Multivariate thinking and the introductory statistics and data science course: preparing students to make sense of observational data

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https://www.github.com/Amherst-Statistics/JSM2018

Thanks and acknowledgements

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- Sarah Anoke, Sonia Hernandez-Diaz, Miguel Hernan, Murray Mittelman, Brendan Seto, and Sonja Swanson for many useful suggestions, curricular models, and examples

Motivation

- Are we teaching what we should be teaching in our introductory statistics and data science courses?

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- OR do students leave our courses and programs with a form of observational data paralysis?
- Are we hiding the power of statistics behind our bushel basket?

Source: causal inference FB

- What evidence do we have that smoking causes lung cancer?

Source: causal inference FB

- While clinical trials are wonderful, we live in a world of 'found' data.
- "It is not that i believe an experiment is the only proper setting for discussing causality, but I do feel that it is the simplest such setting" - Holland (1986)

Teaching multivariate thinking and confounding

1. what are we currently teaching?

AP Statistics curriculum

Four broad themes:

1. Exploring Data: Describing patterns and departures from patterns
2. Sampling and Experimentation: Planning and conducting a study
3. Anticipating Patterns: Exploring random phenomena using probability and simulation
4. Statistical Inference: Estimating population parameters and testing hypotheses

AP Stats: Exploring data (20-30%)

1. Univariate graphics
2. Univariate summaries
3. Comparing univariate distributions
4. Exploring bivariate data
5. Exploring categorical data

AP Stats: Sampling and experimentation (10-15%)

1. Methods of data collection
2. Planning and conducting surveys
3. Planning and conducting experiments
4. Generalizability of results and types of conclusions

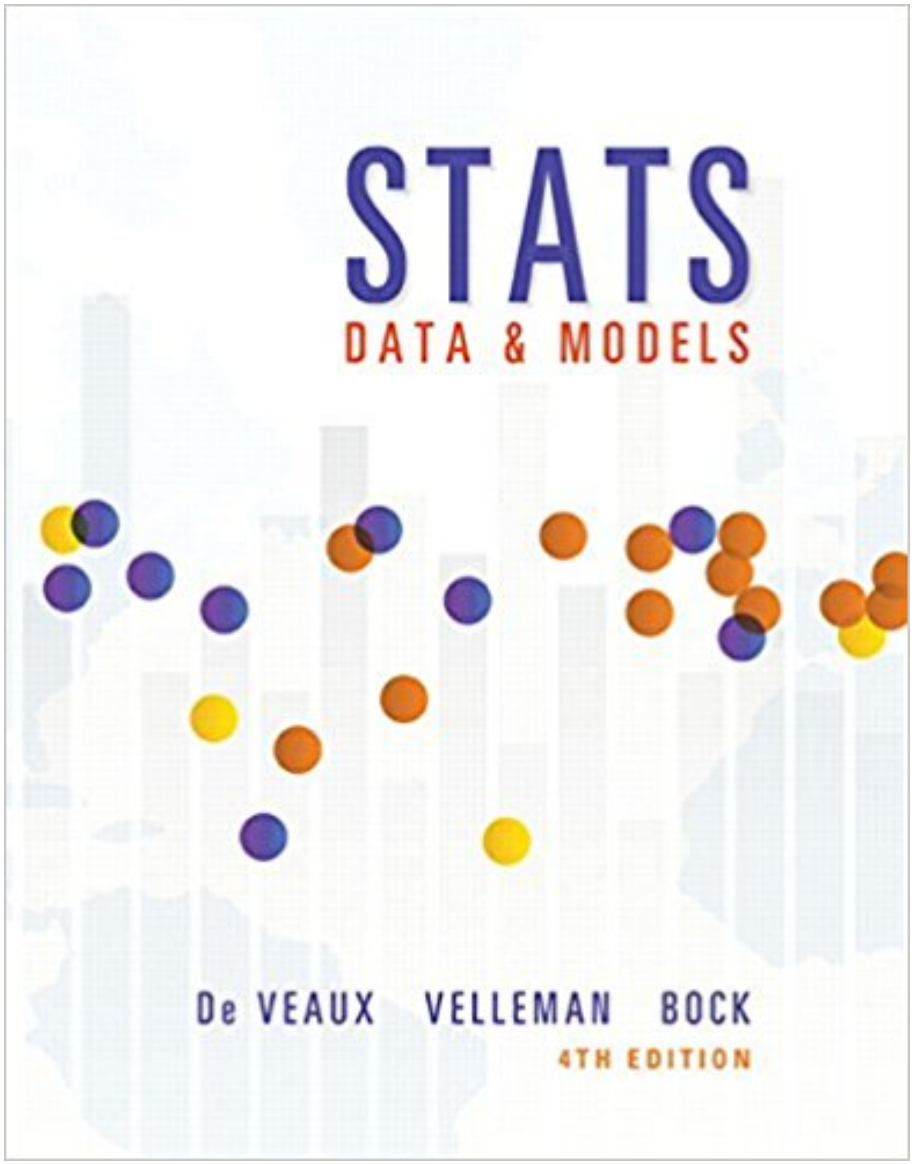
AP Stats: Anticipating patterns (20-30%)

1. Probability
2. Rules for random variables
3. Normal tables(!)
4. Sampling distributions
5. Other distributions (t, χ^2)

AP Stats: Statistical inference (30-40%)

1. Estimation (point estimators and confidence intervals)
2. Tests of significance

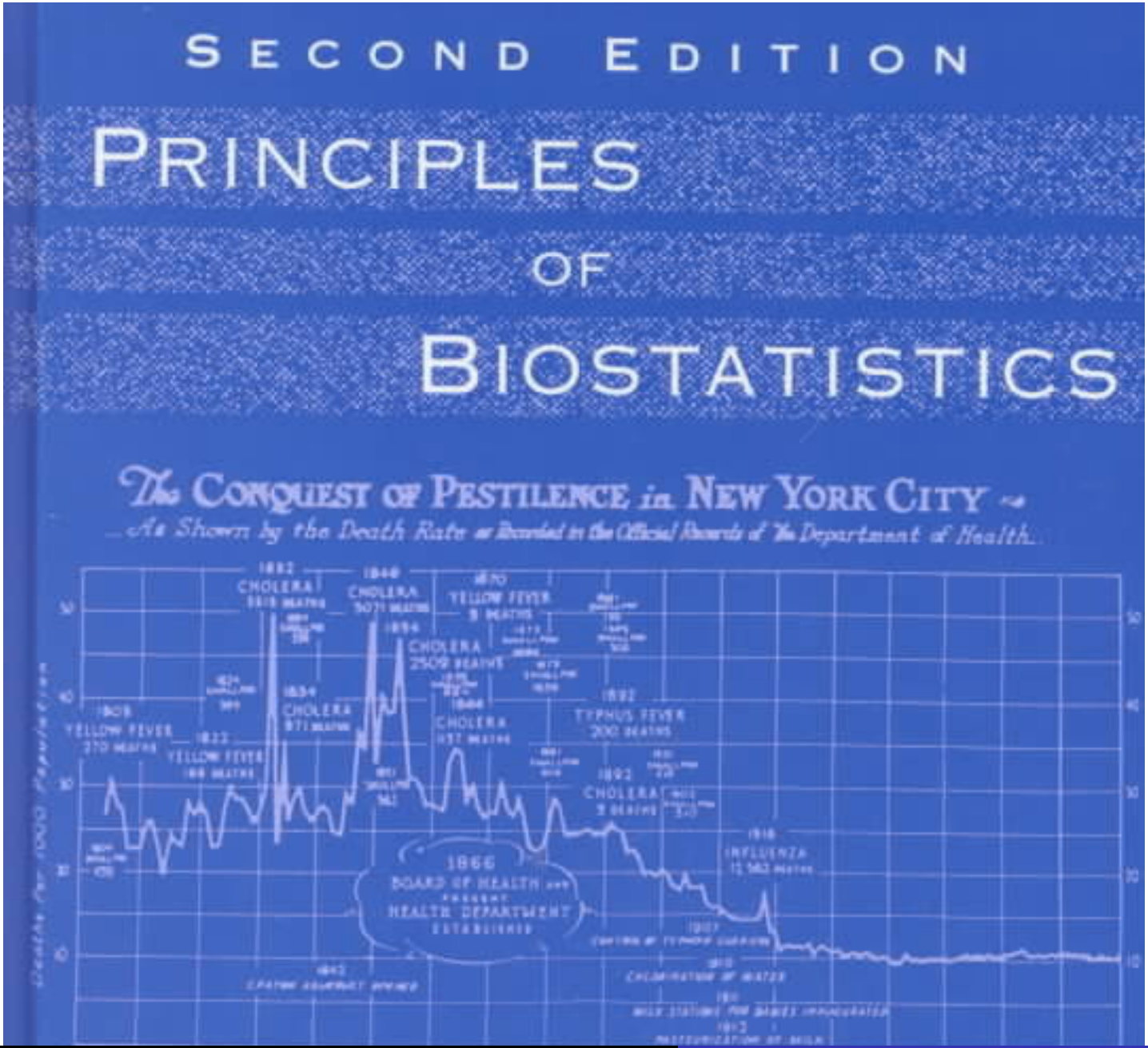
DeVeaux, Velleman, and Bock (SDM4)



DeVeaux, Velleman, and Bock (SDM4)

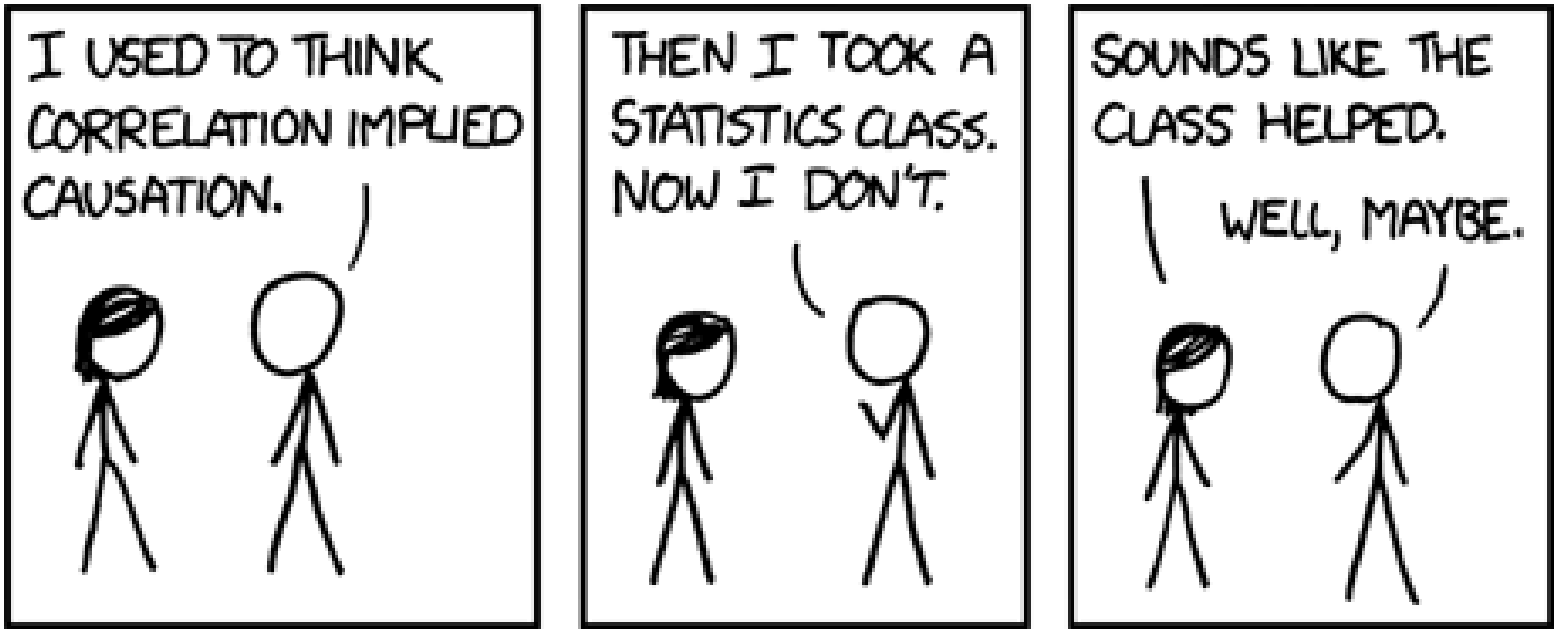
- Chapter 2: "When averages are taken across different groups, they can appear to contradict the overall averages. This is known as *Simpson's paradox*"
- Chapter 12: introduce confounding (in the context of clinical trials)
- Chapter 28 (page 817) multiple regression
- (material slated to appear earlier in future editions...)

