THEORY AND MODEL ASSESSMENT THROUGH SIMULATION

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THEORY ASSESSMENT

Central Limit Theorem

Closed Form Solutions?

- In mathematics and statistics, there are popular theories involving distributions of known values.
- The Central Limit Theorem is a classic example.
- Don't need complicated mathematics for us to approximate distributional assumptions when we use simulations.

Closed Form Solutions?

- This is especially helpful when finding a closed form solution is very difficult if not impossible.
- A closed form solution to a mathematical/statistical distribution problem means that you can mathematically calculate the distribution.
- Real world data can be very complicated and changing based on many different inputs which each have their own distribution.
- Simulation can reveal an approximation of these output distributions.

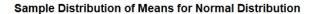
Example – Central Limit Theorem

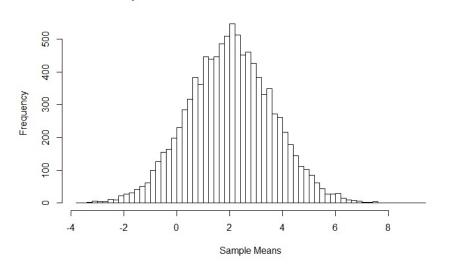
- Assume you do not know the Central Limit Theorem, but you want to understand the sampling distribution of sample means.
- You take samples of size 10, 50, and 100 from the following three population distributions and calculate the sample means:
 - 1. Normal Distribution
 - 2. Uniform Distribution
 - 3. Exponential Distribution
- What is the sampling distribution of sample means from each of these distributions and sample sizes?

Theory Assessment for CLT – R

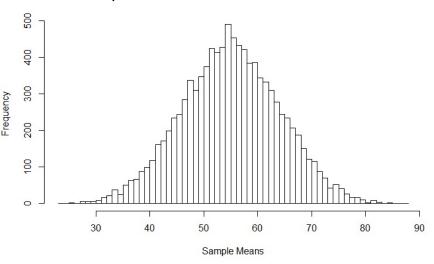
```
sample.size <- 10</pre>
simulation.size <- 10000
X1 <- matrix(data=rnorm(n=(sample.size*simulation.size), mean=2, sd=5),
              nrow=simulation.size, ncol=sample.size, byrow=TRUE)
X2 <- matrix(data=runif(n=(sample.size*simulation.size), min=5, max=105),
              nrow=simulation.size, ncol=sample.size, byrow=TRUE)
X3 <- matrix(data=(rexp(n=(sample.size*simulation.size)) + 3),</pre>
              nrow=simulation.size, ncol=sample.size, byrow=TRUE)
Mean.X1 <- apply(X1,1,mean)</pre>
Mean.X2 \leftarrow apply(X2,1,mean)
Mean.X3 <- apply(X3,1,mean)</pre>
```

Assessment for CLT - R (n = 10)

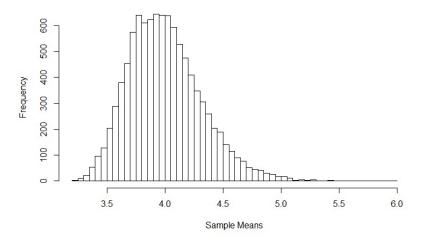




Sample Distribution of Means for Uniform Distribution



Sample Distribution of Means for Exponential Distribution





THEORY ASSESSMENT

Omitted Variable Bias

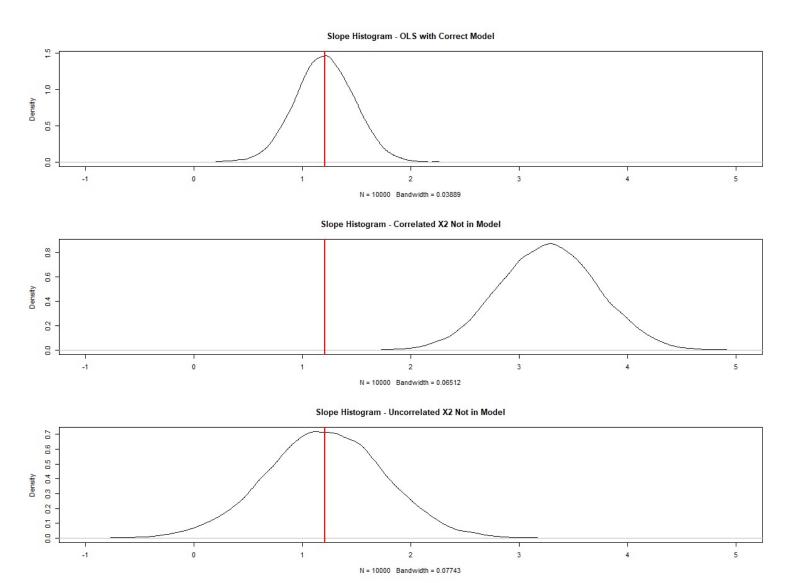
- What if you leave out a variable in a linear regression that should have been in the model?
- From the primer we learned that it would change the variance and bias of the coefficients still in model **depending** on if the variable left out was correlated.
- What if you wanted to know how bad it could get?

