VIB 2015 BANK LEGOTS BANK 1 Teaching Confounding: Part 1

Milo Schield, Augsburg University Fellow: American Statistical Association Member: International Statistical Institute US Rep: International Statistical Literacy Project President National Numeracy Network

USCOTS Workshop Online June 26, 2021 www.StatLit.org/pdf/2021-Schield-USCOTS-Slides.pdf Paper: www.StatLit.org/pdf/2021-Schield-USCOTS.pdf

Should We Teach Confounding? Four Questions

- 1. Who are our students and what kind of data and statistics do they deal with?
- 2. Why statistical ideas do they need?
- 3. What if we don't teach confounding?
- 4. Are we professionally negligent if we don't teach them about confounding and controlling for (taking into account) a confounder?



V0	2	021 Schield USCOTS	
Q1. W	'ho are	e our St	udents?
SAT	Perce	ntile By	y Major
	SAT MATH	PERCENTILE	MAJOR
Most teachers	613	80%	Math/Stats
80 th percentile	585	72%	Physical Sciences
· · · · · · · · · · · · · · · · · · ·	579	70%	Engineering
	554	62%	Comp. Science
	551	61%	Biological
	550	61%	Social Sciences
Most students:	522	51%	Business
51 st percentile	522	51%	English Lang/Lit
1	506	46%	History
	498	43%	Communication
	489	40%	Psychology
	482	38%	Education
	Business In	sider (2014), C	ollege Board (2015





Reasons We Should Teach Confounding

7

- 1. Who are our students? *Majors in Business, Econ, Social Sciences, Health, Psychology...*
- 2. What statistical ideas do they need? *Association, observational study, quasi-experiment, causation, confounding...*
- 3. What if we don't teach confounding? *Students* will treat association as evidence of causation. *E.g., social justice, gender justicie*
- 4. Are we professionally negligent if we don't teach our students what they need? *Absolutely!*

Six Reasons We Should NOT Teach Confounding

- 1. Statisticians got burned on causation: eugenics
- 2. Confounding is irrelevant with randomization
- 3. Confounding isn't statistics. Stats = variation
- 4. Confounding => multivariate and assumptions
- 5. Confounding course requires new FTE
- 6. Confounding creates statistical cynics







Galton proposed that mating be regulated so as to enhance the breeding stock of the human race.

- Fitter families for Future Firesides.
- Better breeding
- Sow just the good seed

If the goal is improvement and progress, then eugenics would not just ameliorate social problems – it would eradicate them! An irresistible allure!









Compartmentalization or hypocrisy?

Bottom line: Statistical educators should not 'touch' causation in observational studies.





* https://www.tandfonline.com/doi/full/10.1080/10691898.2016.1263493



Teaching Confounding: Part 1

Confounder-Based Statistical Literacy

19

Different: Less than a 30% overlap with traditional stats.

Quick overview of a confounder-based statistical literacy.

- 1. Statistical Literacy versus critical thinking?
- 2. Different kinds of association?

VO

- 3. Grammatical signs of association and causation?
- 4. Kinds of influences on a statistic?
- 5. Overlap between StatLit and traditional statistics?









ASSOCIATION (statistical)

Comparison (Two-groups)	Туре	Co-Variation (Two factors) As height increases, weight increase For each additional inch in height, weight increases by five pounds	
Women live longer than men	Ordered		
US women live five years (6.6%) longer than men.	Arithmetic		



Teaching Confounding: Part 1

V0	2021 Schield USCOTS	25
Disparity	' is not D iscrin	nination:
Stu	dy the Gramm	lar
	-	
Simple applica	tion of "Association is	not Causation"
Simple applied		not causation .
Compantier: Differe	near or Disposition are not increased	ihil Discrimination
A: Association	B: Between (moral)	C: Causation (moral)
Math Differences:	Descriptive Differences	Immoral Differences:
Count/Rate/Amount	with a Moral Connotation	Evaluative or Judgemental
different, unequal	unequal/inequality	inequity/inequitable
Rank: first, second, last	disproportionate	unfair/unjust/undeserved
Superlatives: highest/lowest	discriminate: discern difference	discriminate: with prejudice
Comparatives: more, higher,	disparity / disparate impact	discrimination*
times as much, percent more	over/under represented	racism/sexism
* Discrimination: direct/intended (rad	ist/sexist) vs indirect/unintended; individua	l vs social (systemic or structural)
Based on common usage by many	today, but not "etched in stone" for all	v
based on common usage by many	today, but not exched in stone for all	•



Confounded/confounding: Confused, confusing Confounder: Found with, that which confuses

Confounder: A 3rd factor that is related to an association, that causes the outcome and is not caused by the predictor.

Controlling for the influence of a confounder can:

- · Reverse an association
- · Nullify an association
- Decrease but not nullify or reverse an association
- Increase an association

V0	2021 Schield USCOTS	27
	CARE:	
	Confounding	
 Not listed in "possible con 	McKenzie's 2004 survey or re concepts" in statistics eo	of 30 ducation.
 Not listed in Featured in I between smoother 	index of most intro statist Fisher-Cornfield debate on king and lung cancer. Co	ics textbooks association rnfield (1958)
 "Confoundin in learning fi 	g and variations are two n rom data". Tintle, Cobb, et	najor obstacles tc. (2013)

• Can be visually demonstrated. Wainer (2003).







