## TWO BIG IDEAS FOR TEACHING BIG DATA

Coincidence \& Confounding

## by

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www.StatLit.org/pdf/2014-Schield-eCOTS-Slides.pdf


## True Confession

I have been teaching introductory statistics for over two decades. I have a confession.



## \#1 Run of Heads

A common occurrence. Given enough tries, the unlikely is expected.


Flip coins in rows. 1=Heads (Red fill) Adjacent Red cells is a Run of heads.


Run of 4 heads: 1 chance in $\mathbf{2 N}^{\wedge} \mathbf{4}=1 / 16$
Run of 19 heads: 1 in $\mathbf{2 N 1}^{\wedge} 19=1 / 524,288$


## Consider a run of 10 heads? What is the chance of that?

Question is ambiguous! Doesn't state context!

1. Chance of 10 heads on the next $\mathbf{1 0}$ flips?
$\mathrm{p}=1 / 2 ; \mathrm{k}=10$.
$\mathrm{P}=\mathrm{p}^{\wedge \mathrm{k}}=(1 / 2)^{\wedge} 10=$ one chance in 1,024
2. What is the chance of at least one set of 10 heads [somewhere] when flipping 1,024 sets of 10 coins each? At least 50\%.*

* Schield (2012)




## Coincidence Outcomes

Students must "see" that coincidence -may be more common than expected -depends on the context -may be totally spurious

- may be a sign of causation

Quantitative form: Event: one chance in N. In N tries, one event is

Law of Very-Large Numbers


Second Big Idea: Confounding

As sample size increases,

- Margin of error decreases,
- Coincidence increases (becomes more likely)
- Confounding remains unchanged.

Big data doesn't minimize confounding.
If anything, Big Data gives unjustified support for confounder-spurious associations.


Modeling NAEP data
Based on 2001 NAEP Math 4 Scores

|  | Low\$ (0) | High\$ (1) | Total |
| :--- | :---: | :---: | :---: |
| Utah (0) | 209 | 234 | 2284 |
| Okla (1) | 218 | 244 | 224 |
| Total | $214 \longrightarrow 239$ | 226 |  |

\$ indicates student has low or high family income
Source: www.StatLit.org/pdf/2004TerwilligerSchieldAERA.pdf Data at www.StatLit.org/Excel/2014-Schield-eCOTS-Data.xls

Forecast with Confounder; Reversal is Incidental

Data based on 2001 NAEP $4^{\text {th }}$ Grade Math Scores. Compare Utah (0) and Oklahoma (1)

| Score $=228-4.5^{*}$ State |  |  | Score $=208.7+9.5 *$ State |  |
| :---: | :---: | :---: | :---: | :---: |
| Regression Statistics |  |  | + 25.0*Income |  |
| R Square | 0.02 | $\rightarrow$ Increase $\rightarrow$ | R Square | 0.42 |
| Standard Error | 16.23 ] |  | Standard Error | 12.48 |
| p-value (Intercept | 0.00 | Decrease | Pvalue (Intercept) | 0.00 |
| p-value (STATE) | 0.02 |  | p-value (STATE) | 0.00 |
| Observations | 300 |  | p-value (INCOME) | 0.00 |

Adding more factors typically improves the quality of the model


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> Explain with Confounder; Reversal is Essential
Based on 2001 NAEP 4th Grade Math Scores

|  | Low\$ (0) | High\$ (1) | Total | \%High\$ |
| :--- | :---: | :---: | :---: | :---: |
| Utah (0) | 209 | 234 | 228 | 228 |
| Okla (1) | 218 | $\mathbf{v}$ | 244 |  |

Causal Question:
Which State has the better education system?


Score $=208.7+9.5 *$ State $+25.0 *$ Income
Oklahoma (1) is better
Data at www.StatLit.org/Excel/2014-Schield-eCOTS-Data.xls


Teaching Confounding: Reasons To...
\#1: The Cornfield conditions ${ }^{1}$ set a minimum on the size confounder that can negate or reverse an association. Schield (1999). These conditions can offset excessive skepticism/cynicism.
\#2: When the predictor and confounder are binary, there are graphical techniques ${ }^{2}$ that allow students to work problems without software and without a second course in regression. Schield (2006)
This material has been taught for over 10 years.
\#1: Using Cornfield's Condition


Cornfield's condition: To reverse an association, the confounder must be bigger than the association.

## Conclusion

Many - if not most - big-data users want causal explanations (C.f., business intelligence). Modeling and prediction are just a means to this end.

To be relevant for these users of Big Data,

1. We must focus more on Coincidence \& Confounding. These are two big influences on many statistics. Our students deserve a broader education.
2. We must say more about causes than "Association is not Causation." We must introduce confounding, the Cornfield conditions and standardization.
\#2: Standardizing with binary predictor and confounder

For a step-by-step overview of this new graphical standardizing procedure:

- See Schield (2006).
-Listen to audio; view the slides.


Audio: www.statlit.org/Audio/2009StatLitText-Overview-Ch3.mp3
Slides: www.statlit.org/pdf/2009StatLitTextHandoutCh3.pdf

Q5. Business majors deal with causes. What fraction of a Business Statistics course should focus on coincidence and confounding?
$\qquad$ 0-5\%; $\qquad$ 5 -15\%; $\qquad$ 15-30\%30-50\% $\qquad$ At least half

Q6. If you taught Business Statistics, would you investigate an introductory textbook with a strong emphasis on coincidence and confounding?
$\qquad$ No way; $\qquad$ Conceivably; ___ Possibly; ___ Probably; $\qquad$ Almost certain.

## Questions 5 and 6

## Suggested Readings

1. Pearl, Judea (2000). Simpson’s Paradox: An Anatomy. http://bayes.cs.ucla.edu/R264.pdf
2. Pearl, Judea (2014). Understanding Simpson's Paradox. The American Statistician, 2/2014, V68, N1 http://ftp.cs.ucla.edu/pub/stat_ser/r414-reprint.pdf
3. Pearl, J. (2014). Statistics and Causality: Separated to Reunite. Commentary. Health Service Research. http://ftp.cs.ucla.edu/pub/stat_ser/r373-reprint.pdf
4. Gelman blog (2014). On Simpson's Paradox. http://andrewgelman.com/2014/02/09/keli-liu-xiao-li-meng-simpsons-paradox/