Pagano and Gauvreau

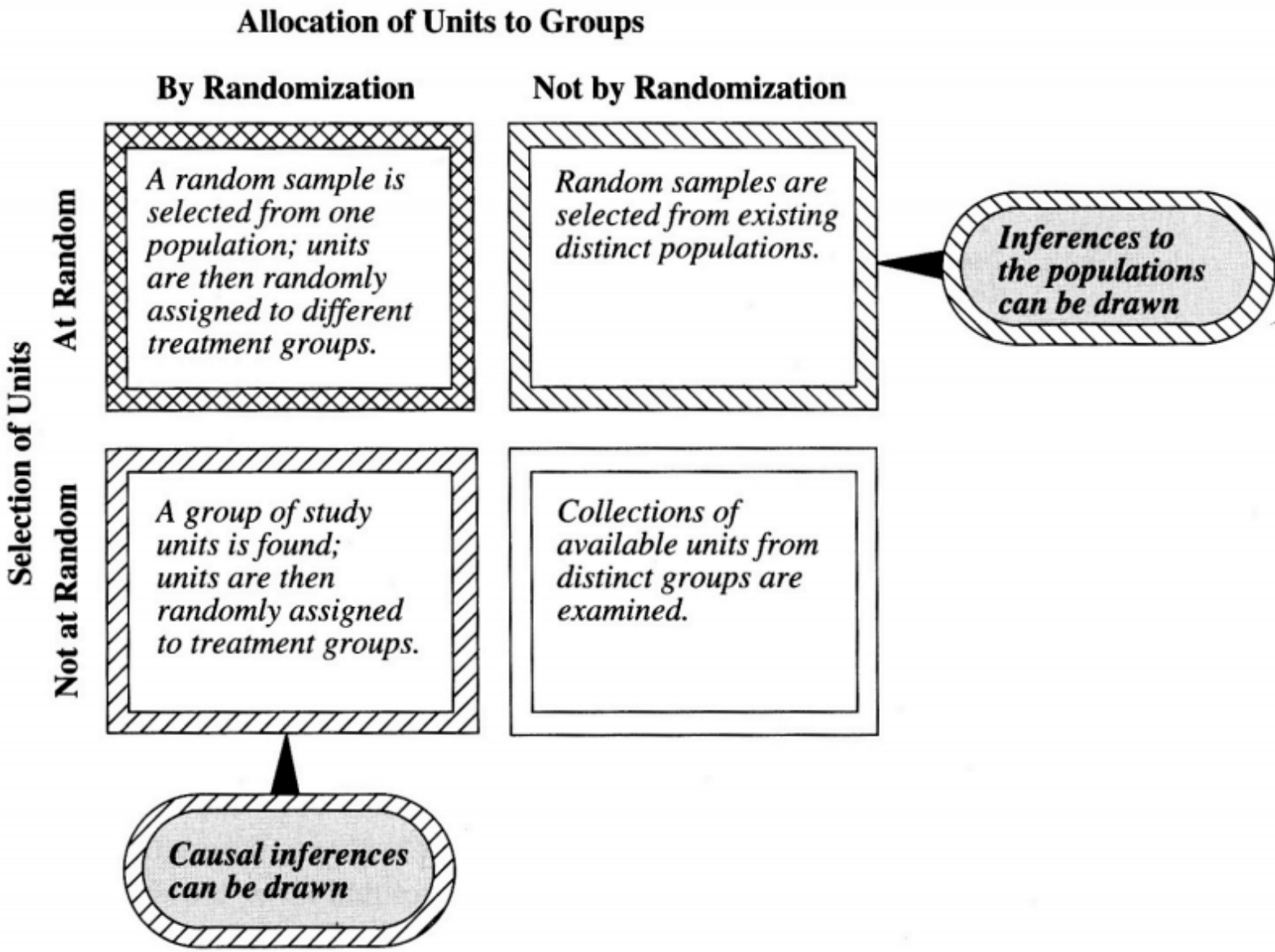


- Chapter 4: Confounding defined (page 71, standardization as an approach to address p. 84–89)
- Chapter 16: Simpson's paradox introduced via multiple 2x2 tables (page 374 of 525)
- Chapter 19: multiple regression to move beyond bivariate questions
- Why wait?

Do we teach in a way that encourages paralysis?



Other factors may be responsible for observed associations



Example from SDM4 (De Veaux, Velleman, and Bock) p. 575

Exercise 20.41: It's widely believed that regular mammogram screening may detect breast cancer early, resulting in fewer deaths from that disease. One study that investigated this issue over a period of 18 years was published during the 1970's. Among 30,565 who had never had mammograms, 196 died of breast cancer (0.64%) while only 153 of 30,131 who had undergone screening died of breast cancer (0.50%).

Do these results suggest that mammograms may be an effective screening tool to reduce breast cancer deaths?

Solution to Exercise 20.41 SDM4 (De Veaux, Velleman, and Bock) p. 575

$H_0 : p_1 - p_2 = 0$ vs. $H_A : p_1 - p_2 > 0$ (one-sided test? That's a different sermon.)

Solution to Exercise 20.41 SDM4 (De Veaux, Velleman, and Bock) p. 575

$H_0 : p_1 - p_2 = 0$ vs. $H_A : p_1 - p_2 > 0$ (one-sided test? That's a different sermon.) where p_1 is the proportion of women who never had mammograms who died of breast cancer and p_2 is the proportion of women who had undergone screening who died of breast cancer (z=2.17, p=0.0148).

With a p-value this low, we reject H_0. The data suggest that mammograms may reduce breast cancer deaths.

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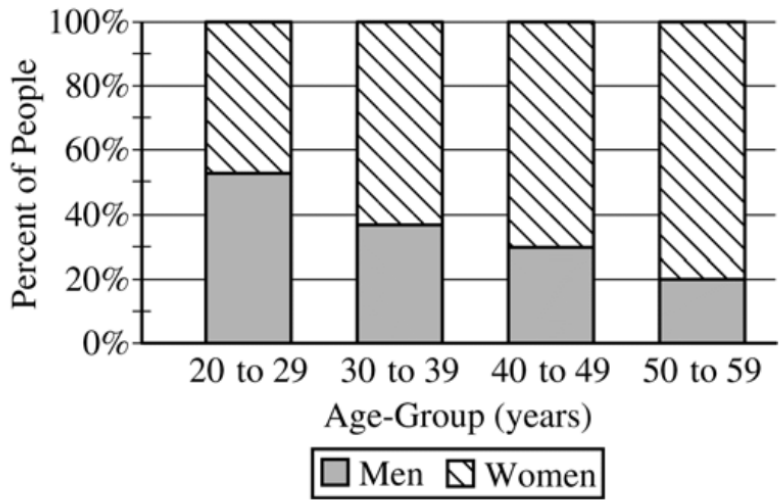
(But what about possible confounders?)

2017 AP® STATISTICS FREE-RESPONSE QUESTIONS

5. The table and the bar chart below summarize the age at diagnosis, in years, for a random sample of 207 men and women currently being treated for schizophrenia.

	Age-Group (years)				
	20 to 29	30 to 39	40 to 49	50 to 59	Total
Women	46	40	21	12	119
Men	53	23	9	3	88
Total	99	63	30	15	207



Do the data provide convincing statistical evidence of an association between age-group and gender in the diagnosis of schizophrenia?

Open Intro Statistics

6.34 Prenatal vitamins and Autism. Researchers studying the link between prenatal vitamin use and autism surveyed the mothers of a random sample of children aged 24 - 60 months with autism and conducted another separate random sample for children with typical development. The table below shows the number of mothers in each group who did and did not use prenatal vitamins during the three months before pregnancy (periconceptional period).[57]

		Autism		
		Autism	Typical development	Total
Periconceptional prenatal vitamin	No vitamin	111	70	181
	Vitamin	143	159	302
	Total	254	229	483

(a) State appropriate hypotheses to test for independence of use of prenatal vitamins during the three months before pregnancy and autism.

(b) Complete the hypothesis test and state an appropriate conclusion. (Reminder: Verify any necessary conditions for the test.)

(c) A New York Times article reporting on this study was titled "Prenatal Vitamins May Ward Off Autism". Do you find the title of this article to be appropriate? Explain your answer. Additionally, propose an alternative title.[58]

1. Since the p-value $< \alpha$, we reject H_0. There is strong evidence of a difference in the rates of autism of children of mothers who did and did not use prenatal vitamins during the first three months before pregnancy.

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2. The p-value is small and we reject H0. The data provide convincing evidence to suggest that autism and vitamin use in women are associated.
3. Yes, this is an observational study. Based on this study we can't deduce that taking vitamins leads to less autism. There may be other factors, lurking variables, that may cause autism and be associated with vitamin use.

(Non-scientific) survey of isolated statisticians and Stat Ed section members

question: "what assumptions do you have students check when using the two sample t-test?"

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1. Randomness in the data collection process (either **random samples** or **experiment**)
2. Independent samples
3. Either normal looking samples or sample sizes larger than 25

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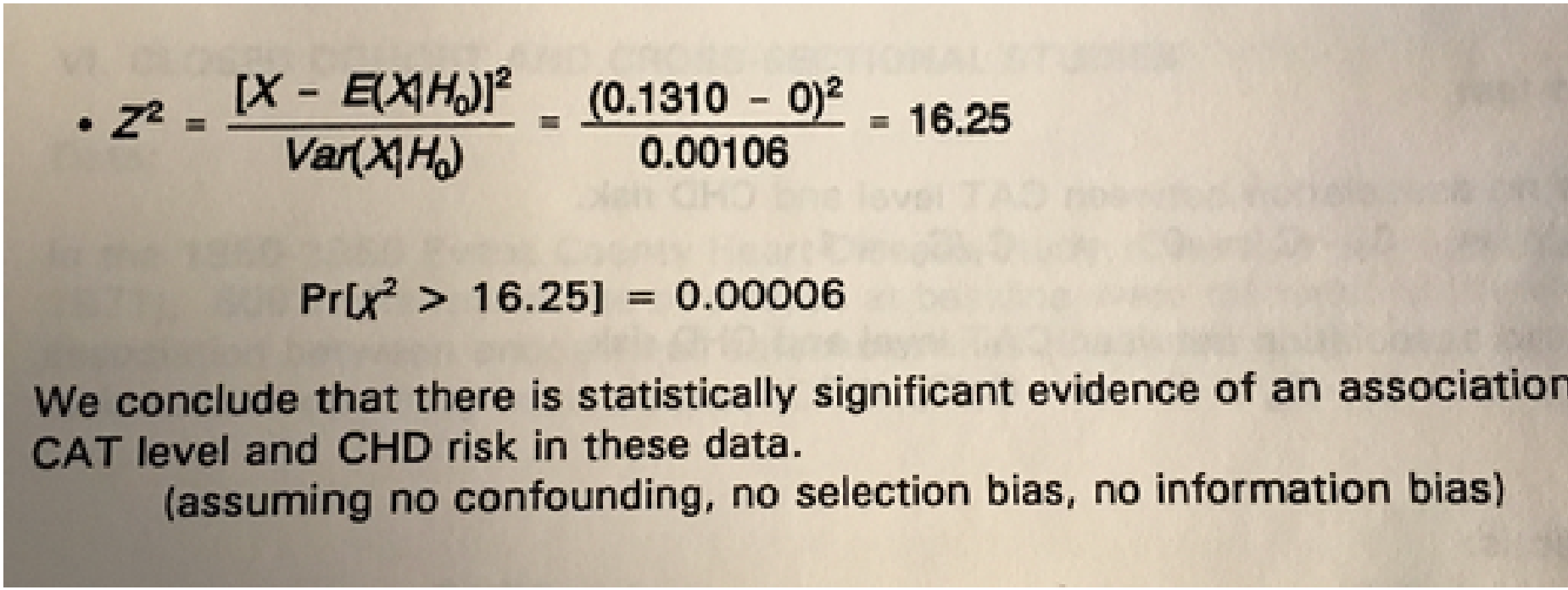
What about possible confounders? (Only one other respondent out of more than 20 mentioned "random assignment": almost all emphasis was on technical conditions).

Harvard University EPI202b (circa 1995)



$$\bullet\ Z^2 = \frac{[X - E(X|H_0)]^2}{Var(X|H_0)} = \frac{(0.1310 - 0)^2}{0.00106} = 16.25$$

$$Pr[\chi^2 > 16.25] = 0.00006$$

We conclude that there is statistically significant evidence of an association
CAT level and CHD risk in these data.
(assuming no confounding, no selection bias, no information bias)

Guidelines for Assessment and Instruction in Statistics Education (GAISE) College Report 2016

revised GAISE College Report (2016)

1. Teach statistical thinking.
2. Focus on conceptual understanding.
3. Integrate real data with a context and purpose.
4. Foster active learning.
5. Use technology to explore concepts and analyze data.
6. Use assessments to improve and evaluate student learning.

revised GAISE College Report (2016)