4

Teaching Confounding: Part 2

Milo Schield, Augsburg University Fellow: American Statistical Association Member: International Statistical Institute US Rep: International Statistical Literacy Project President National Numeracy Network

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GAISE 2016 Add Multivariable Thinking

- · give "students experience with multivariable thinking"
- understand "the possible impact of ... confounding"
- See how "a third variable can change our understanding"
- Help students "identify observational studies"
- · teach multivariate thinking "in stages" and
- use "simple approaches (such as stratification)"

This change is HUGE! It may be the biggest content change since dropping combinations in the 1980s.

GAISE 2016 Appendix B: Observational Data

3

5

VO

V0

Multivariable thinking is critical to make sense of the *observational data* around us. The real world is complex and can't be described well by one or two variables. [Italics added]

Multivariable Thinking

2016 GAISE Appendix B: Closing Thoughts (1)

"Multivariable thinking is critical to make sense of the observational data around us. This type of thinking might be introduced in stages":

1. Learn to identify observational studies

VO

- 2. Why randomized assignment ... improves things
- 3. Wary: cause-effect conclusions from observational data
- 4. Consider and explain -- confounding factors
- 5. Simple approaches (stratification) to show confounding

http://www.amstat.org/education/gaise/collegeupdate/GAISE2016_DRAFT.pdf

2016 GAISE Appendix B Closing Thoughts (2)

"If students do not have exposure to simple tools for disentangling complex relationships, they may dismiss statistics as an old-school discipline only suitable for small sample inference of randomized studies."

"This report recommends that students be introduced to multivariable thinking, preferably early in the introductory course and not as an afterthought at the end of the course."







Scottish Hill Races (Time in seconds) Response variable is: Women's Record	
Response variable is: Women's Record	
R squared = 85.2% R squared (adjusted) = 84.9% s = 1126 with 70-2 = 68 degrees of freedom	
Variable Coefficient SE(Coeff) t-ratio	P-value
Intercept 320.528 222.2 1.44	0.1537
Climb 1.755 0.088 19.8	< 0.0001

V0		2016 IASE-2		10
	#3 Show	Multiva	ariate:	
Re	gression	X1-X 2	-Y Outpu	ut
Scottish H	ill Races (Tim	ie in second	ls)	
Response var	riable is: Wo	omen's Recor	d	
R squared =	97.5% R so	quared (adju	sted) = 97.4%	6
s = 468.0 v	vith 70 - 3 =	67 degrees	of freedom	
Variable	Coefficient	SE(Coeff)	t-ratio	P-value
Intercept	-497.656	102.8	-4.84	< 0.0001
Distance	387.628	21.45	18.1	< 0.0001
Climb	0.852	>0.0621	13.7	< 0.0001
Controlling	o for Distance	decreases C	limb coeffici	ent
from 1 755	$t_0 = 0.852$ incr	eases \mathbb{R}^2 from	m 85% to 97	0/2
110111./33	0.052, 110	Cases Nº 110	111 05 /0 10 9 /	/0.

Problems with these Three Techniques

- 1. Do these visualizations "explain" confounding?
- 2. Can students use these to work problems with numerical answers?
- 3. Will this be on the final?

V0

If all three answers are "No", teachers are unlikely to spend much time showing multivariable thinking on observational data. The GAISE 2016 update may be DOA: Dead on Arrival ☺

Today's students want to engage in social issues

Most social issues involve social statistics: counts and ratios (averages, percents & rates)

- Most ratio (per) statistics are still *crude statistics*: they don't take anything else into account.
- To really understand 'per' statistics, students need to see how to *control for per confounders*.
- Students get engaged in "seeing" there may be "a *story behind the statistics*".

11

V1

12







V1 2016 BARLAND STAND 16 Confounder Solutions: Effect Size and Study Design				
_	CONTROL OF	CON	FOUNDERS	
	Physical Control	(Gr	ade = Quality)	
Experiment		Oł	oservational Study	
A+	Scientific	С	Longitudinal	
A-	Random Assign	D	Cross-sectional	
B	Quasi-Exper	F	Anecdotal story	

V1 "Taking into Account": "Controlling FOR": Mental

Computer methods: Powerful, but may obscure.

Manual methods are easy to do (weighted average) and can "show" students the key ideas (graphical).

	CONTROLLING	F	OR	CONFOUNDERS
	Take into a	c	co	unt (mental)
	Can do by hand			Calculator/Computer
1	Select/Stratify		4	Linear Regression
2	Form Ratios		5	Logistic Regression
3	Standardize		6	Multivariate Regress

18 **Standardizing Ratios:** MV Analysis w/o Software

Standardizing converts a crude comparison* of averages, rates or percents into a adjusted comparison.

* a mixed fruit -- apples and oranges -- comparison

Standardizing adjusts the weights: the mix!