Build the following regression model:

$$Y = -13 + 1.21X_1 + 3.45X_2 + \varepsilon$$

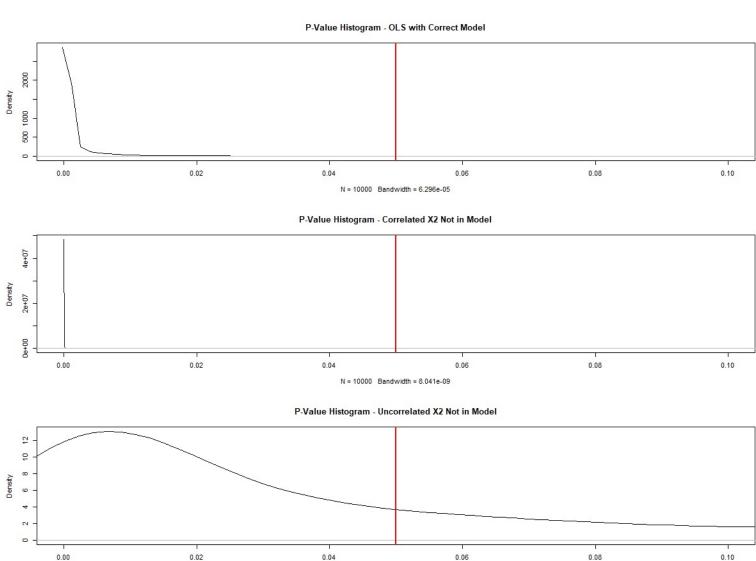
- Assume the errors are normally distributed with mean of 0 and standard deviation of 1.5.
- Assume the predictors follow standard normal distributions.

- Build 10,000 linear regressions (each of sample size 50) and record the coefficients from the regression model when one of the variables is omitted. Look at the following:
 - Distribution of coefficient in the model
 - What if the omitted variable isn't correlated with the others?
 - What if the omitted variable is correlated with the others?



- Build 10,000 linear regressions (each of sample size 50) and record the coefficients from the regression model when one of the variables is omitted. Look at the following:
 - Distribution of coefficient in the model
 - What if the omitted variable isn't correlated with the others? UNBIASED,
 MORE VARIANCE
 - What if the omitted variable is correlated with the others? BIASED, MORE VARIANCE

- Build 10,000 linear regressions (each of sample size 50) and record the coefficients from the regression model when one of the variables is omitted. Look at the following:
 - 2. How many times did you incorrectly NOT reject the null hypothesis on the coefficient in each of these scenarios?



N = 10000 Bandwidth = 0.01327

- Build 10,000 linear regressions (each of sample size 50) and record the coefficients from the regression model when one of the variables is omitted. Look at the following:
 - 2. How many times did you incorrectly NOT reject the null hypothesis on the coefficient in each of these scenarios?

Model	Percentage of Time NOT Rejecting Null
Correct Model – OLS	1.39%
Correlated X2 Not in Model	0.00%
Uncorrelated X2 Not in Model	40.84%

TARGET SHUFFLING

- Target shuffling has been around for a long time, but has recently been brought back into popularity by John Elder.
- **Target shuffling** is when you randomly reorder the target variable values among the sample, while keeping the predictor variable values fixed.

Age	Gender	Buy Product?		
25	M	1		
31	F	0		
28	F	1		
42	M	0		
39	М	1		
34	F	0		



Age	Gender	Buy Product?	Y_1	
25	M	1	0	
31	F	0	1	
28	F	1	1	
42	M	0	0	
39	M	1	0	
34	F	0	1	

Age	Gender	Buy Product?	Y ₁	
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28	F	1	1	
42	M	0	0	
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- Target shuffling is when you randomly reorder the target variable values among the sample, while keeping the predictor variable values fixed.
- Build model from each of these reshuffled targets and record some measurement of model success (R_A^2 , c, MAPE, etc.)