1. Teach statistical thinking.
   - Teach statistics as an investigative process of problem-solving and decision-making.
   - Give students experience with **multivariable thinking**.
2. Focus on conceptual understanding.
3. Integrate real data with a context and purpose.
4. Foster active learning.
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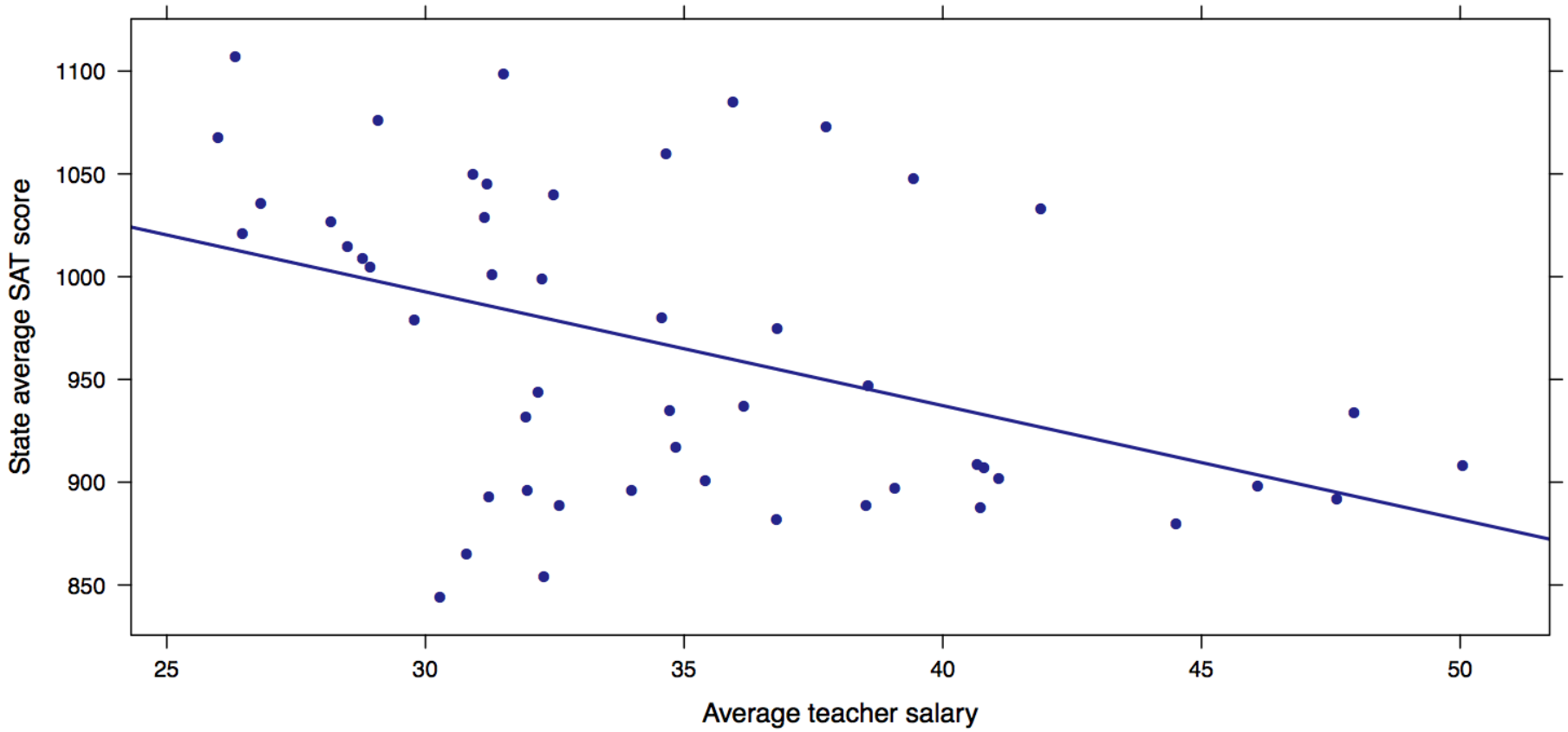
Teaching multivariate thinking and confounding

1. what are we currently teaching?
2. motivating multivariate examples

SAT scores and teacher salaries (state data from 2010)



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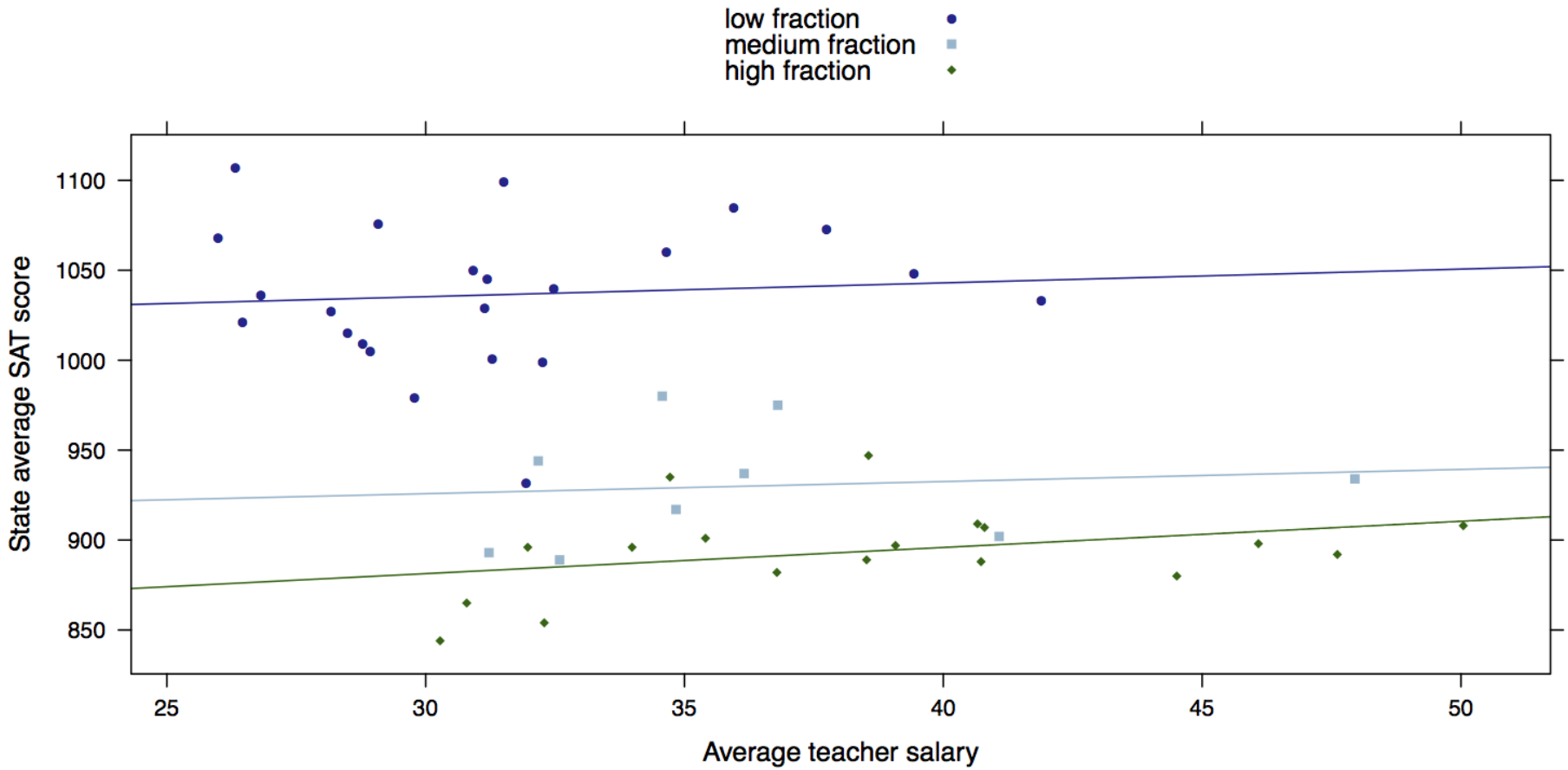
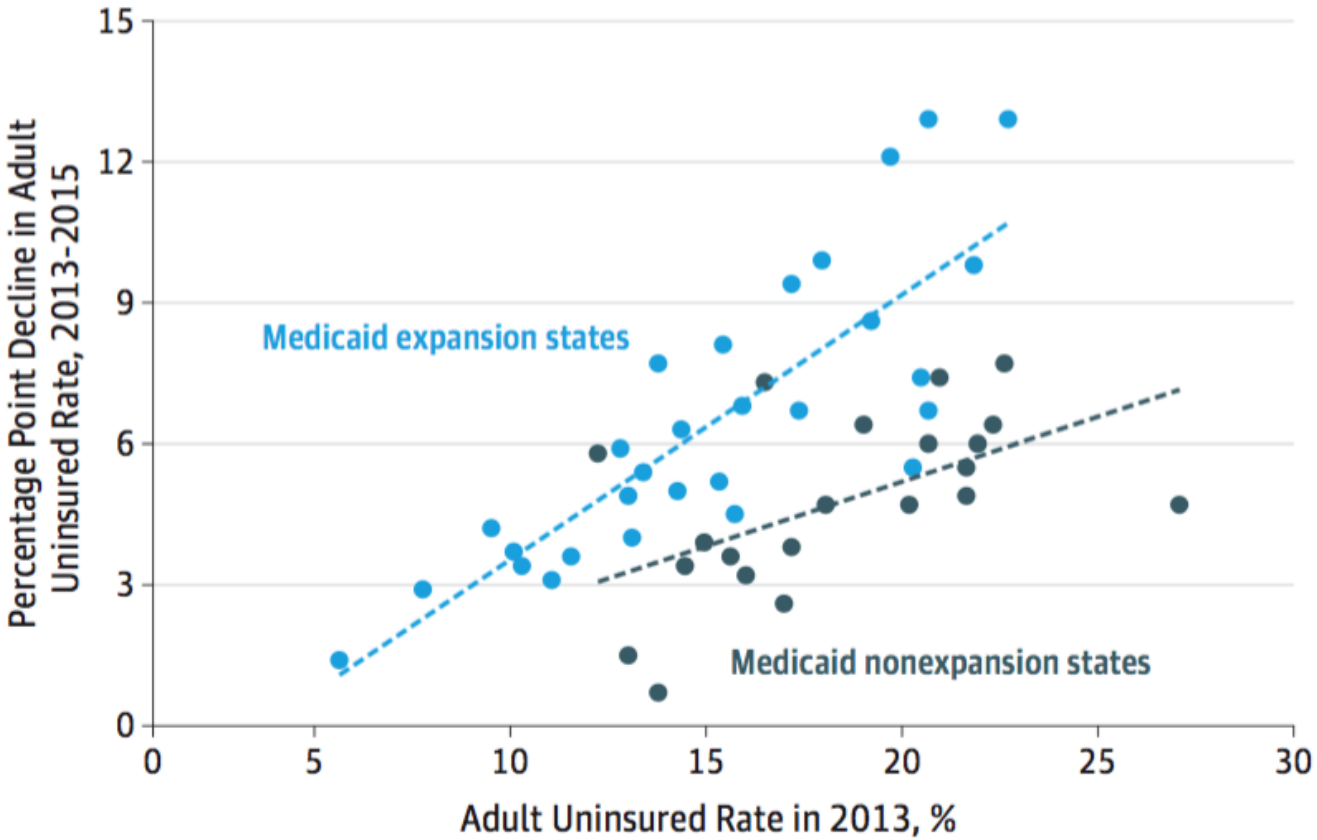


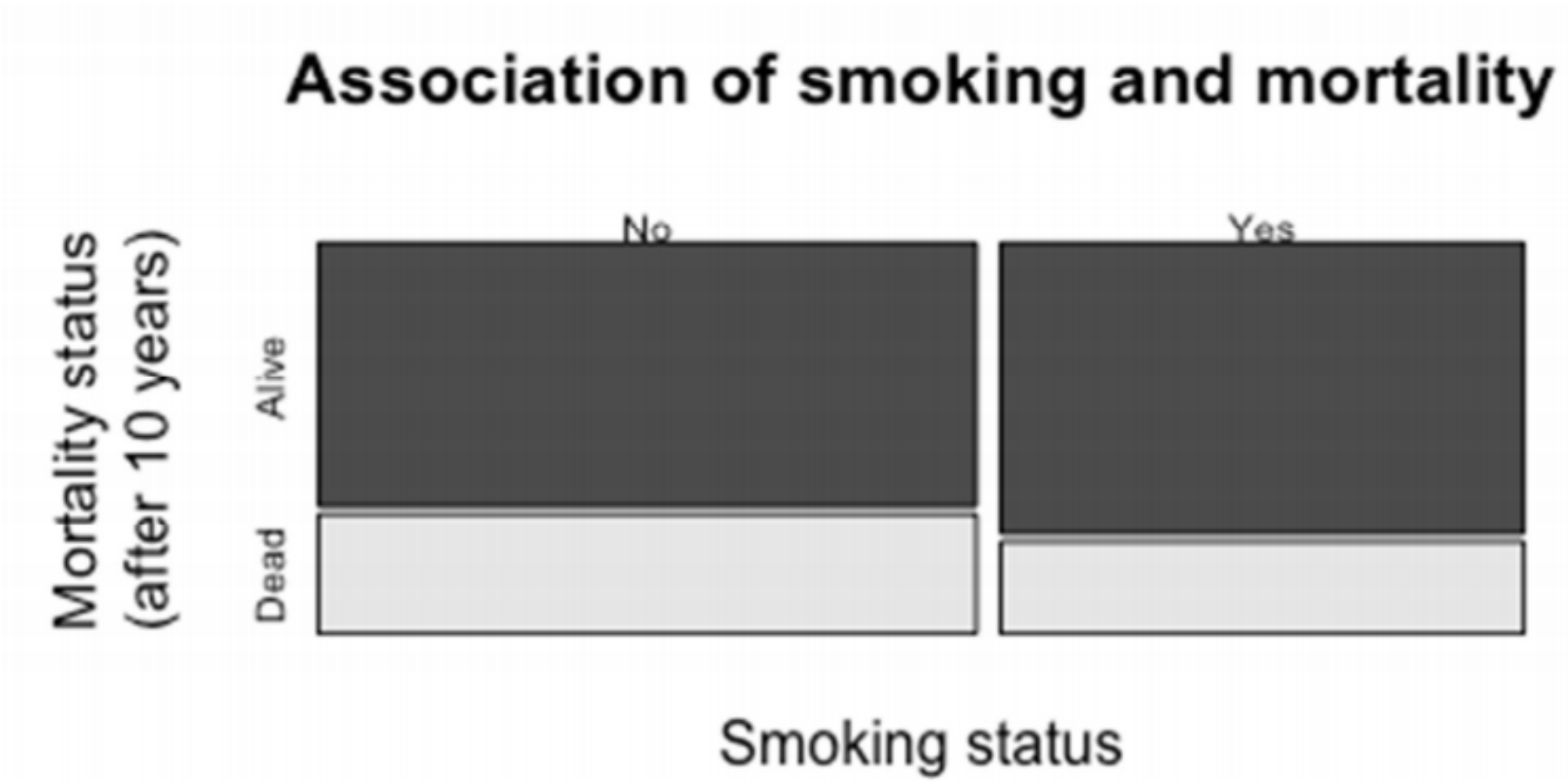
stratification and/or multiple regression: Obama's 2016 single author JAMA paper