Standardizing with a binary confounder can be:

- · Algebraic: categorical predictor
- · Graphical: binary predictor

V1

17

V1	2021 Schield US	COTS Slides2	19
H	ospital De	eath Rate	es:
	crude coi	npariso	
	Mixed-fruit Co	omparison	
Patients' D	eath Rate (Mix:	Percentage in th	nis condition)
Hospital	Good Cond.	Poor Cond.	All
City	1% (10%)	6% (90%)	5.5%
Rural	3% (70%)	7% (30%)	4.2%
All: City	= 0.1*1% + 0	1.3 points	
All: Rural	= 0.7*3% + 0	0.3*7%	City higher

Combined Mix: Algebra #2A: Adjust All Mixes to Combined
Standardized (adjusted) for patient mix.
Match City & Rural Mixes to Combined Mix: 70%

2021 Schield LISCOTS Sides

V1

Patients' D	eath Rate (Mix:	Percentage in th	is condition)
Hospital	Good Cond.	Poor Cond.	All
City	1% (30%)	6% (70%)	4.5%
Rural	3% (30%)	7% (70%)	5.8%
All: City	= 0.3*1% + 0).7*6%	-1.3 pts
All: Rural	= 0.3*3% + 0).7*7%	City lower











68% of black is <i>explain</i>	-white fa ned by fai	amily incom mily struct	ne gap ure
Controlling for	Crude	Adjusted	
Marital Status	Before	After	Change
Whites	55K	53K	-2K
Blacks	33K	45K	+12K
BW Income Gan	22K	8K	-15K

V1

2021 Schield USCOTS Slides2 **Family Income Gap:** "Explained by"

V1

V1

27

20

If 68% of black-white family income gap is explained by family structure, doesn't this prove that most of the black-white income gap is NOT due to racism?

How would you answer this???

28 2021 Schield LISCOTS Sides2 **Teaching Social Statistics** Is Our Job

Our students want to understand social inequalities and inequities;

Our students want to understand social disparities and discrimination.

One side quotes a crude comparison. The other sides says "BS" (bad statistics).

This 'conversation' is not socially productive.

2021 School LISCOTS Sides2 **Statistical Educators** can make a Big Difference

By teaching confounding, statistical educators may be able to improve • the quality of the arguments

- the quality of the critical thinking, and
- the quality of our social and political life.

If you really want to make a difference, think about teaching a confounder-based statistical literacy course.

V1B

2

4

6

Teaching Confounding: Part 3: UNM and Cornfield

Milo Schield, Augsburg University Fellow: American Statistical Association Member: International Statistical Institute US Rep: International Statistical Literacy Project President National Numeracy Network

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Another Reason: Can't field a second course

• Lack of sections (FTE limit)

University of New Mexico (Albuquerque) is offering MATH 1300: Statistical Literacy.

UNM is using sections normally allocated to the traditional statistical inference course: MATH 1350 Introductory Statistics.



- Math 1350 Introductory statistical inference. UNM offers ~20 sections (35 max) in ABQ.
- 2. Dr. Erik Erhardt (above left) looked for an updated complement to Math 1350.
- 3. Dean Peceny (above right) provided funds.
- 4. After interviewing several candidates, the committee choose Schield to implement his statistical literacy course.



V1B

Getting Course Approved

Getting a new course approved at a large public university is not a simple matter. Dr. Erhardt supervised the process.

This new statistical literacy course needed to satisfy a mathematics requirement:

- in the university core curriculum.
- in the state higher-education general education curriculum.

Getting Course Approved

Registrar:

- 1. New course request (Form B)
- 2. Catalog description
- 3. Sample syllabus

University of New Mexico (ABQ)

- 1. New course signoff
- 2. Budgetary load implications



Getting Course Approved

New Mexico Higher Education Department

- 1. Add Common Course Number (CCN)
- 2. Student Learning Outcomes (SLOs)

NM Higher Education General Education

- 1. Add a course to Gen Ed curriculum
- 2. Goals and Student Learning Outcomes
- 3. Assess Student Learning Outcomes
- 4. Sample Assessment

5

12





- Write a short response
- No free riders and anonymous
- Grading by instructor and peers

Odyssey: A Journey to Life-Long Statistical Literacy www.statlit.org/pdf/2014-Schield-ICOTS.pdf

Course Component #2: Moodle Exercises: 30% of grade

Multiple choice exercises

- 8-12 exercises per chapter.
- One topic per exercise; 5-10 questions each.
- Two tries (if more than 2 choices)
- Immediate feedback

One-line essay exercises:

• Describe and compare counts, averages and percentages presented in tables and graphs.

Course Component #3: Confounder StatLit Textbook

1: Statistical literacy: Take CARE

V1B

V1B

- 2: Comparisons and CARE remedies
- 3: Measurements and Standardization
- 4: Percent and Percentage Grammar
- 5: Rate and Chance Grammar. Social statistics
- 6: Comparisons Using Likely Grammar
- 7: Difficult Ratios and Cornfield Conditions
- 8: Influences on Statistical Significance

Course Component #4: Quizzes and Final: 50% of grade

Two, three or four chapter quizzes

- Chapters 1 and 2
- Chapters 3 and 4
- Chapters 4, 5 and 6
- Chapters 7 and 8
- **Final: Comprehensive**
- Read data in government documents.

Teacher Training A New Prep!!!

Less than a 30% overlap between confounderbased StatLit and traditional intro. Statistics. Recommendations:

- 1. Study Schield papers and StatLit textbook.
- 2. Introduce in last weeks of inference course.
- 3. Read articles in the everyday media
- 4. Analyze news stories in class.
- 5. Teach as a topics course

V1E

V1B

16

18

Another Problem: Statistical Cynics

13

Student: You convinced me: Never trust a statistic! Even if it is not influenced by assembly, randomness, error or bias, it could be confounded! Confounding can affect statistical significance.

Our goal is not to create statistical cynics. Our goal is to help students be critical thinkers! How can we do this?



Does smoking cause cancer? Sir Ronald Fisher (1950s):

Fisher was pre-eminent statistician of that time!

He noted that association is not causation!

Fisher, a smoker, provided data showing a correlation between twinship (fraternal vs. identical) and smoking preference.

