

Economics 217 - Sampling and Resampling methods

- Topics covered in this lecture
 - Monte Carlo Simulation
 - Bootstrap Resampling
 - Bootstrap percentile intervals
- We will be doing lots of coding in these lectures, so make sure you follow lecture with trying examples at home.

Introduction to Monte Carlo

- Most of the models we have discussed utilize large sample properties and the central limit theorem
 - With large samples, we know something about the distribution of the estimates.
 - Small sample properties are much more difficult to derive, and in practice the sampling distribution is often unknown
- Sampling and resampling techniques help us test our models under small samples and evaluate the bias that might come from results using small samples and real data.
- We will first study **Monte Carlo Analysis**.
- Simple put, we generate fake data and then test the statistics of interest using the fake data
- Model should perform well in two dimensions
 - Estimate should be centered around the actual value
 - Should not over or under reject true parameter.

A simple Monte Carlo to test small sample OLS

- Suppose we start with the following very simple model:

$$y_i = x_i + u_i$$

- Intercept is zero, slope coefficient $\beta = 1$
- Let's test this model using the following procedure:
 - ① Pick a sample size of N
 - ② Generate N values of x_i between zero and 1
 - ③ Randomly generate N values of u_i between zero and 1 using some distribution
 - ④ Using values of x_i and u_i , generate y_i
 - ⑤ Estimate model and collect estimates for β
- Repeat procedure B times.
- What do you think will happen if we have a small sample?

R example: 10 replications

```
B<-10
N<-50
results<-data.frame(matrix(NA, nrow=B, ncol=3))
names(results)<-c("rep", "B0", "B1")

for(rep in 1:B){
  x<-rnorm(N, mean=0, sd=1)
  u<-rnorm(N, mean=0, sd=1)
  y<-x+u
  fit.B<-lm(y~x)
  results$rep[rep]<-rep
  results$B0[rep]<-as.numeric(coef(fit.B)[1])
  results$B1[rep]<-as.numeric(coef(fit.B)[2])
}

par(mfrow=c(2, 2))
plot(density(results$B0), main="Sampling Distribution of B0, B=10")
abline(v=0)
plot(density(results$B1), main="Sampling Distribution of B1, B=10")
abline(v=1)
```

Monte Carlo to Bootstrap

- To summarize, Monte Carlo analysis is great for assessing the performance of an estimator
 - Is it biased?
 - Is inference reasonable?
- However, there is a big down-side
 - We're testing a known function with fake data. Need a technique to evaluate bias within a real-world context
 - If we are running a monte carlo on a linear regression, we're essentially evaluating the central limit theorem (which we know works in the limit)
- There is no silver bullet, but the *Bootstrap* is as close as we get.
 - **Resamples** from observational data to create an **empirical distribution** of a test statistic
 - Develops confidence intervals and other techniques for inference from this empirical distribution

Bootstrap Logic

- The "Bootstrap" is a technique that was originally proposed by Bradley Efron in the 70's
 - The cliché is apt here - we pick the data up by its "bootstraps".
- The essential bootstrap insight is the following:
 - Typical inference is justified via the central limit theorem
 - The central limit theorem is crucial since we usually only have one sample to work with.
 - However, as the sample is from the population, a **resample** of the sample is also a sample from the population.
 - Hence, we can generate sampling variation by resampling from the sample of the population.
- Critical Questions for a bootstrap analysis
 - How do we resample?
 - What statistic do we use (T-stat, CI, etc..)?

Three Methods of Resampling

- Data resampling:

- Sampling observations of (y_i, x_i) from the original data, *with replacement*.

- Residual Resampling

- Collect residuals from the original model, \hat{u}
- Sample these residuals with replacement to construct a new vector of residuals of equal size, \tilde{u}
- Define new dependent variable as

$$\tilde{y} = \hat{y} + \tilde{u}$$

- Wild Bootstrap

- Collect residuals from the original model, \hat{u}
- Randomly multiply them by -1 or 1 with equal probability, getting \tilde{u}
- Define new dependent variable as

$$\tilde{y} = \hat{y} + \tilde{u}$$

After resampling

- After choosing a method of resampling, we run the resampling procedure B times, getting B observations of a statistic of interest
 - Usually parameter estimates
 - Could be t-statistics
- Assuming that we are collecting parameters, it is most straightforward to calculate bootstrap confidence intervals.
- Precisely, after collecting B estimates using the bootstrap samples, the "Percentile Confidence Interval" is simply the following:

$$C = (q(\alpha/2) , q(1 - \alpha/2))$$

where α is the desired level of significance (say, 5%), and $q(x)$ is the x th percentile of the bootstrap estimates

- For example, if $\alpha = 10$, $q(\alpha/2)$ is the 5th percentile of the bootstrap estimates, and $q(1 - \alpha/2)$ is the 95th percentile.