Figure 2. Decline in Adult Uninsured Rate From 2013 to 2015 vs 2013 Uninsured Rate by State



See also "Statistical methods in the NEJM" (2007)

Whickham cohort: smoking and mortality



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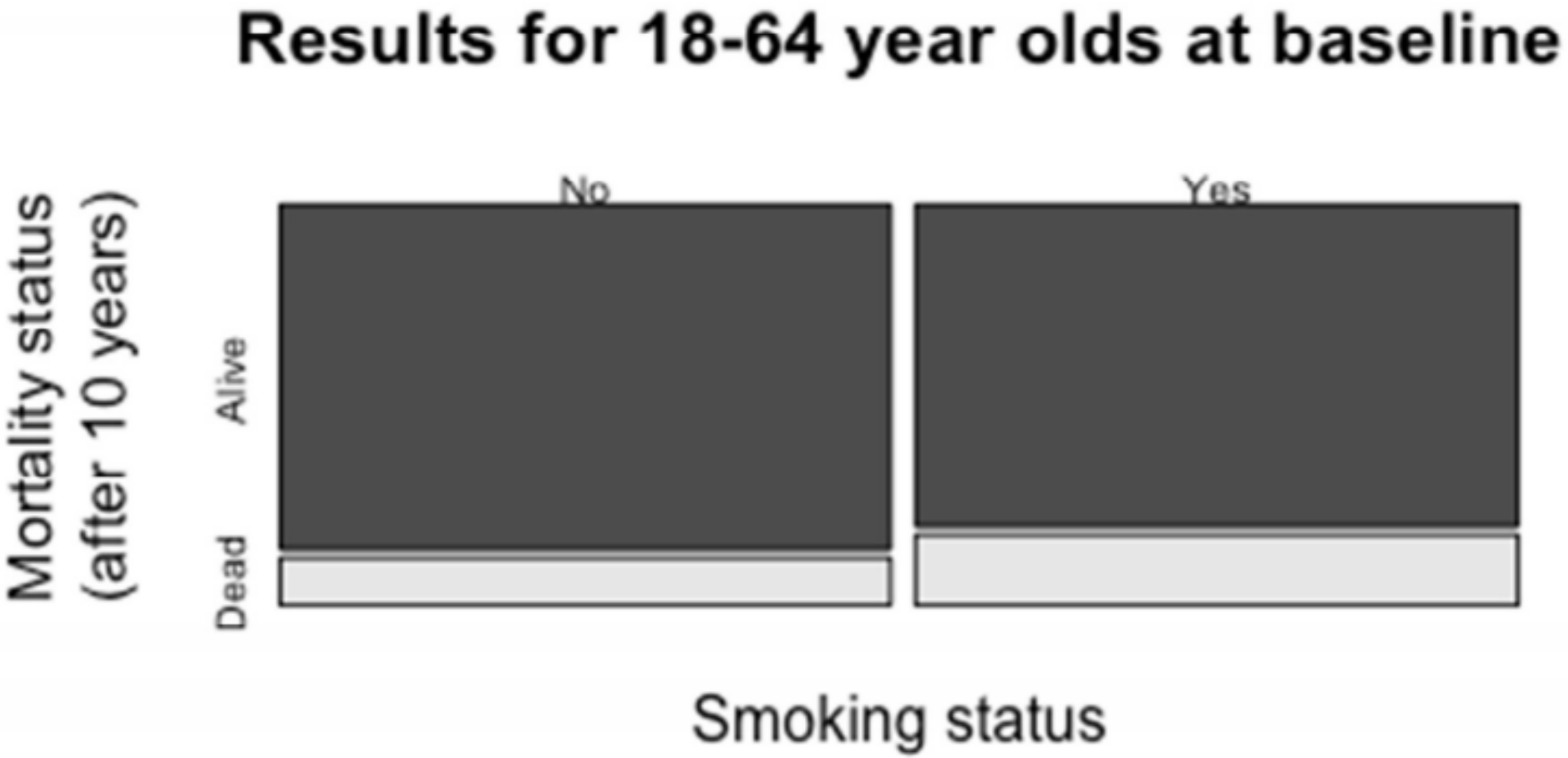

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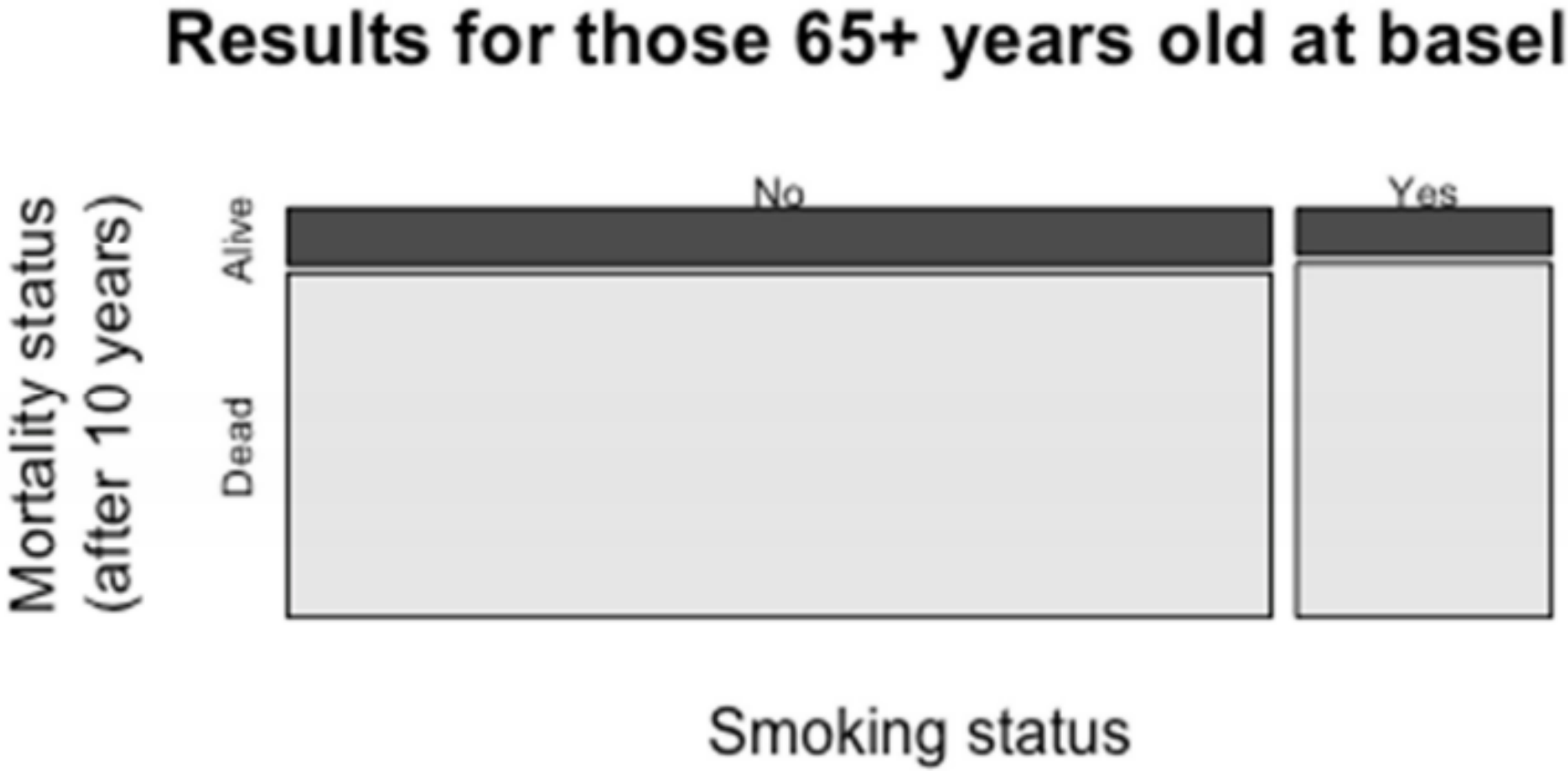

Kidney stones (Wikipedia Simpson's Paradox)

	Treatment A	Treatment B
Small stones	*Group 1* **93% (81/87)**	*Group 2* 87% (234/270)
Large stones	*Group 3* **73% (192/263)**	*Group 4* 69% (55/80)
Both	78% (273/350)	**83% (289/350)**

How to handle more than two variables?

- "Data Viz on Day One" (TISE, `http://escholarship.org/uc/item/84v3774z`)

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- new emphasis on causal graphs and confounding (more to come on this front)

Teaching multivariate thinking and confounding

1. what are we currently teaching?
2. motivating multivariate examples
3. confounding 101 and 201

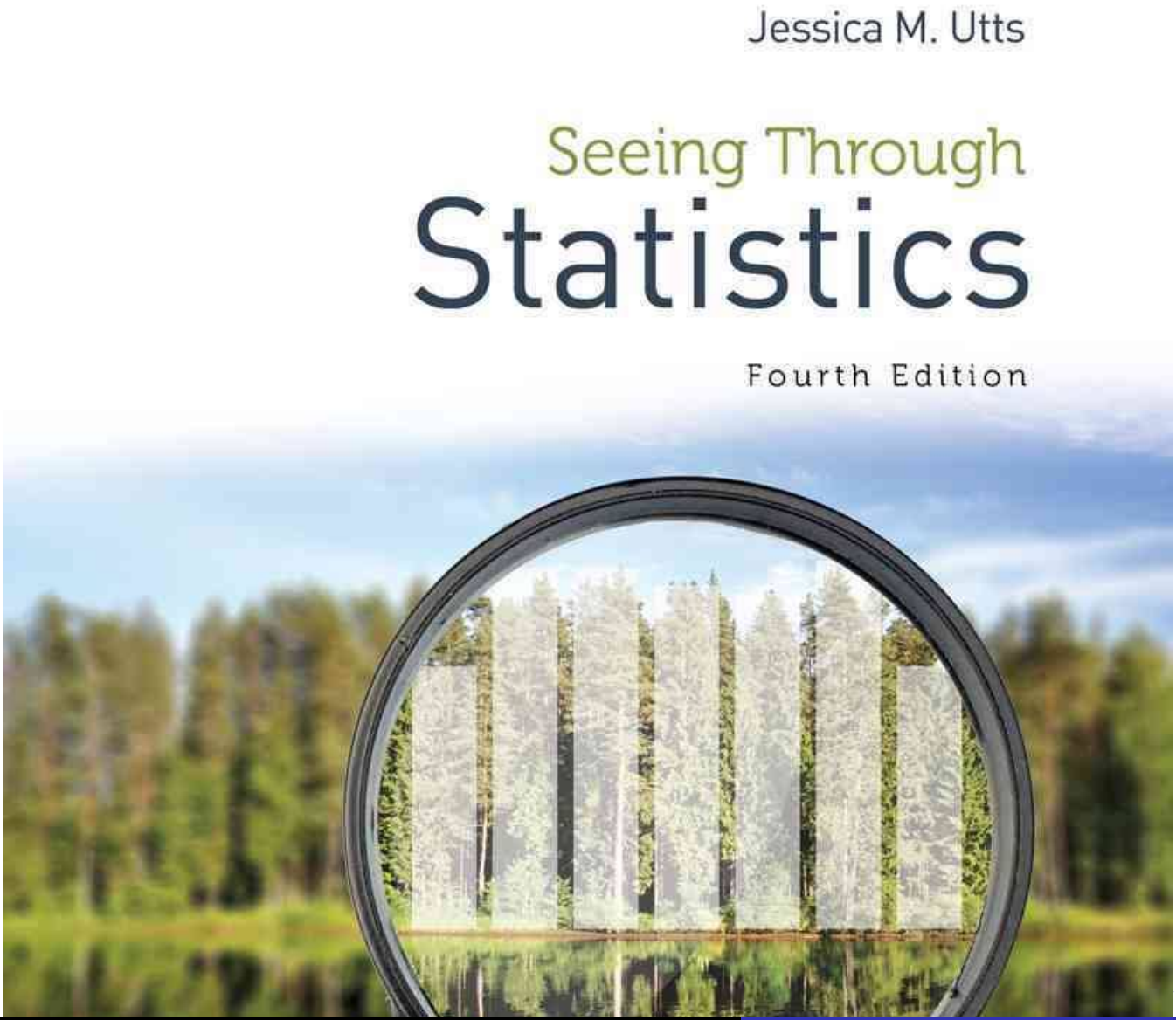
AP Statistics Vocabulary

Both Sides

confounding

when the levels of one factor are associated with the levels of another factor so their effects cannot be separated