Fisher's data supported the claim that genetics could be a cause of smoking and lung cancer.

Who would think of confronting Fisher?

Cornfield Conditions Jerome Cornfield

There is no test for confounding!

V1B

Cornfield proved a necessary condition for a confounder **to nullify** an observed association.

"Cornfield's minimum effect size is as important to observational studies as is the use of random assignment to experimental studies." Schield (1999) Simpson's Paradox & the Cornfield Conditions www.statlit.org/pdf/1999SchieldASA.pdf

Three Greatest Contributions of Statistics to Human Knowledge

- 1. Standard error: Error expected in random samples between parameter and statistic.
- 2. Random assignment: statistically controls pre-existing confounders. Fisher (1930)
- 3. Cornfield conditions: Conditions necessary for a confounder to nullify or reverse an observed association. Cornfield (1958)

Patient Condition: Good versus Poor Patients' Death Rate Hospital Good Cond. Poor Cond. ALL 1%↓ 6%↓ City 5.5% Rural 3% 7% 4.2%↓ 2.75% 6.25% ALL 4.85% * 1.6 pts more likely to die at City (5.5) than Rural (4.2)

ASA TC 2013

1.0 pts more interval to the at entry (5.5) than real (1.2)

Good condition: walked in. Poor condition: carried in. * 3.7 pts more likely to die if Poor (6.25) than Good (2.75)

3.7 points > 1.6 points. So Cornfield #1 is satisfied.

Cornfield Condition for Nullification or Reversal

19

V1E

An association is nullified or reversed only if

- confounder (patient condition) has a stronger association with the outcome (death) than does the predictor (hospital).
- predictor (hospital) has a stronger association with the confounder (patient condition) than with the outcome (death).



How does Confounding Interact with Statistical Significance?

Statistical educators know that a statisticallysignificant difference in observational data can become statistically insignificant after controlling for a related factor.

But our students never see this.

This is statistical negligence!

Here is how it is shown in statistical literacy.





VIB 2014 BOUND LIGGGTS BOUND 24 Meaning of Statistically Significant

If a sample outcome is statistically significant, what does this mean?

- 1. Outcome is very unlikely IF* due to chance
- 2. Outcome is very unlikely due to chance
- 3. Outcome is very unlikely TO BE due to chance
- #1 is accurate (* given or assuming)
- #3 is wrong: opens the door to causation.
- #2 is in-between and ambiguous.

Why We Should Teach Statistical Literacy

25

V1B

1. Most students need it, see value in it.

V1B

- 2. Separating stats from math has benefits
- 3. Link statistics to critical thinking (rhetoric)
- 4. Can show influence of confounding, assembly and bias on statistical significance
- 5. Can show the story behind the statistics
- 6. Cornfield conditions offset cynicism
- 7. Can improve debate on social issues

Schield Resources

Read papers: www.StatLit.org/Schield-Pubs.htm

Buy textbook: Wiley to publish in 2022.

Teaching Confounding: Part 1

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Q1. Who are our Students? By School



Q1. Who are our Students? SAT Percentile By Major

	SAT MATH	PERCENTILE	MAJOR	
Most teachers	613	80%	Math/Stats	
80 th percentile	585	72%	Physical Sciences	
	579	70%	Engineering	
	554	62%	Comp. Science	
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	506	46%	History	
	498	43%	Communication	
	489	40%	Psychology	
	482	38%	Education	
	Business Insider (2014), College Board (2015)			

Students Taking Intro Stats at US Four-Year Colleges

Based on their majors, 57% of four-year college students take introductory statistics: statistical inference.

US Students tal	king College St	atistics by	/ Major	
Business/Econ	Sociology /SocWork	Health	Pysch	Bio
40%	<mark>20</mark> %	18 %	12%	10 %

Most college students taking introductory statistics (inference) deal mainly with observational studies.

Harvard Business Review: Search 40K Papers: Title, Abstract

#	INFERENTIAL	1077	CONTR	OL/CONFOUND
22	"clinical trial" 18	10X	2,263	control
7	"statistical significance"	-	234	"control of" 200
4	"statistically significant"	-	113	"take (ing) into account"
3	"standard error"		30	"compensate (ing) for"
1	"sampling error"	-	19	"control (ed, ing) for"
1	"margin of error"	-	18	confound (er, ing)
1	"prediction interval"	-	17	"adjust(ed, ing) for"
1	p-value		3	"sampling bias"
0	"sampling distribution"		0	"alternate explanation"
0	"confidence interval"		0	"common cause"
0	"null hypothesis"		0	"effect modifier"
0	"reject the null"		0	"Simpson's paradox"
0	"random assignment"		0	"lurking variable"

Reasons We Should Teach Confounding

- 1. Who are our students? *Majors in Business, Econ, Social Sciences, Health, Psychology...*
- 2. What statistical ideas do they need? *Association, observational study, quasi-experiment, causation, confounding...*
- 3. What if we don't teach confounding? Students will treat association as evidence of causation.
 E.g., social justice, gender justicie
- 4. Are we professionally negligent if we don't teach our students what they need? *Absolutely!*

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- 1. Statisticians got burned on causation: eugenics
- 2. Confounding is irrelevant with randomization
- 3. Confounding isn't statistics. Stats = variation
- 4. Confounding => multivariate and assumptions
- 5. Confounding course requires new FTE
- 6. Confounding creates statistical cynics

1834: Allis Exterendum



To be threshed out by others

1883: Galton coined Eugenics



https://www.nature.com/articles/s41437-020-00394-6.