R Bootstrapping

- The function "boot" takes care of much of bootstrapping, but we will do it ourselves to build on the understanding of the procedure.
- The main item we need is a function of resample from a vector or data frame, with replacement.

```
sample(x, size, replace = FALSE, prob = NULL)
```

- If "x" is a number, it draws samples from 1 x
 - "size" is the number of observations in the desired sample
 - "replace" indicates if you want sampling done with replacement.
- To construct a random sample from a data frame, defining our data frame as "df", write the following

```
df[sample(nrow(df), n, replace=TRUE), ]
```

- We use this syntax to construct bootstrap samples.

R Bootstrapping

- One can place the random sampling within a function to make the entire procedure modular

```
randomSample = function(df,n) {  
  return(df[sample(nrow(df),n),])  
}
```

- Finally, we run the bootstrap procedure via the following

```
form<-as.formula(log(rw)~educ)  
fit.full<-lm(form,subd)  
  
B<-1000  
N<-1000  
resultsB<-matrix(NA,nrow=B,ncol = (length(coef(fit.B))+1))  
for(rep in 1:B){  
  fit.B<-lm(form,randomSample(subd,N))  
  coef.B<-as.numeric(coef(fit.B))  
  resultsB[rep,1]<-rep  
  resultsB[rep,2:ncol(resultsB)]<-t(as.matrix(coef.B))  
}  
  
resultsB<-as.data.frame(resultsB)  
names(resultsB)<-c("rep",names(coef(fit.full)))
```

R Bootstrapping

- To construct 95% confidence intervals, run:

```
quantile(resultsB$(Intercept), prob=c(0.025, 0.975), na.rm=TRUE)
```

```
quantile(resultsB$educCollege, prob=c(0.025, 0.975), na.rm=TRUE)
```

```
quantile(resultsB$educAdvanced, prob=c(0.025, 0.975), na.rm=TRUE)
```

- Also, compare the original estimate of *educAdvanced* against the entire distribution of bootstrap estimates

```
plot(density(resultsB$educAdvanced) main="Coefficient on Advanced  
Degree")
```

```
abline(v=coef(fit.full)[5])
```

Residual Resampling

- Another approach to bootstrapping is "residual bootstrapping".
- Estimate a base model, and then use the model and "new" residuals to generate new outcome variables.
- New residuals are resampled, with replacement, from the old residuals

```
resid.full<-as.numeric(fit.full$residuals)
predict.full<-as.numeric(fit.full$fitted.values)

B<-1000
resultsR<-matrix(NA,nrow=B,ncol = (length(coef(fit.B))+1))

for(rep in 1:B){
  rand.resid<-sample(residuals.full, nrow(subd),replace=TRUE)
  subd$rw_boot<-predict.full+newresid
  fit.B<-lm(rw_boot~educ,subd)
  coef.B<-as.numeric(coef(fit.B))
  resultsR[rep,1]<-rep
  resultsR[rep,2:ncol(resultsR)]<-t(as.matrix(coef.B))
}
```

Wild Bootstrap

- The Wild bootstrap generates new residuals by randomly multiplying old residuals by -1 or 1.
- New residuals are resampled, with replacement, from the old residuals

```
resid.full<-as.numeric(fit.full$residuals)
predict.full<-as.numeric(fit.full$fitted.values)

B<-1000
resultsW<-matrix(NA,nrow=B,ncol = (length(coef(fit.B))+1))

for(rep in 1:B){
  newresid<-ifelse(runif(nrow(subd),0,1)>0.5,rand.resid,-rand.resid)
  subd$rw_boot<-predict.full+newresid
  fit.B<-lm(rw_boot~educ,subd)
  coef.B<-as.numeric(coef(fit.B))
  resultsW[rep,1]<-rep
  resultsW[rep,2:ncol(resultsW)]<-t(as.matrix(coef.B))
}
```