Model metric from each model!

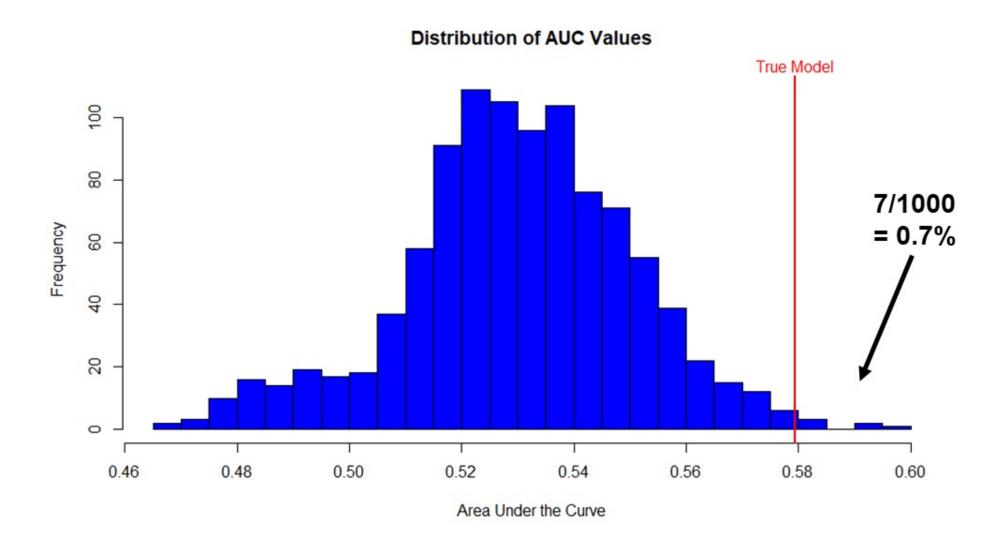
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•••	•••				
34	F	0	1	0	

Placebo Effect

- Build model from each of these reshuffled targets and record some measurement of model success (R_A^2 , c, MAPE, etc.)
- This should remove the pattern from the data, but some pattern may exist due to randomness.
- Look at distribution of all measurements of model success and find your value from the true model!

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- This should remove the pattern from the data, but some pattern may exist due to randomness.
- Look at distribution of all measurements of model success and find your value from the true model!
- What is probability your model would have occurred due to randomness?



- Randomly generated 8 variables that follow a Normal distribution with mean of 0 and standard deviation of 8.
- Defined relationship with target variable:

$$y = 5 + 2x_2 - 3x_8 + \varepsilon$$

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Performed target shuffle on the model.

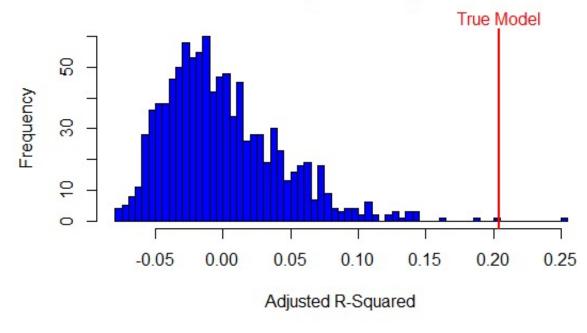
```
Fake <- data.frame(matrix(rnorm(n=(100*8)), nrow=100, ncol=8))
Err <- rnorm(n=100, mean=0, sd=8)</pre>
Y <- 5 + 2*Fake$X2 - 3*Fake$X8 + Err
Fake <- cbind(Fake, Err, Y)</pre>
sim <- 1000
Y.Shuffle <- matrix(0, nrow=100, ncol=sim)
for(j in 1:sim){
  Uniform <- runif(100)</pre>
  Y.Shuffle[,j] <- Y[order(Uniform)]
Y.Shuffle <- data.frame(Y.Shuffle)</pre>
colnames(Y.Shuffle) <- paste('Y.',seq(1:sim),sep="")</pre>
Fake <- data.frame(Fake, Y.Shuffle)</pre>
R.sq.A \leftarrow rep(0,sim)
for(i in 1:sim){
  R.sq.A[i] < summary(lm(Fake[,10+i] \sim Fake$X1 + Fake$X2 + Fake$X3 + Fake$X4
                           + Fake$X5 + Fake$X6 + Fake$X7 + Fake$X8))$adj.r.squared
True.Rsq.A <- summary(lm(Fake$Y ~ Fake$X1 + Fake$X2 + Fake$X3 + Fake$X4
                          + Fake$X5 + Fake$X6 + Fake$X7 + Fake$X8))$adj.r.squared
```