1907: Eugenics Society Formed

Galton proposed that mating be regulated so as to enhance the breeding stock of the human race.

- Fitter families for Future Firesides.
- Better breeding
- Sow just the good seed

If the goal is improvement and progress, then eugenics would not just ameliorate social problems – it would eradicate them! An irresistible allure!

Karl Pearson

Galton's chair in Eugenics. Scientific racism?

Imperialism justified by nature: Social Darwinism



12

- 1896: Created correlation coefficient
- 1900: Created chi-squared test. Start of Math-Stats!

1911: Causation: another fetish among the inscrutable arcana of ... modern science.

1912: Fisher (21): Steward at International Eugenics Conf.

1914: "Some hopes of a Eugenist"

1935: *Design of Experiments* Null hypothesis; random assignments

1938: "Pay mothers for A1 babies"



https://www.adelaide.edu.au/library/special/ exhibitions/significant-life-fisher/eugenics/

Correlation vs Causation Google nGrams



Conclusion by early Statistical Educators

Many of statistics' founders flirted with eugenics as a causal solution to social problems.

Compartmentalization or hypocrisy?

Bottom line: Statistical educators should not 'touch' causation in observational studies.

Association vs. Causation What about Confounding?



Teaching Statistics

We teach the **wrong things** in the **wrong way** in the **wrong order**. Richard de Veaux*

Consider teaching "Association is not causation"

- 1973 Berkeley sex discrimination case
- Ice cream sales and burglaries

Problem: These involve confounding – not chance. Students are exposed to confounding one time!

* https://www.tandfonline.com/doi/full/10.1080/10691898.2016.1263493

Confounder-Based Statistical Literacy

Literacy deals with arguments.

The point of the argument

The more disputable the point, the stronger the evidence must be

Statistics as Evidence

"All Statistics are Socially Constructed" So, "Take CARE"!! Statistics may be influenced

Confounder-Based Statistical Literacy

Different: Less than a 30% overlap with traditional stats.

Quick overview of a confounder-based statistical literacy.

- 1. Statistical Literacy versus critical thinking?
- 2. Different kinds of association?
- 3. Grammatical signs of association and causation?
- 4. Kinds of influences on a statistic?
- 5. Overlap between StatLit and traditional statistics?

Statistics: Socially Constructed; Are Influenced

Lots of influences on a given statistic.

Need to group these influences into three to five categories

CARE: Four kinds of influence on a statistic

- **C** Confounding: Influenced by related factors
- A Assembly: Influenced by other choices
- **R** Randomness: Influenced randomly by chance
- **E Error**: Influenced systematically (e.g, bias)

Take CARE: Good advice in life and in statistics!

Statistics Can Be Influenced


Separate Critical Thinking from Statistical Litearcy

Statisticians may use arguments involving causation (critical thinking) to illustrate statistical literacy.



Statisticians may argue for a causal explanation personally – but not as a statistician.

Introduce Association; Study Grammar!

Students have difficulty with statistical association. Technical definition: quantitatively-based connection Two group comparison versus two factor co-variation.

ASSOCIATION (statistical)

Comparison (Two-groups)	Туре	Co-Variation (Two factors)
Women live longer than men	Ordered	As height increases, weight increases
US women live five years	A rith motio	For each additional inch in height,
(6.6%) longer than men.	Antimetic	weight increases by five pounds

Association is Not Causation: Study Grammar

Semantics: Association is not [necessarily] Causation

A: Association	B: Between	C: Causation
Asserts an association;	Asserts an association	Asserts causation;
Says "what"	but suggest causation	Asserts "how" *
associated/association	increases, raises, ups; cut	cause, create, produce
correlation	"As x \uparrow , y \downarrow "; "more x, less y"	effect, result, consequence
Two-group comparisons:	before/after; linked, factor	Sufficient: prevent, stop
"Women live longer than men"	leads to; causal factor	"If X, then Y will happen"
"Men more likely to drink beer"	due to, because of	Contra-factual

Based on common usage by many today, but not "etched in stone" for all.

 $\ensuremath{^*}$ Other words OK in context. Schield V0K

Disparity is not Discrimination: Study the Grammar

Simple application of "Association is not Causation".

A: Association	B: Between (moral)	C: Causation (moral)
Math Differences:	Descriptive Differences	Immoral Differences:
Count/Rate/Amount	with a Moral Connotation	Evaluative or Judgemental
different, unequal	unequal/inequality	inequity/inequitable
Rank: first, second, last	disproportionate	unfair/unjust/undeserved
Superlatives: highest/lowest	discriminate: discern difference	discriminate: with prejudice
Comparatives: more, higher,	disparity / disparate impact	discrimination*
times as much, percent more	over/under represented	racism/sexism

Semantics: Differences or Disparities are not [necessarily] Discrimination

* Discrimination: direct/intended (racist/sexist) vs indirect/unintended; individual vs social (systemic or structural) Based on common usage by many today, but not "etched in stone" for all.

CARE: Influence of Confounding

Confounded/confounding: Confused, confusing

Confounder: Found with, that which confuses

Confounder: A 3rd factor that is related to an association, that causes the outcome and is not caused by the predictor.

Controlling for the influence of a confounder can:

- Reverse an association
- Nullify an association
- Decrease but not nullify or reverse an association
- Increase an association

CARE: Confounding

- Not listed in McKenzie's 2004 survey of 30 "possible core concepts" in statistics education.
- Not listed in index of most intro statistics textbooks
- Featured in Fisher-Cornfield debate on association between smoking and lung cancer. Cornfield (1958)
- "Confounding and variations are two major obstacles in learning from data". Tintle, Cobb, etc. (2013)
- Can be visually demonstrated. Wainer (2003).