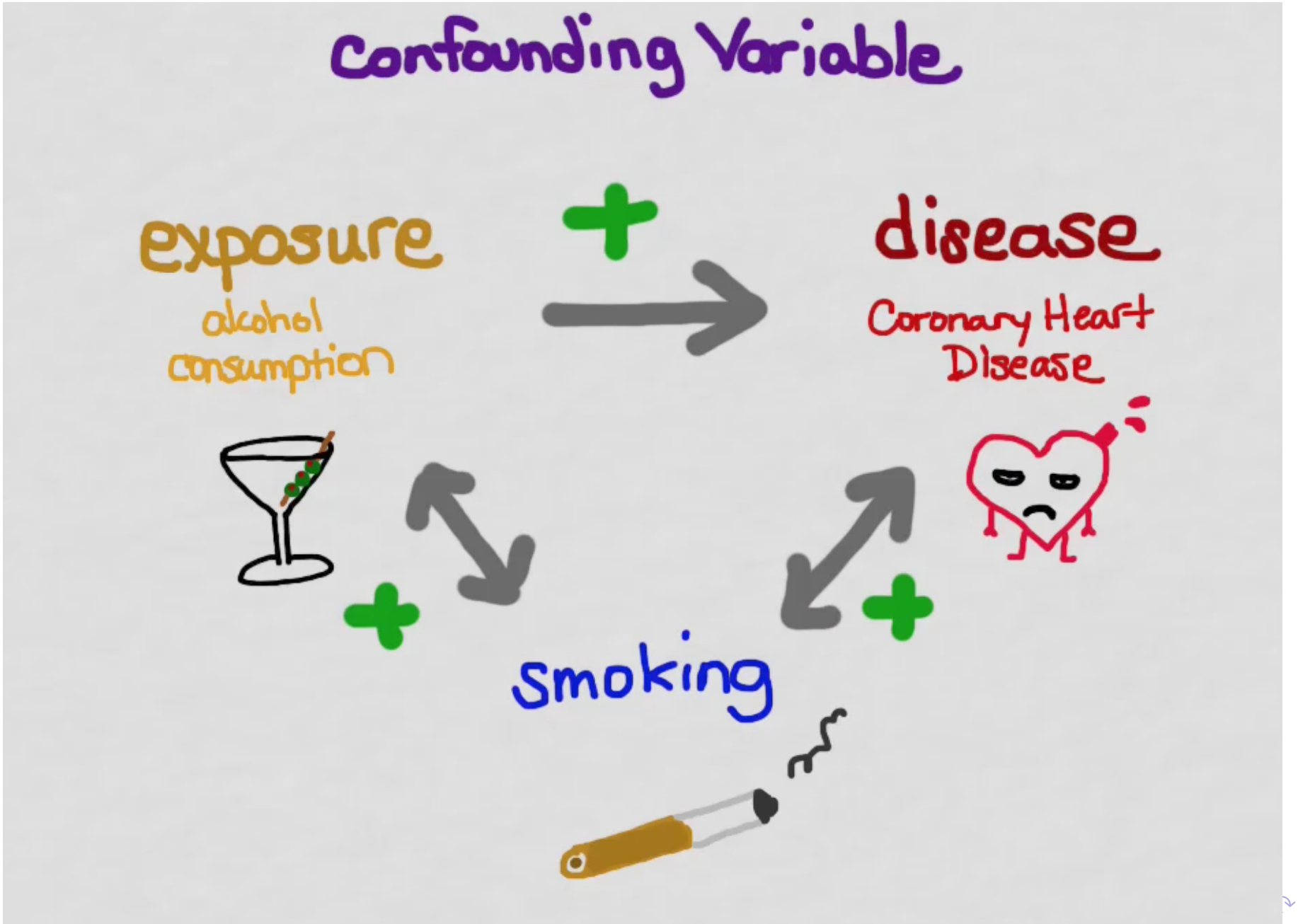
Utts: Seeing through Statistics (4th edition)



A confounding variable is one that has two properties.

1. A confounding variable is related to the explanatory variable in the sense that individuals who differ for the explanatory variable are also likely to differ for the confounding variables.
2. A confounding variable affects the response variable. Because of these two properties, the effect of a confounding variable on the response variable cannot be separated from the effect of the explanatory variable on the response variable.

causal graphs (Elizabeth Lynch)



Learning outcomes (Hernan and Swanson, EPI 524)

Confounding is a ubiquitous bias that arises when non-comparable groups are compared. It is one of the greatest threats to valid causal inferences from observational data. Therefore, controlling for confounding is a fundamental component of epidemiologic research.

Wikipedia definition

In statistics, a confounder (also confounding variable or confounding factor) is a variable that influences both the dependent variable and independent variable causing a spurious association. Confounding is a causal concept, and as such, cannot be described in terms of correlations or associations.

Wikipedia talk page

WIKIPEDIA
The Free Encyclopedia

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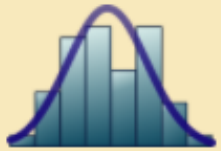
Talk:Confounding

From Wikipedia, the free encyclopedia

157.27.198.235 (talk) 11:37, 16 September 2016 (UTC)



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Statistics portal

C

This article has been rated as **C-Class** on the quality scale.

High

This article has been rated as **High-importance** on the importance scale.

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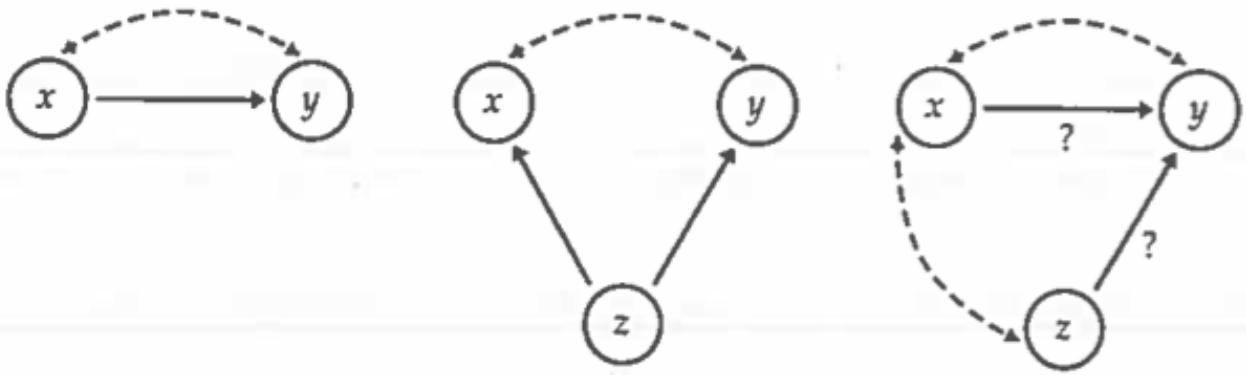
Explaining association: causation

Figure 2.29 shows in outline form how a variety of underlying links between variables can explain association. The dashed double-arrow line represents an observed association between the variables x and y. Some associations are explained by a direct cause-and-effect link between these variables. The first diagram in Figure 2.28 shows "x causes y" by a solid arrow running from x to y.

Items 1 and 2 in Example 2.42 are examples of direct causation. *Even when direct causation is present, very often it is not a complete explanation of an association between two variables.* The best evidence for causation comes from experiments that actually change x while holding all other factors fixed. If y changes, we have good reason to think that x caused the change in y.

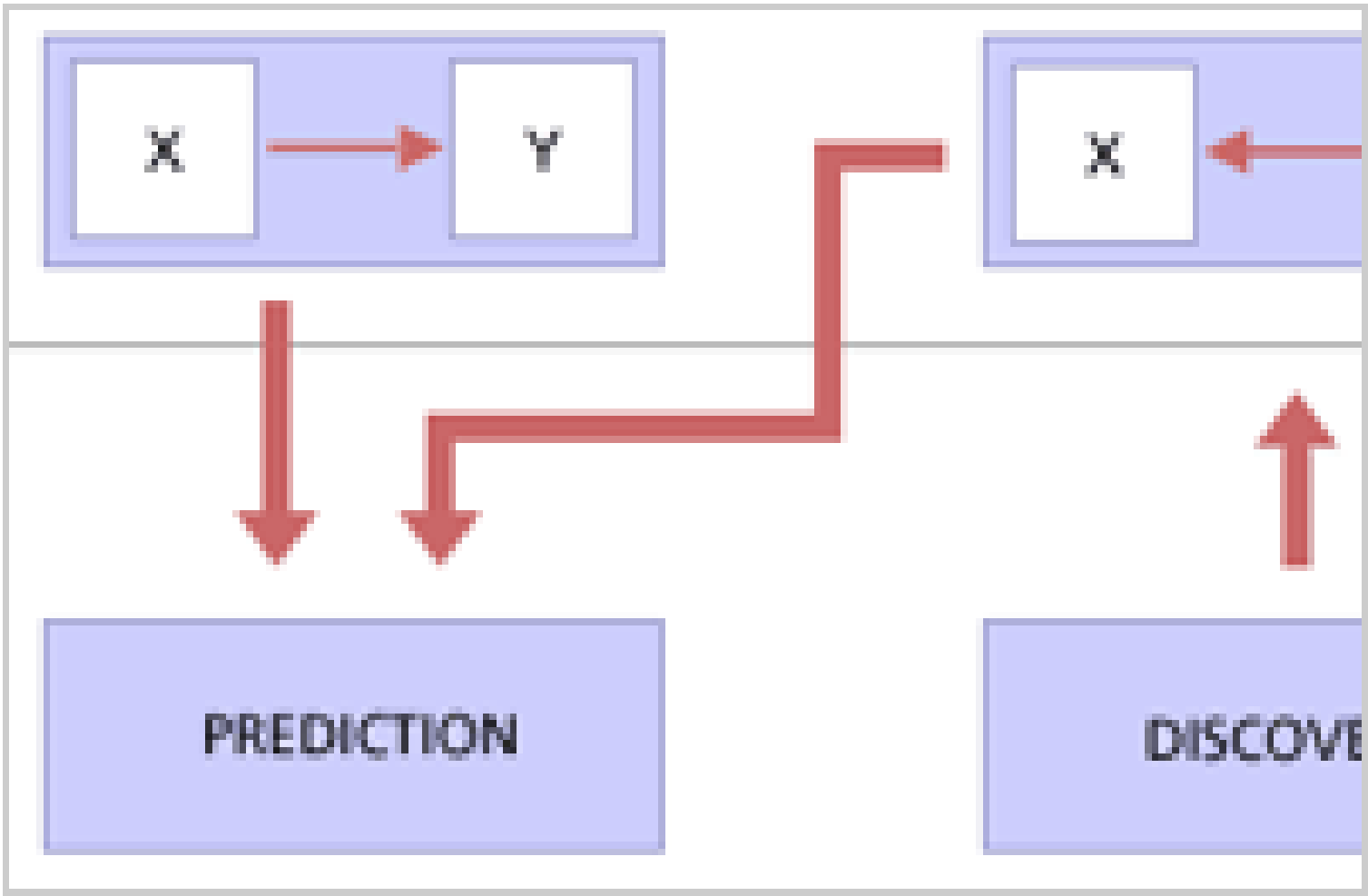


Causation (a) | Common response (b) | Confounding (c)

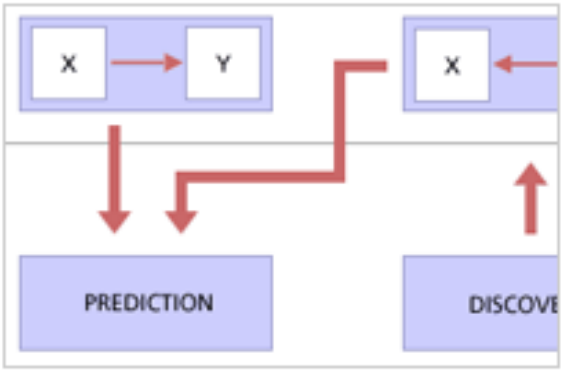
What to teach?

We need to go beyond these informal definitions...

CMU Open Learning Initiative (OLI): Causal and Statistical Reasoning



CMU OLI: Causal and Statistical Reasoning



Causal & Statistical Reasoning [Enter Course]

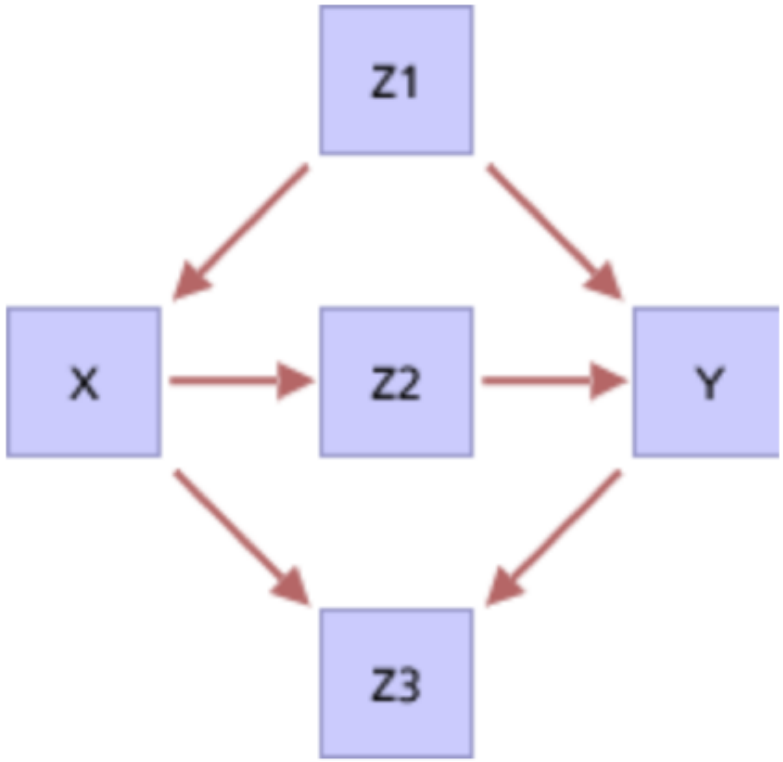
Overview:

This course provides an introduction to causal and statistical reasoning. After taking this course, students will be better prepared to make rational decisions about their own lives and about matters of social policy. They will be able to assess critically—even if informally—claims that they encounter during discussions or when considering a news article or report. A variety of materials are presented, including Case Studies where students are given the opportunity to examine a causal claim, and the Causality Lab, a virtual environment to simulate the science of causal discovery. Students have frequent opportunities to check their understanding and practice their skills.