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$$y = 5 + 2x_2 - 3x_8 + \varepsilon$$

• Adjusted R² from this model: 0.204

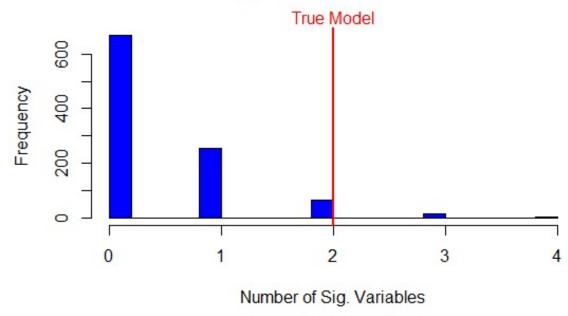
Distribution of Adjusted R-Squared Values



Target Shuffle with 1000 Simulations

Variable	Times Appeared Significant (p < 0.05) in a Model
X1	55
X2	62
X3	47
X4	56
X5	50
X6	57
X7	58
X8	40

Count of Significant Variables Per Model

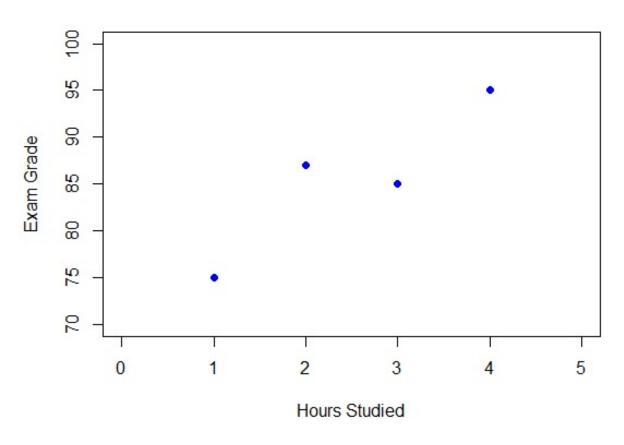


Student Grade Analogy



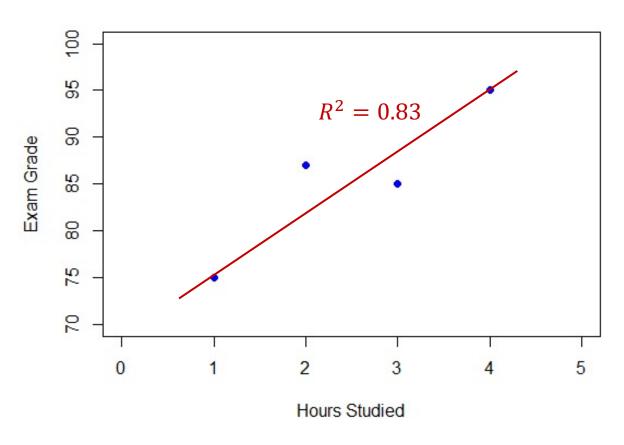
Student Grade Analogy

Hours vs. Grades - Actual



Student Grade Analogy

Hours vs. Grades - Actual



- How many different ways can four students get the grades 75, 85, 87, and 95?
- 24 possible ways this happens!

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1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4
75	85	87	95	75	95	85	87	85	87	75	95	87	75	85	95	87	95	75	85	95	85	75	87
1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4
75	87	85	95	75	95	87	85	85	87	95	75	87	75	95	85	87	95	75	85	95	87	75	85
1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4
75	85	95	87	85	75	87	95	85	95	75	87	87	85	75	95	95	75	85	87	95	85	87	75
1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4
75	87	95	85	85	75	95	87	85	95	87	75	87	85	95	75	95	75	87	85	95	87	85	75

- How many different ways can four students get the grades 75, 85, 87, and 95?
- 24 possible ways this happens!
- There are 3 possible combinations that produce a regression with an \mathbb{R}^2 that is greater than or equal to our actual data.