V0

CARE: Influence of Assembly

How they were collected, defined, grouped, summarized, compared and presented.

The context in which things are counted or measured Small change in syntax; big change in semantics!

- Popes have above-average lifespan
- 90% of shoppers* say Costco is a good place to shop!
 * 1,024 shoppers interviewed outside Costco

CARE: Influence of Randomness

CARE: RANDOM

Extremes	Big Data	Small Samples
Sports Illustrated	Lottery, Words	Galton board
Pilot performance	Runs, Patterns	Sample size
Pre-vs-post	Birthday match	Small classes





CARE: Influence of Error (Bias)

Includes "confusion of the inverse"

CARE: ERROR

Wrong Order	Bias	Lies
Subtract, Divide	Subject	Mistakes
Comparisons	Measurement	Prevarication
Ratios	Sampling	Weasel words

Teaching Confounding: Part 2

Milo Schield, Augsburg University

Fellow: American Statistical Association Member: International Statistical Institute US Rep: International Statistical Literacy Project President National Numeracy Network

USCOTS 2021 June 26, 2021

www.StatLit.org/pdf/2021-Schield-USCOTS-Slides.pdf
Paper: www.StatLit.org/pdf/2021-Schield-USCOTS.pdf

GAISE 2016 Add Multivariable Thinking

- give "students experience with multivariable thinking"
- understand "the possible impact of ... confounding"
- See how "a third variable can change our understanding"
- Help students "identify *observational studies*"
- teach multivariate thinking "in stages" and
- use "simple approaches (such as stratification)"

This change is HUGE! It may be the biggest content change since dropping combinations in the 1980s.

GAISE 2016 Appendix B: Observational Data

Multivariable thinking is critical to make sense of the *observational data* around us. The real world is complex and can't be described well by one or two variables. [Italics added]



2016 GAISE Appendix B: Closing Thoughts (1)

"Multivariable thinking is critical to make sense of the observational data around us. This type of thinking might be introduced in stages":

- 1. Learn to identify observational studies
- 2. Why randomized assignment ... improves things
- 3. Wary: cause-effect conclusions from observational data
- 4. Consider and explain -- confounding factors
- 5. Simple approaches (stratification) to show confounding

http://www.amstat.org/education/gaise/collegeupdate/GAISE2016_DRAFT.pdf

2016 GAISE Appendix B Closing Thoughts (2)

"If students do not have exposure to simple tools for disentangling complex relationships, they may dismiss statistics as an old-school discipline only suitable for small sample inference of randomized studies."

"This report recommends that students be introduced to multivariable thinking, preferably early in the introductory course and not as an afterthought at the end of the course."

Show Multivariable #1: Ekisogram

Show probabilities as areas:

Association of smoking and mortality



Smoking status

Comparing height and width: not compelling.

V0

Show Multivariable: #2: XY Plot (2 factors)



State Average SAT Score by Average Teacher Salary Series: Fraction of Students that took the SAT



#3 Show Multivariable Regression X-Y Output

Scottish Hill Races (Time in seconds)

Response variab R squared = 85. s = 1126 with	le is: Women's 2% R squared 70-2 = 68 degr	s Record d (adjusted) = rees of freedom	84.9% n	
Variable Intercept	Coefficient 320.528	SE(Coeff) 222.2	t-ratio 1.44	P-value 0.1537
Climb	1.755	> 0.088	19.8	< 0.0001

Assumes that all modelling assumptions are satisfied Assumes that all coefficients are statistically significant. http://www.scottishhillracing.co.uk/

#3 Show Multivariate: Regression X1-X2-Y Output

Scottish Hill Races (Time in seconds)

Response v	/ariable is:	Women's Recor	d	
R squared	= 97.5% R	squared (adju	sted) = 97.4%	
s = 468.0	with 70 - 3	= 67 degrees	of freedom	
Variable	Coefficien	t SE(Coeff)	t-ratio	P-value
Intercept	-497.656	102.8	-4.84	< 0.0001
Distance	387.628	21.45	18.1	< 0.0001
Climb	0.852	0.0621	13.7	< 0.0001

Controlling for Distance decreases Climb coefficient from 1.755 to 0.852; increases R^2 from 85% to 97%.

Problems with these Three Techniques

- 1. Do these visualizations "explain" confounding?
- 2. Can students use these to work problems with numerical answers?
- 3. Will this be on the final?

If all three answers are "No", teachers are unlikely to spend much time showing multivariable thinking on observational data. The GAISE 2016 update may be DOA: Dead on Arrival ⊗

Today's students want to engage in social issues

Most social issues involve social statistics: counts and ratios (averages, percents & rates)

- Most ratio (per) statistics are still *crude statistics*: they don't take anything else into account.
- To really understand 'per' statistics, students need to see how to *control for per confounders*.

Students get engaged in "seeing" there may be "a story behind the statistics".

Most Social Statistics are Observational Statistics

This is an opportunity for hypothetical thinking!



Observational Statistics: Covid19 Death Rates: RI vs CT

RI: lower per case (horiz), higher per capita (vert)



Compare Covid Death Rates: South Africa with Czechia

SA: lower per capita (horiz.); higher per case (vert.)



