# THEORY AND MODEL ASSESSMENT THROUGH SIMULATION

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# THEORY ASSESSMENT

#### 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 – SAS

```
data CLT;
    do sim = 1 to &Simulation Size;
         do obs = 1 to &Sample Size;
             call streaminit (12345);
             X1 = RAND('Normal', 2, 5);
             X2 = 5 + 100*RAND('Uniform');
             X3 = 3 + RAND('Exponential');
             output;
         end:
    end;
run;
proc means data=CLT noprint mean;
    var X1 X2 X3;
    by sim;
    output out=Means mean(X1 X2 X3) =
                      Mean X1 Mean X2 Mean X3;
run;
```

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#### Theory Assessment for CLT – R

```
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), nrow=simulation.size, ncol=sample.size,
byrow=TRUE)
Mean.X1 \leftarrow apply (X1, 1, mean)
Mean.X2 \leftarrow apply(X2, 1, mean)
Mean.X3 \leftarrow apply (X3,1,mean)
```



# 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	M	1		
34	F	0		

Age	Gender	Buy Product?	Y <sub>1</sub>	
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?	$Y_1$	<i>Y</i> <sub>2</sub>	
25	M	1	0	1	
31	F	0	1	1	
28	F	1	1	1	
42	M	0	0	0	
39	M	1	0	0	
34	F	0	1	0	

Age	Gender	Buy Product?	<i>Y</i> <sub>1</sub>	$Y_2$	
25	M	1	0	1	
31	F	0	1	1	
28	F	1	1	1	
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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.)

#### Misclassification Rate from each model!

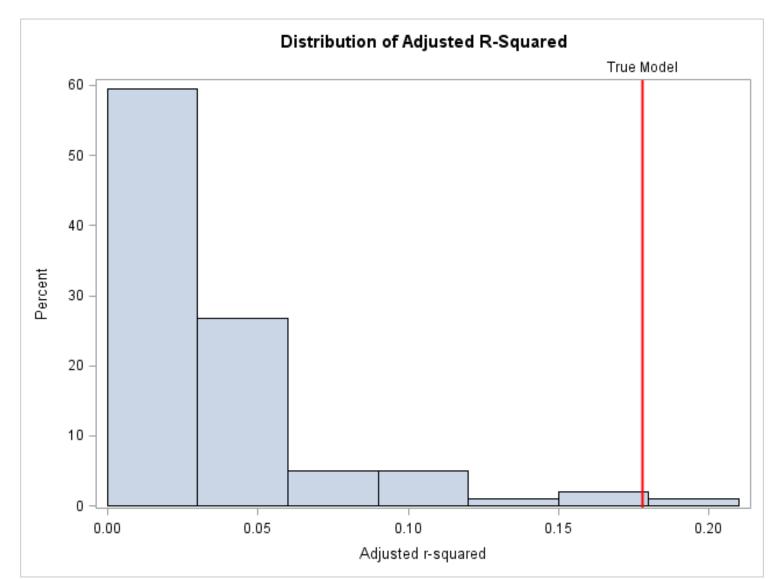
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#### Placebo Effect

- 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?



#### Fake Data Example

- 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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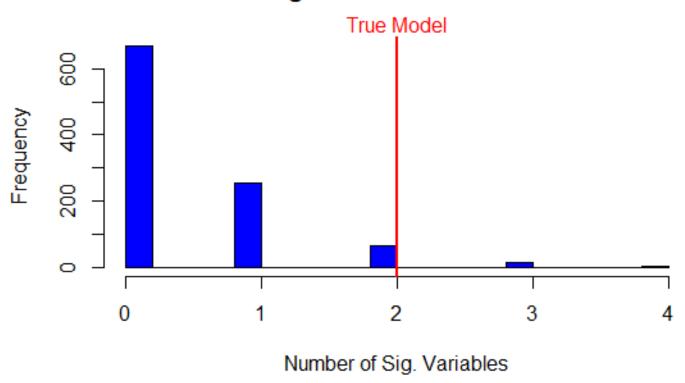
Performed target shuffle on the model.

#### 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

#### Target Shuffle with 1000 Simulations

#### Count of Significant Variables Per Model



#### Fake Data Example

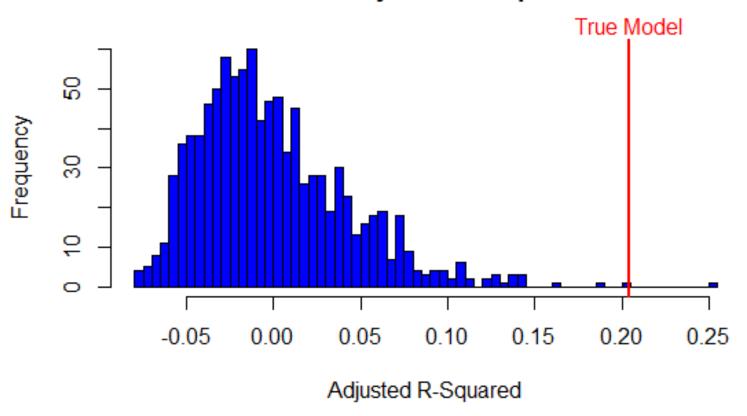
- Randomly generated 8 variables that follow a Normal distribution with mean of 0 and standard deviation of 8.
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Adjusted R<sup>2</sup> from this model: 0.204