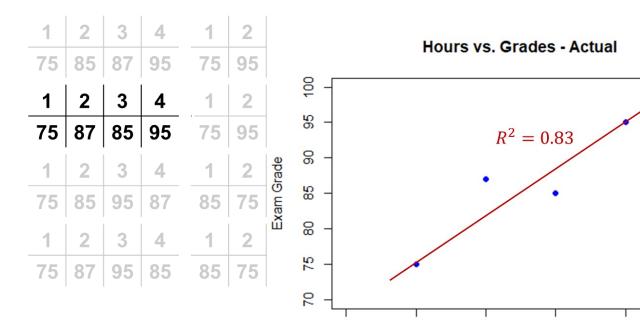
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1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4
75	87	85	95	75	95	87	85	85	87	95	75	87	75	95	85	87	95	75	85	95	87	75	85
1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4
75	25	ΩE	07																		$\overline{}$		
	03	90	87	85	75	87	95	85	95	75	87	87	85	75	95	95	75	85	87	95	85	87	75
1	2	3	 	85 1	 	 	95 4	85 1	l I	75 3	l I	87 1	 	75 3	l I			 	l I		85 2	 	75 4

How many different ways can four students get the grades 75, 85, 87, and 95?

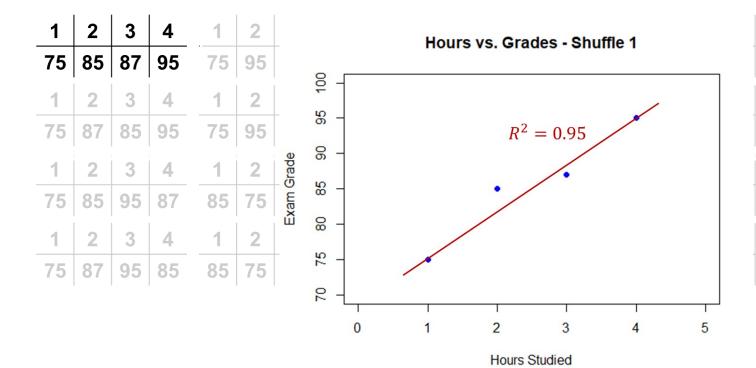
Hours Studied

24 possible ways this happens!



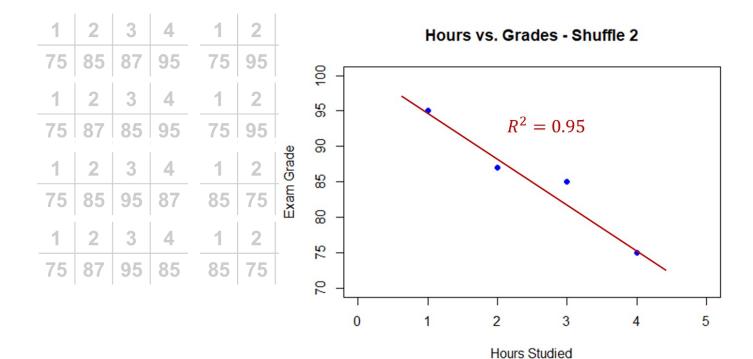
3	4	1	2	3	4
75	85	95	85	75	87
3	4	1	2	3	4
75	85	95	87	75	85
3	4	1	2	3	4
85	87	95	85	87	75
3	4	1	2	3	4
87	85	95	87	85	75

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75	85	95	85	75	87
3	4	1	2	3	4
75	85	95	87	75	85
3	4	1	2	3	4
	87			3 87	
	87		85	87	75

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3	4	1	2	3	4
75	85	95	85	75	87
3	4	1	2	3	4
75	85	95	87	75	85
3	4	1	2	3	4
85	87	95	85	87	75
3	87		85	l I	75 4

- How many different ways can four students get the grades 75, 85, 87, and 95?
- 24 possible ways this happens!
- There are 4 possible combinations that produce a regression with an \mathbb{R}^2 that is greater than or equal to our actual data.

$$\frac{4}{24} = \frac{1}{6} = 16.67\%$$

Permutations vs. Target Shuffling

4 possible test grades:

$$4! = 24$$

• 40 possible test grades:

$$40! = 8.16 \times 10^{47}$$

Permutations vs. Target Shuffling

4 possible test grades:

$$4! = 24$$

40 possible test grades:

$$40! = 8.16 \times 10^{47}$$

NEED TO SAMPLE!!!

Student Grade Example

```
x <- c(75, 85, 87, 95)

y.all <- data.frame(t(permutations(4,4,x)), input = 1:4)

my_lms <- lapply(1:24, function(x) lm(y.all[,x] ~ y.all$input))
summaries <- lapply(my_lms, summary)
rsq <- sapply(summaries, function(x) c(r_sq = x$r.squared))</pre>
```