Confounder Solutions: Effect Size and Study Design

	CONTROL OF CONFOUNDERS				
Physical Control (Grade = Quality)					
Exp	periment		Ob	servational Study	
A+	Scientific		С	Longitudinal	
A-	Random Assign		D	Cross-sectional	
В	Quasi-Exper		F	Anecdotal story	

"Taking into Account": "Controlling FOR": Mental

Computer methods: Powerful, but may obscure.

Manual methods are easy to do (weighted average) and can "show" students the key ideas (graphical).

CONTROLLING FOR CONFOUNDERS				
Take into account (mental)				
	Can do by hand			Calculator/Computer
1	Select/Stratify		4	Linear Regression
2	Form Ratios		5	Logistic Regression
3	Standardize		6	Multivariate Regress

Standardizing Ratios: MV Analysis w/o Software

Standardizing converts a crude comparison* of averages, rates or percents into a adjusted comparison.

* a mixed fruit -- apples and oranges -- comparison

Standardizing adjusts the weights: the mix!

Standardizing with a binary confounder can be:

- Algebraic: categorical predictor
- Graphical: binary predictor

Hospital Death Rates: Crude Comparison

Mixed-fruit Comparison

Patients' Death Rate (Mix: Percentage in this condition)					
Hospital	Good Cond.	Poor Cond.	All		
City	1% (10%)	6% (90%)	5.5%		
Rural	3% (70%)	7% (30%)	4.2%		
All: City	= 0.1*1% + (1.3 points			
All: Rural	= 0.7*3% + (City higher			

Combined Mix: Algebra #2A: Adjust All Mixes to Combined

Standardized (adjusted) for patient mix.

Match City & Rural Mixes to Combined Mix: 70%					
Patients' De	eath Rate (Mix:	Percentage in th	is condition)		
Hospital	Good Cond.	Poor Cond.	All		
City	1% (30%)	6% (70%)	4.5%		
Rural	3% (30%)	7% (70%)	5.8%		
All: City	-1.3 pts				
All: Rural	City lower				

20

Combined Mix: Graph #2G: Adjust All Mixes to Combined



Combined Mix: Graph #2G: Adjust All Mixes to Combined



What about Race-Based Statistics?

Consider 1994 US family incomes by race:

- \$55K for white families
- \$33K for black families

This \$22K black-white income gap is HUGE. Could it be due to racism? Certainly.

Does this disparity

- demonstrate the influence of racism? Maybe
- prove discrimination (racism)? No

Family Income: White (55k) versus Black (33k)



Family Income Standardized: White (53k) versus Black (45k)



Family Income Gap: "Explained by"

68% of black-white family income gap is *explained* by family structure

Controlling for	Crude	Adjusted			
Marital Status	Before	After	Change		
Whites	55K	53K	-2K		
Blacks	33K	45K	+12K		
BW Income Gap	22K	8K	-15K		
Percentage of gap explained: 15K/22K = 68%					

Family Income Gap: "Explained by"

If 68% of black-white family income gap is explained by family structure, doesn't this prove that most of the black-white income gap is NOT due to racism?

How would you answer this???
Teaching Social Statistics Is Our Job

Our students want to understand social inequalities and inequities;

Our students want to understand social disparities and discrimination.

One side quotes a crude comparison. The other sides says "BS" (bad statistics).

This 'conversation' is not socially productive.

Statistical Educators can make a Big Difference

By teaching confounding, statistical educators may be able to improve

- the quality of the arguments
- the quality of the critical thinking, and
- the quality of our social and political life.

If you really want to make a difference, think about teaching a confounder-based statistical literacy course.

Teaching Confounding: Part 3: UNM and Cornfield

Milo Schield, Augsburg University

Fellow: American Statistical Association Member: International Statistical Institute US Rep: International Statistical Literacy Project President National Numeracy Network

USCOTS Workshop Online June 26, 2021

www.StatLit.org/pdf/2021-Schield-USCOTS-Slides.pdf Paper: www.StatLit.org/pdf/2021-Schield-USCOTS.pdf

Another Reason: Can't field a second course

• Lack of sections (FTE limit)

University of New Mexico (Albuquerque) is offering MATH 1300: Statistical Literacy.

UNM is using sections normally allocated to the traditional statistical inference course: MATH 1350 Introductory Statistics.



- 1. Math 1350 Introductory statistical inference. UNM offers ~20 sections (35 max) in ABQ.
- 2. Dr. Erik Erhardt (above left) looked for an updated complement to Math 1350.
- 3. Dean Peceny (above right) provided funds.
- 4. After interviewing several candidates, the committee choose Schield to implement his statistical literacy course.





Getting a new course approved at a large public university is not a simple matter. Dr. Erhardt supervised the process.

This new statistical literacy course needed to satisfy a mathematics requirement:

- in the university core curriculum.
- in the state higher-education general education curriculum.

Getting Course Approved

Registrar:

- 1. New course request (Form B)
- 2. Catalog description
- 3. Sample syllabus

University of New Mexico (ABQ)

- 1. New course signoff
- 2. Budgetary load implications



Getting Course Approved

New Mexico Higher Education Department

- 1. Add Common Course Number (CCN)
- 2. Student Learning Outcomes (SLOs)

NM Higher Education General Education

- 1. Add a course to Gen Ed curriculum
- 2. Goals and Student Learning Outcomes
- 3. Assess Student Learning Outcomes
- 4. Sample Assessment

UNM 2021-22 Catalog



Statistical Literacy



MATH 1300 (3)

Participants will study the social statistics encountered by consumers. Investigate the story behind the statistics. Study the influences on social statistics. Study the techniques used to control these influences. Strong focus on confounding.