CMU OLI: Causal and Statistical Reasoning criteria

- X and Y are D-separated by Z just in case there are no undirected paths between X and Y that are active relative to Z
- A path is active iff all the variable on the path are active
- Non-colliders are active if they are not in the conditioning set Z, and inactive if they are in Z
- Colliders are active if they are in Z or have an effect in Z, and inactive otherwise

- First identify all undirected paths
- Count number of active (causally connected) paths
  - No mediators or common causes in Z
  - All common effects in Z
- If an active path exists, it is D-connected by that path
- If not, D separated



Used these materials in a second course in statistics circa 2009 (but tough going)

Wikipedia definition

Definition [edit | edit source]

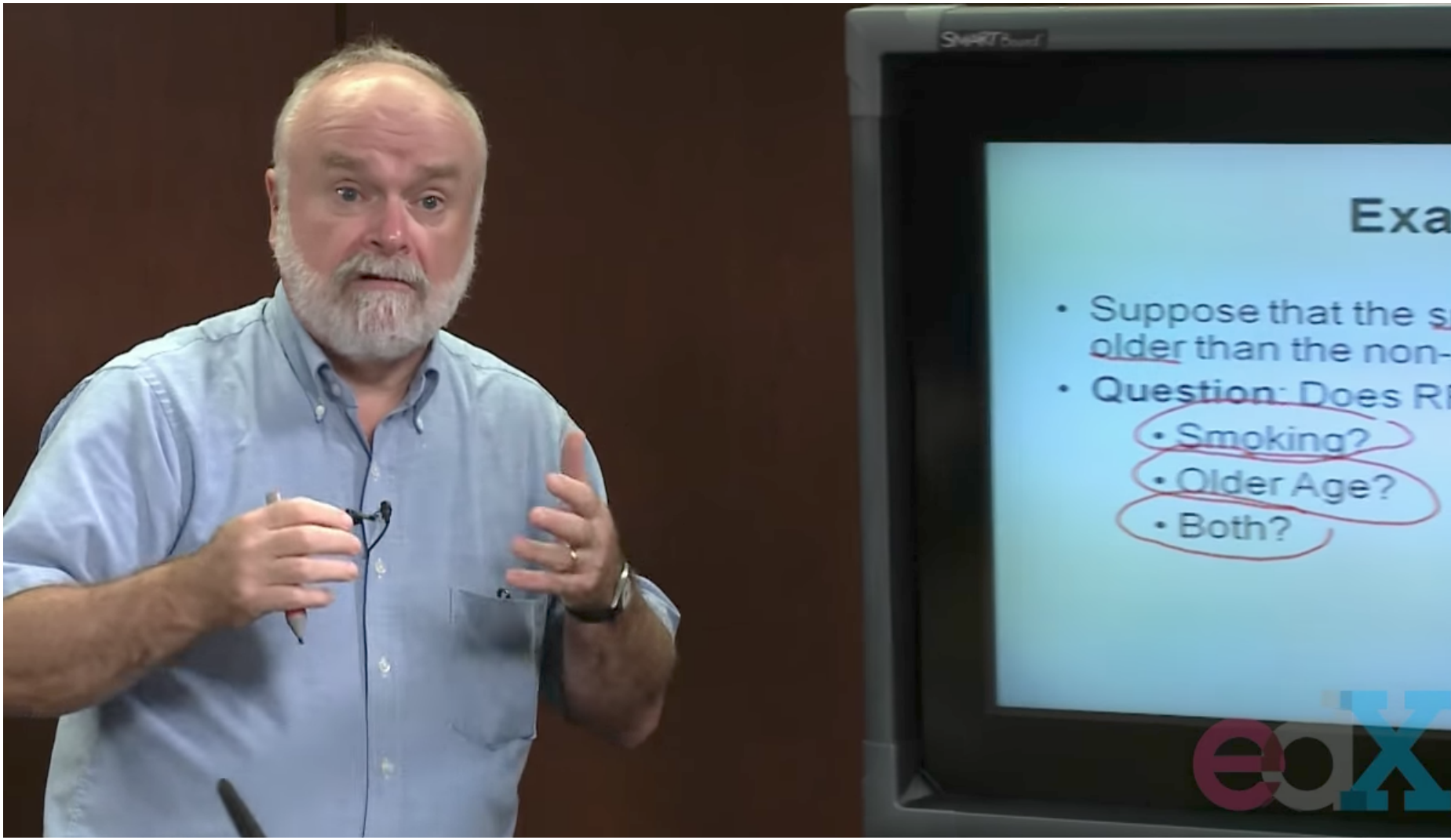
Confounding is defined in terms of the data generating model (as in the Figure above). Let X be some independent variable, Y some dependent variable. To estimate the effect of X on Y, the statistician must suppress the effects of extraneous variables that influence both X and Y. We say that, X and Y are confounded by some other variable Z whenever Z is a cause of both X and Y.

Let $P(y \mid \mathrm{do}(x))$ be the probability of event $Y = y$ under the hypothetical intervention $X = x$. X and Y are not confounded if and only if the following holds:

$$P(y \mid \mathrm{do}(x)) = P(y \mid x) \tag{1}$$

for all values $X = x$ and $Y = y$, where $P(y \mid x)$ is the conditional probability upon seeing $X = x$. Intuitively, this equality states that X and Y are not confounded whenever the observationally witnessed association between them is the same as the association that would be measured in a controlled experiment, with x randomized.

Causal graphs version 2.0 (Fran Cook videos)



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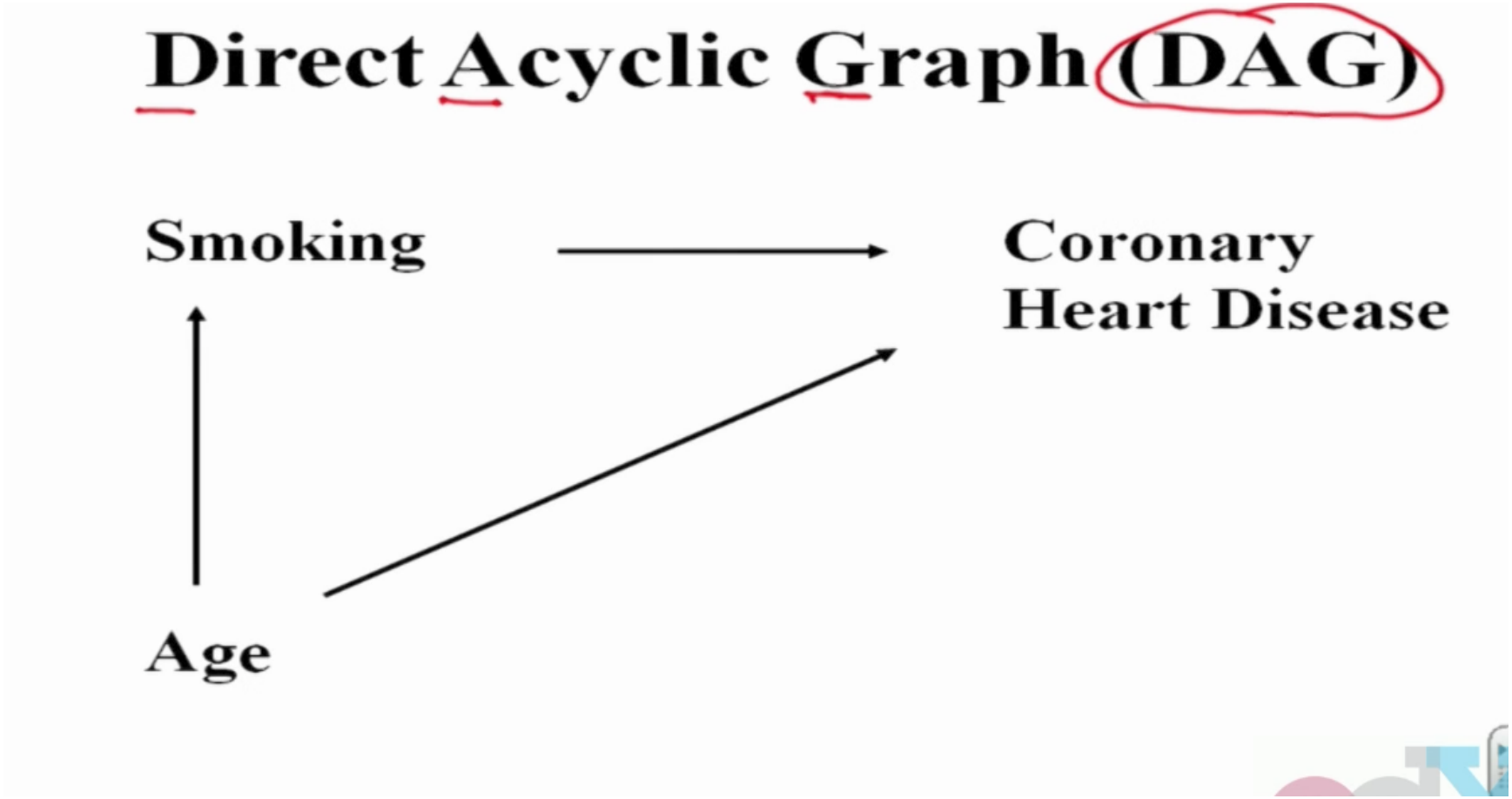
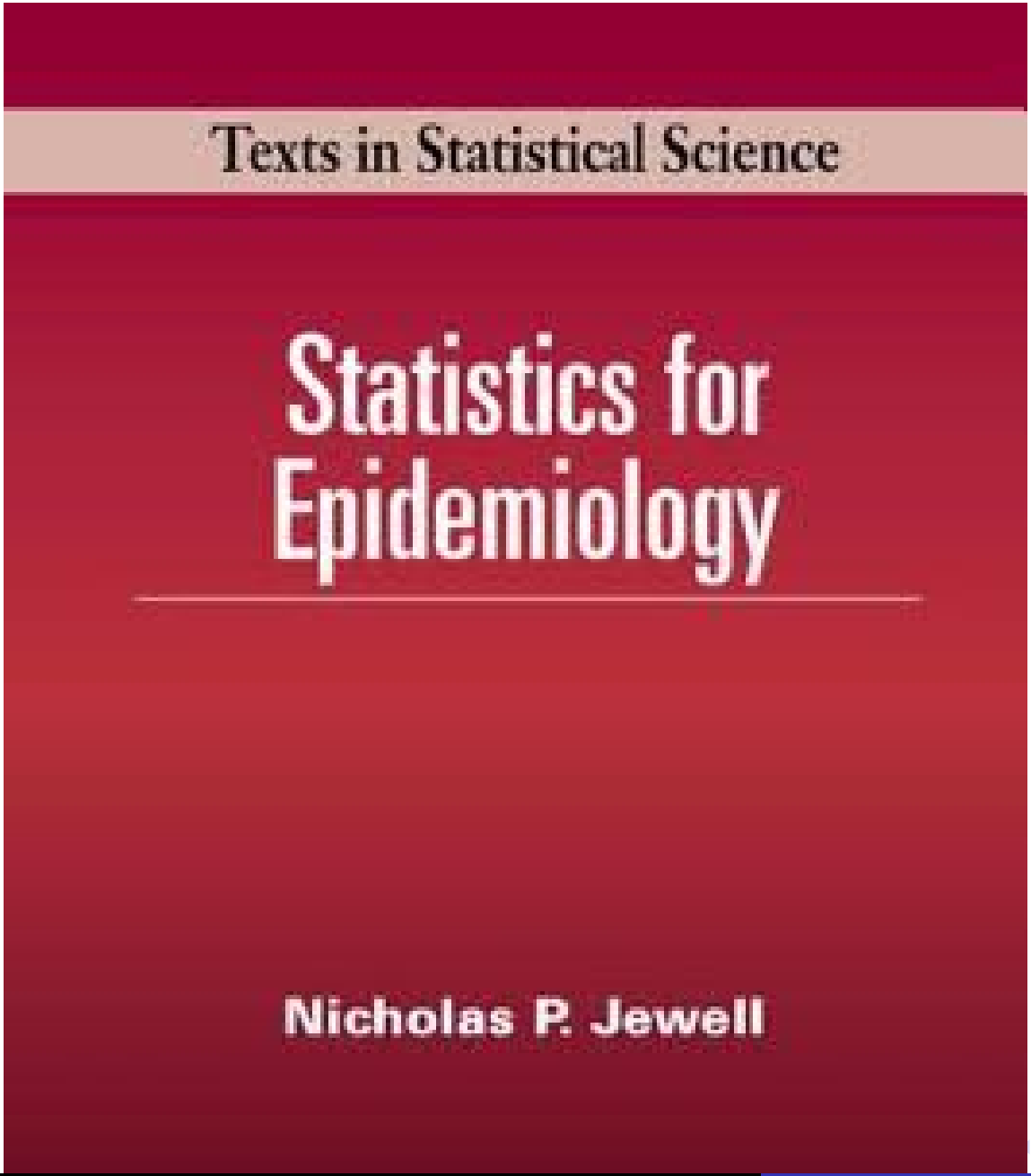
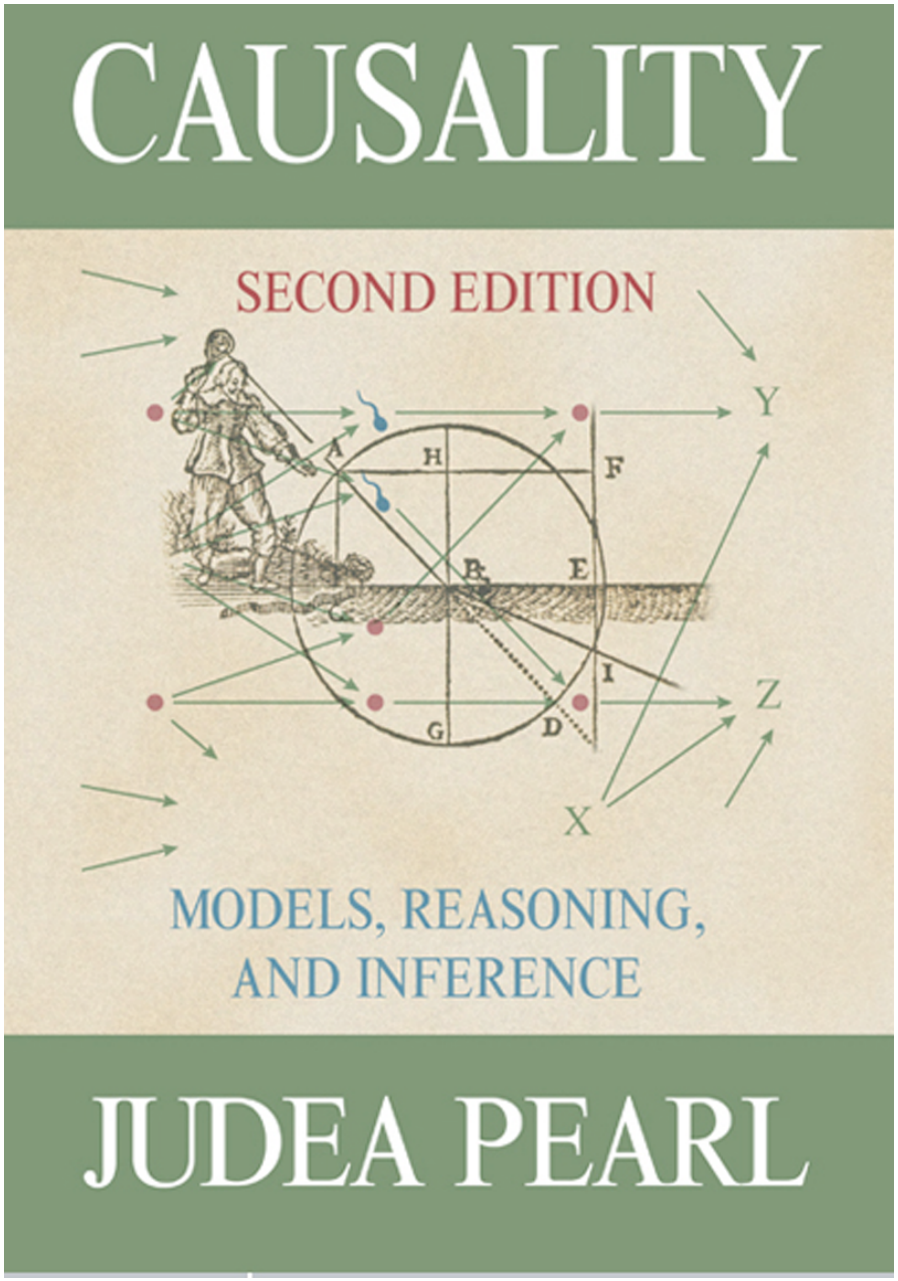