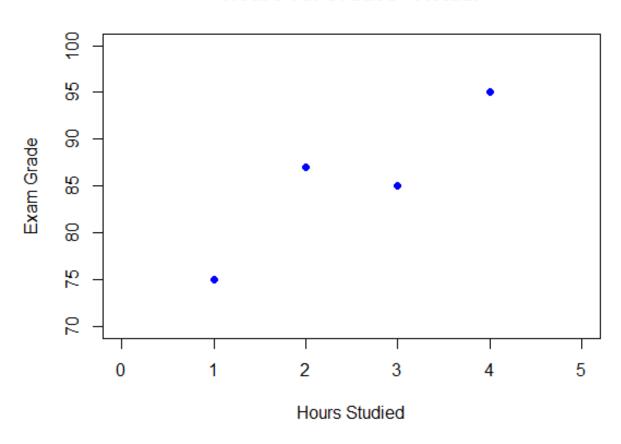
#### Target Shuffle with 1000 Simulations

#### Distribution of Adjusted R-Squared Values

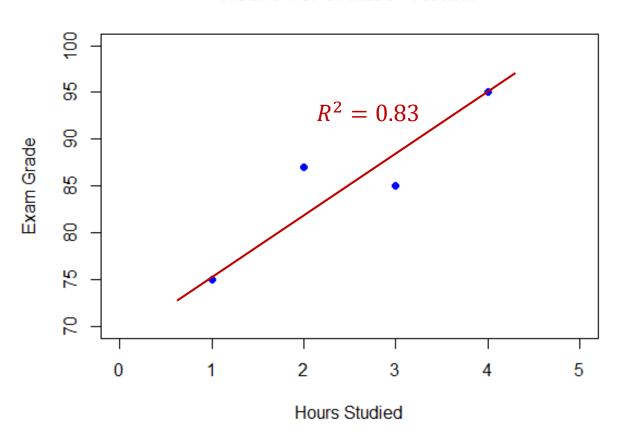




Hours vs. Grades - Actual



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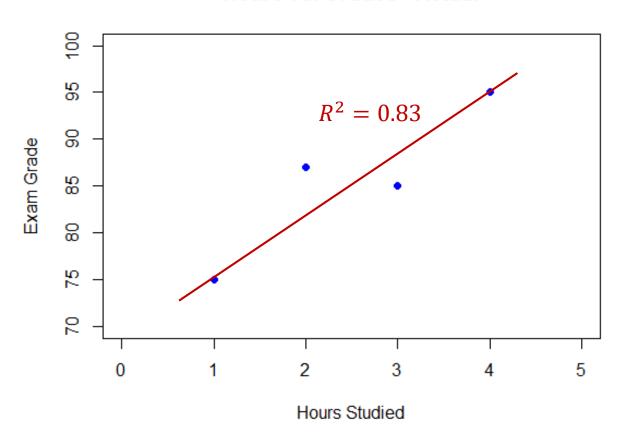
#### Permutations?

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

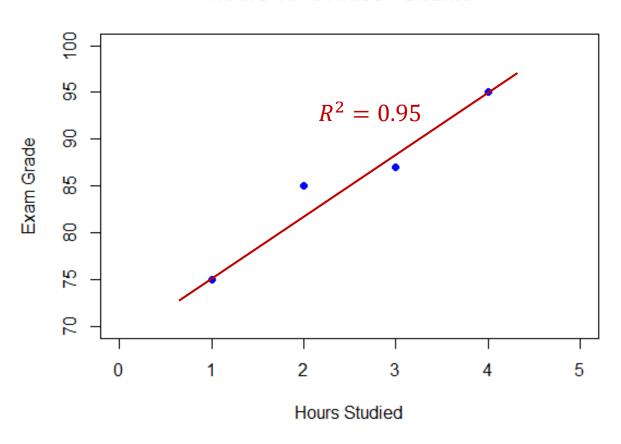
#### Permutations?

- How many different ways can four students get the grades
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- There are 3 possible combinations that produce a regression with an R<sup>2</sup> that is greater than or equal to our actual data.

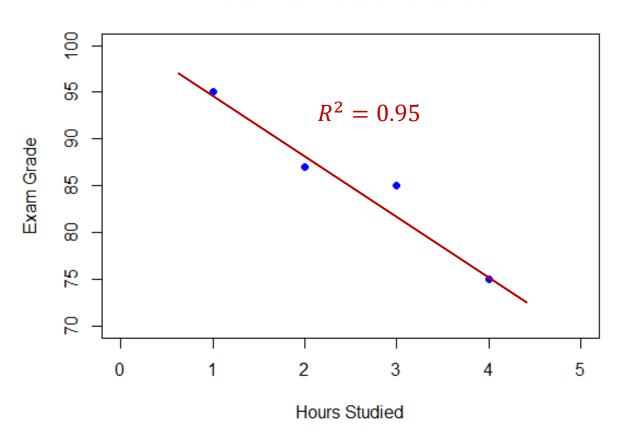
Hours vs. Grades - Actual



Hours vs. Grades - Shuffle 1



Hours vs. Grades - Shuffle 2



#### Permutations?

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   75, 85, 87, and 95?
- 24 possible ways this happens!
- There are 3 possible combinations that produce a regression with an R<sup>2</sup> 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:

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

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NEED TO SAMPLE!!!