Meets New Mexico General Education Curriculum Area 2: Mathematics and Statistics.

Course Component #1: Literacy Forum; 20% of grade

Online forum (Odyssey).

- Two challenges per week.
- Write a short response
- No free riders and anonymous
- Grading by instructor and peers

Odyssey: A Journey to Life-Long Statistical Literacy www.statlit.org/pdf/2014-Schield-ICOTS.pdf

Course Component #2: Moodle Exercises: 30% of grade

Multiple choice exercises

- 8-12 exercises per chapter.
- One topic per exercise; 5-10 questions each.
- Two tries (if more than 2 choices)
- Immediate feedback

One-line essay exercises:

• Describe and compare counts, averages and percentages presented in tables and graphs.

Course Component #3: Confounder StatLit Textbook

- 1: Statistical literacy: Take CARE
- 2: Comparisons and CARE remedies
- 3: Measurements and Standardization
- 4: Percent and Percentage Grammar
- 5: Rate and Chance Grammar. Social statistics
- 6: Comparisons Using Likely Grammar
- 7: Difficult Ratios and Cornfield Conditions
- 8: Influences on Statistical Significance

Course Component #4: Quizzes and Final: 50% of grade

Two, three or four chapter quizzes

- Chapters 1 and 2
- Chapters 3 and 4
- Chapters 4, 5 and 6
- Chapters 7 and 8

Final: Comprehensive

• Read data in government documents.

Teacher Training A New Prep!!!

Less than a 30% overlap between confounderbased StatLit and traditional intro. Statistics. Recommendations:

- 1. Study Schield papers and StatLit textbook.
- 2. Introduce in last weeks of inference course.
- 3. Read articles in the everyday media
- 4. Analyze news stories in class.
- 5. Teach as a topics course

Another Problem: Statistical Cynics

Student: You convinced me: Never trust a statistic! Even if it is not influenced by assembly, randomness, error or bias, it could be confounded! Confounding can affect statistical significance.

Our goal is not to create statistical cynics. Our goal is to help students be critical thinkers! How can we do this?

Association between smoking and lung cancer deaths (1960)



Does smoking cause cancer? Sir Ronald Fisher (1950s):

Fisher was pre-eminent statistician of that time! He noted that association is not causation! Fisher, a smoker, provided data showing a correlation between twinship (fraternal vs. identical) and smoking preference.

Fisher's data supported the claim that genetics could be a cause of smoking and lung cancer.

Who would think of confronting Fisher?

Cornfield Conditions Jerome Cornfield

There is no test for confounding! Cornfield proved a necessary condition for a confounder **to nullify** an observed association.

"Cornfield's minimum effect size is as important to observational studies as is the use of random assignment to experimental studies." Schield (1999) Simpson's Paradox & the Cornfield Conditions www.statlit.org/pdf/1999SchieldASA.pdf

Three Greatest Contributions of Statistics to Human Knowledge

- 1. Standard error: Error expected in random samples between parameter and statistic.
- 2. Random assignment: statistically controls pre-existing confounders. Fisher (1930)
- 3. Cornfield conditions: Conditions necessary for a confounder to nullify or reverse an observed association. Cornfield (1958)

Patient Condition: Good versus Poor

Patients' Death Rate			
Hospital	Good Cond.	Poor Cond.	ALL
City	1%↓	6%↓	5.5%
Rural	3%	7%	4.2%↓
ALL	2.75%	6.25%	4.85%

* 1.6 pts more likely to die at City (5.5) than Rural (4.2)

Good condition: walked in. Poor condition: carried in. * 3.7 pts more likely to die if Poor (6.25) than Good (2.75) 3.7 points > 1.6 points. So Cornfield #1 is satisfied.

Cornfield Condition for Nullification or Reversal

An association is nullified or reversed only if

- confounder (patient condition) has a stronger association with the outcome (death) than does the predictor (hospital).
- predictor (hospital) has a stronger association with the confounder (patient condition) than with the outcome (death).

Cornfield Condition for Nullification or Reversal



Condition: bigger death separation than Hospital. So Hospital-Death association could be reversed.

How does Confounding Interact with Statistical Significance?

Statistical educators know that a statisticallysignificant difference in observational data can become statistically insignificant after controlling for a related factor.

But our students never see this. This is statistical negligence! Here is how it is shown in statistical literacy.

Confounder Influence: Non-Overlap = Statistical Significance



Confounder Influence on Statistical Significance



Meaning of Statistically Significant

If a sample outcome is statistically significant, what does this mean?

- 1. Outcome is very unlikely IF* due to chance
- 2. Outcome is very unlikely due to chance
- 3. Outcome is very unlikely TO BE due to chance
 - #1 is accurate (* given or assuming)
 - #3 is wrong: opens the door to causation.
 - #2 is in-between and ambiguous.

Why We Should Teach Statistical Literacy

- 1. Most students need it, see value in it.
- 2. Separating stats from math has benefits
- 3. Link statistics to critical thinking (rhetoric)
- 4. Can show influence of confounding, assembly and bias on statistical significance
- 5. Can show the story behind the statistics
- 6. Cornfield conditions offset cynicism
- 7. Can improve debate on social issues

Schield Resources

Read papers: www.StatLit.org/Schield-Pubs.htm

Buy textbook: Wiley to publish in 2022.