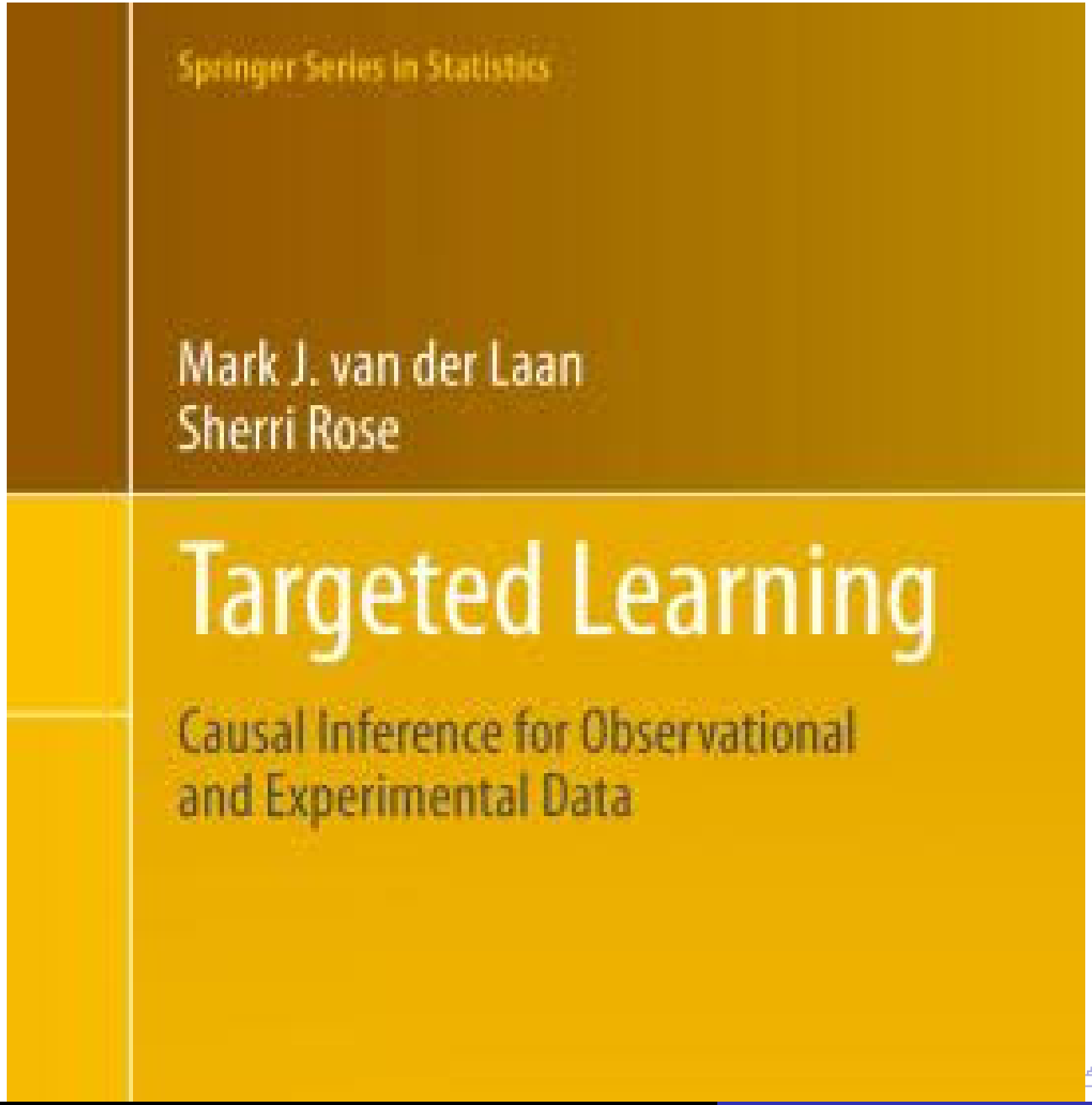
Jewell (2003)


Texts in Statistical Science
Statistics for Epidemiology
Nicholas P. Jewell

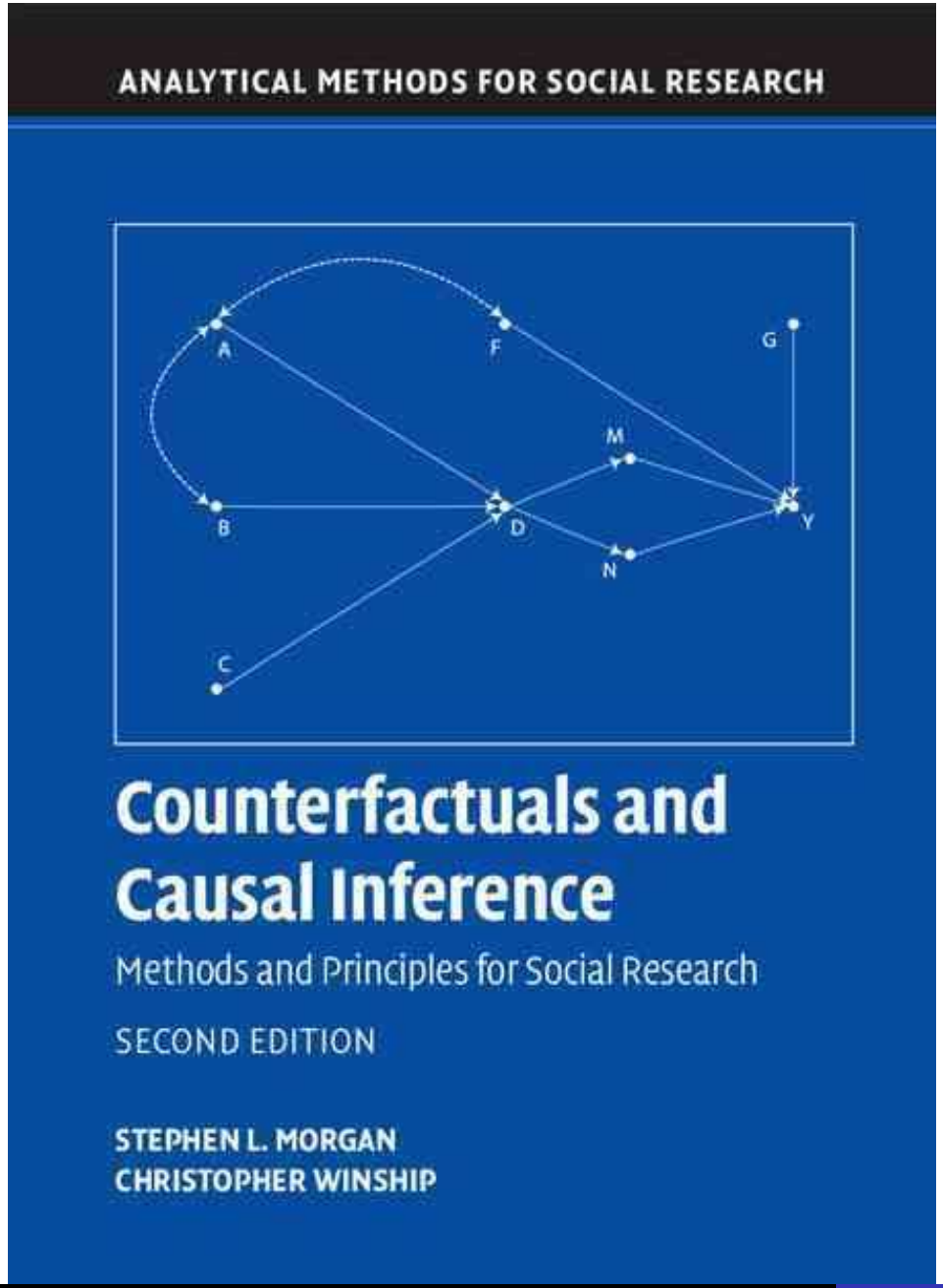
Pearl, second edition (2009)



