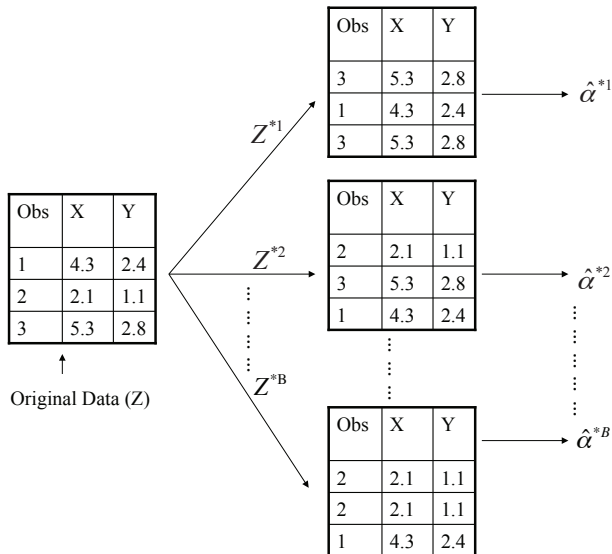
$$\sigma_X^2 = 1, \sigma_Y^2 = 1.25, \sigma_{XY} = 0.5$$

$$\therefore \alpha = 0.6$$

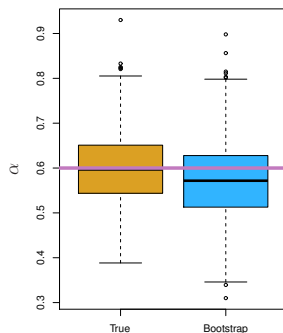
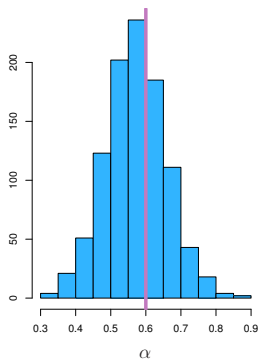
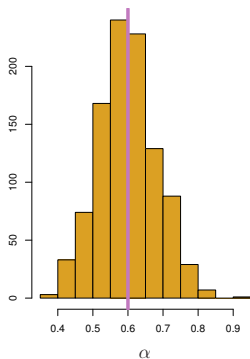
$$\bar{\alpha} = \frac{1}{1000} \sum_{r=1}^{1000} \hat{\alpha}_r = 0.5996$$

$$SE(\hat{\alpha}) = \sqrt{\frac{1}{999} \sum_{r=1}^{1000} (\hat{\alpha}_r - \bar{\alpha})^2} = 0.083$$

# Bootstrap Approach (Sampling from Data)



# 1000 Simulated Data Sets from the True Population vs 1000 Bootstrap Samples from a Single Data Set



1000 Simulated Data Sets

$$SE(\hat{\alpha}) = 0.087$$

$$\sqrt{\frac{1}{B-1} \sum_{r=1}^B (\hat{\alpha}^{*r} - \frac{1}{B} \sum_{r'=1}^B \hat{\alpha}^{*r'})^2}$$

$$SE_B(\hat{\alpha}) = 0.083$$



```
alpha.fn=function(data,index){  
  X=data$X[index]  
  Y=data$Y[index]  
  return((var(Y)-cov(X,Y))/(var(X)  
    +var(Y)-2*cov(X,Y)))  
}  
alpha.fn(Portfolio,1:100)
```

**0.576**

```
set.seed(1); library(boot)
```

```
alpha.fn(Portfolio,sample(100,100,  
replace=T))
```

**0.596**

```
boot(Portfolio,alpha.fn,R=1000)
```

```
Bootstrap Statistics :  
      original      bias      std. error  
t1* 0.5758321 0.002705445  0.09197062
```

# Bootstrap and OLS

```
boot.fn=function(data,index)
return(coef(lm(mpg~horsepower,data=data,subset=index)))
set.seed(1); boot(Auto,boot.fn,1000)
```

Bootstrap Statistics :

	original	bias	std. error
t1*	39.9358610	0.0269563085	0.859851825
t2*	-0.1578447	-0.0002906457	0.007402954

```
summary(lm(mpg~horsepower,data=Auto))$coef
```

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	39.9358610	0.717498656	55.65984	1.220362e-187
horsepower	-0.1578447	0.006445501	-24.48914	7.031989e-81

# set.seed(1)

```
boot.fn=function(data,index)
coefficients(lm(mpg~horsepower+I(horsepower^2),
data=data,subset=index))
boot(Auto,boot.fn,1000)
```

	original	bias	std. error
t1*	56.900099702	6.098115e-03	2.0944855842
t2*	-0.466189630	-1.777108e-04	0.0334123802
t3*	0.001230536	1.324315e-06	0.0001208339

```
summary(lm(mpg~horsepower+I(horsepower^2),data=Auto))$coef
```

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	56.900099702	1.8004268063	31.60367	1.740911e-109
horsepower	-0.466189630	0.0311246171	-14.97816	2.289429e-40
I(horsepower^2)	0.001230536	0.0001220759	10.08009	2.196340e-21