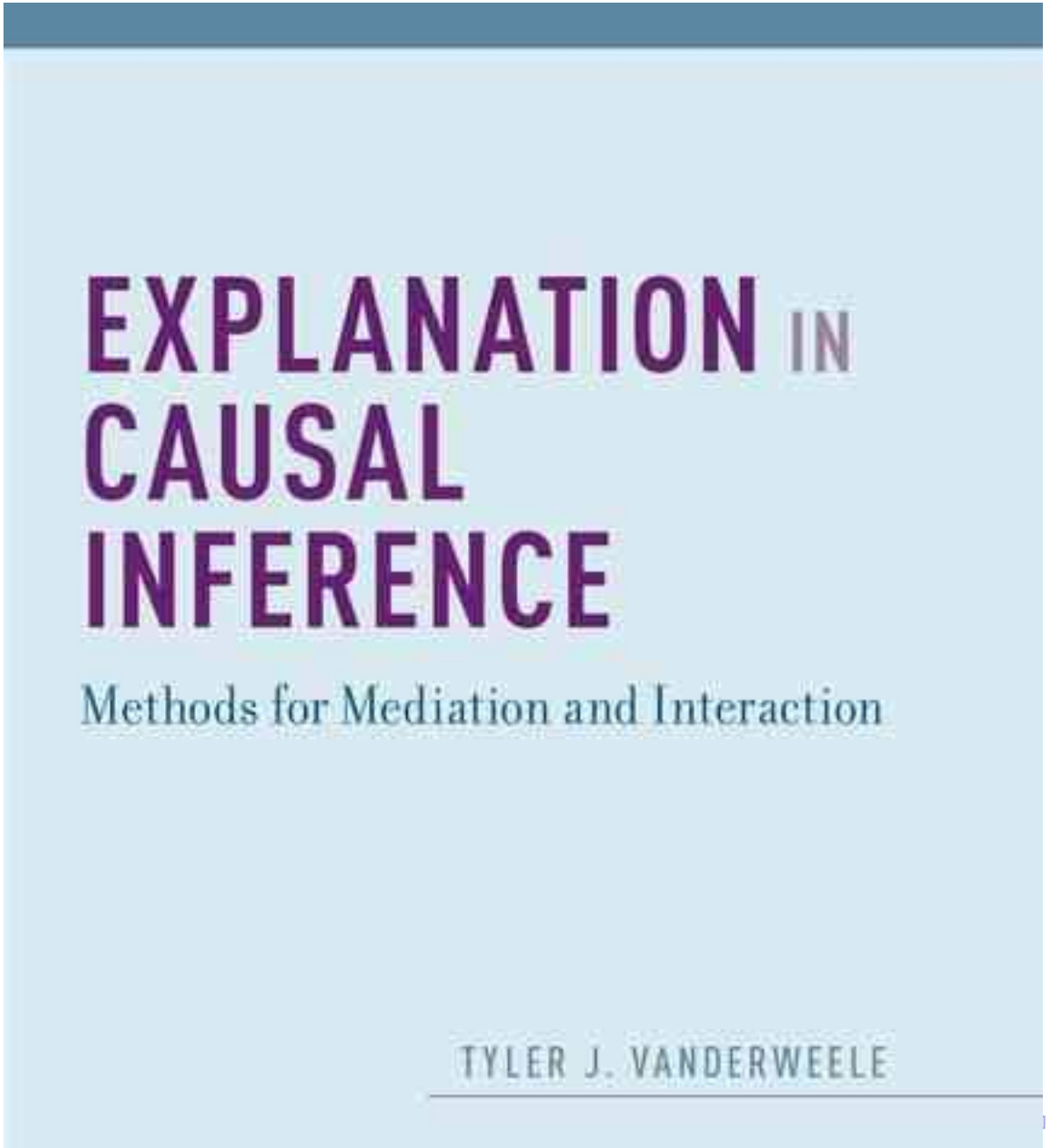
van der Laan and Rose (2011)



Winship and Morgan, second edition (2015)



Vanderweele (2015)



6.6 The structure of effect modificati

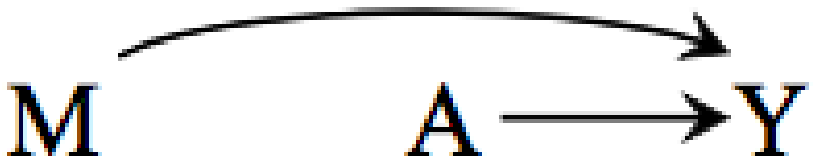


Figure 6.11

Identifying pot
use our causal
association bet
to illustrate th

Suppose he
identify the ave
that there is n
Computing the
association is
$\Pr[Y = 1|A =$

7.1 The structure of confounding

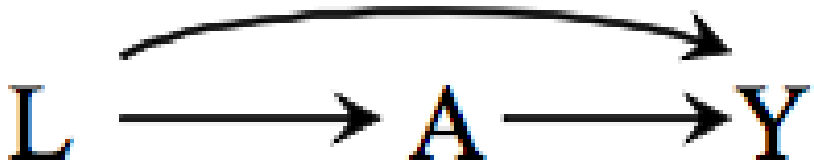


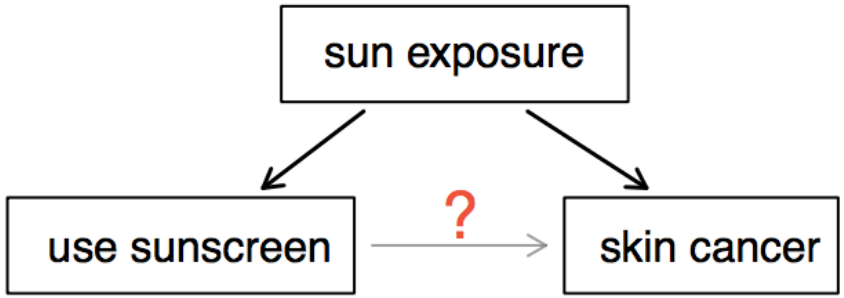
Figure 7.1

Confounding i
a cause. The
diagrams. For
a treatment A
diagram show
the path $A \rightarrow$
$A \leftarrow L \rightarrow Y$
graph theory,
cause L is an

Example

Suppose an observational study tracked sunscreen use and skin cancer, and it was found that the more sunscreen someone used, the more likely the person was to have skin cancer. Does this mean sunscreen causes skin cancer?

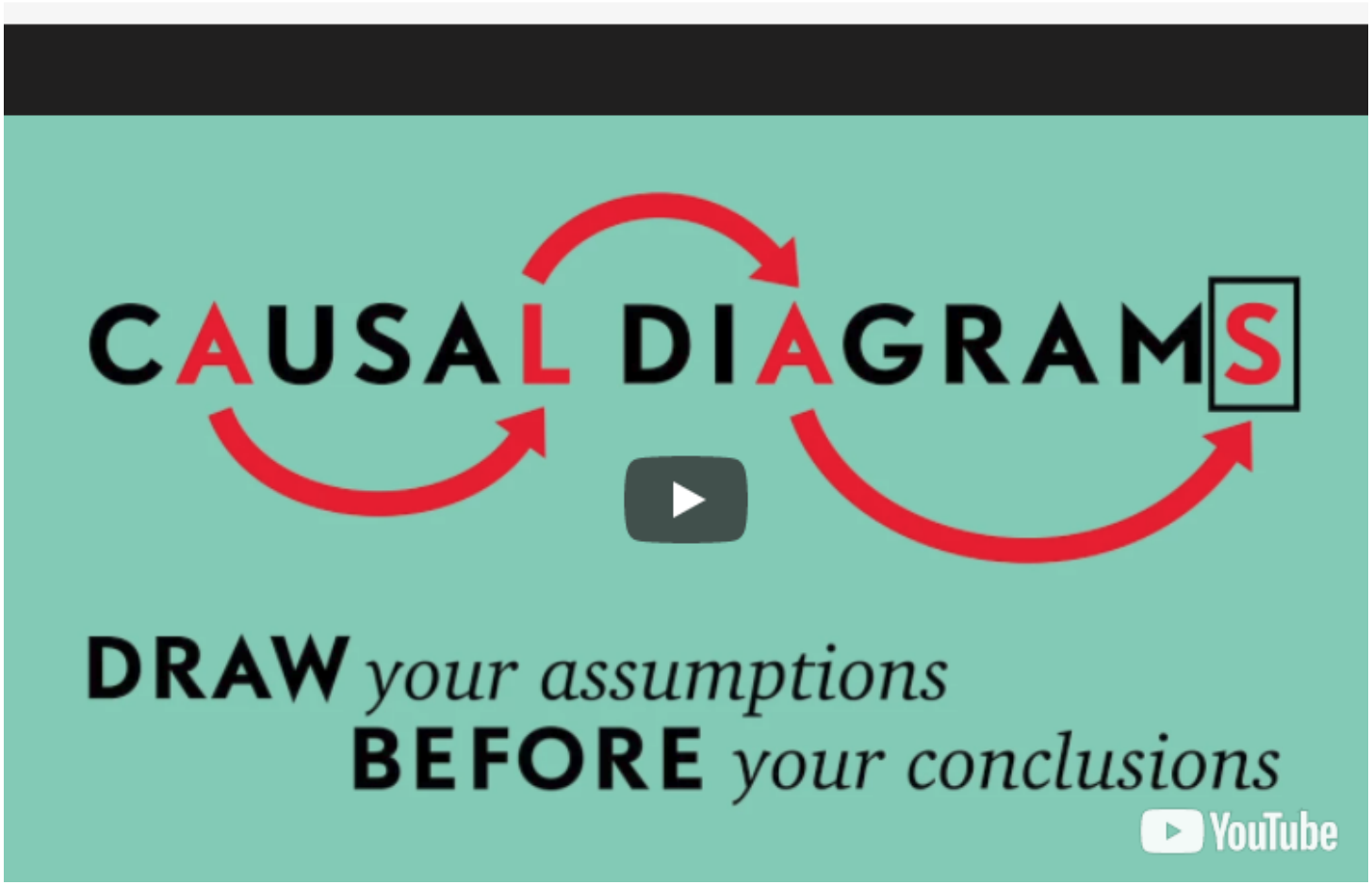
Causal graphs version 3.0 (Open Intro)



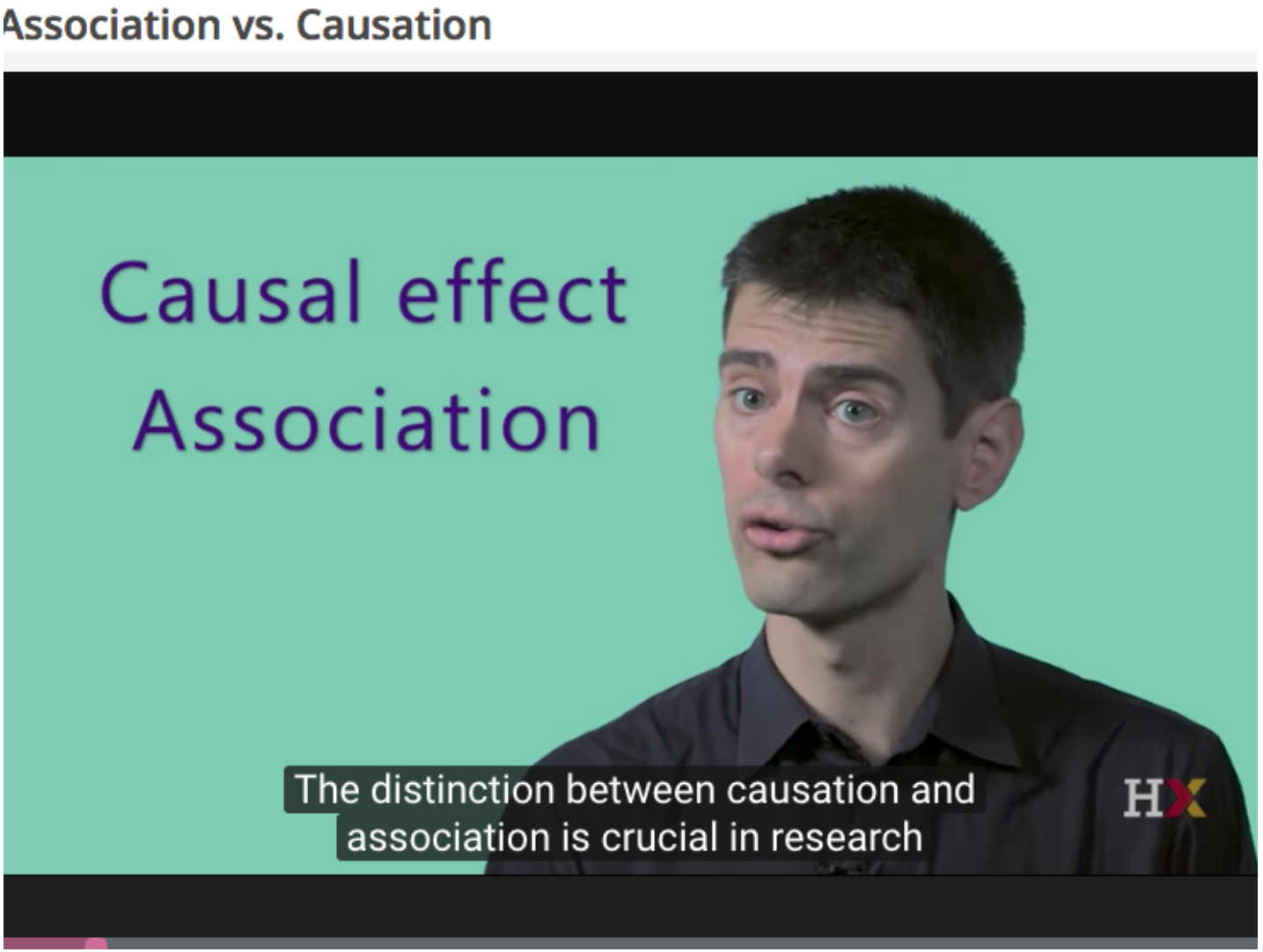
Sun exposure is what is called a **confounding variable**,[13] which is a variable that is correlated with both the explanatory and response variables. While one method to justify making causal conclusions from observational studies is to exhaust the search for confounding variables, there is no guarantee that all confounding variables can be examined or measured.

version 3.0: EdX Causal Diagrams (Draw Your Assumptions Before Your Conclusions course)

2. What is a DAG?



version 3.0: EdX Causal Diagrams (Draw Your Assumptions Before Your Conclusions course)



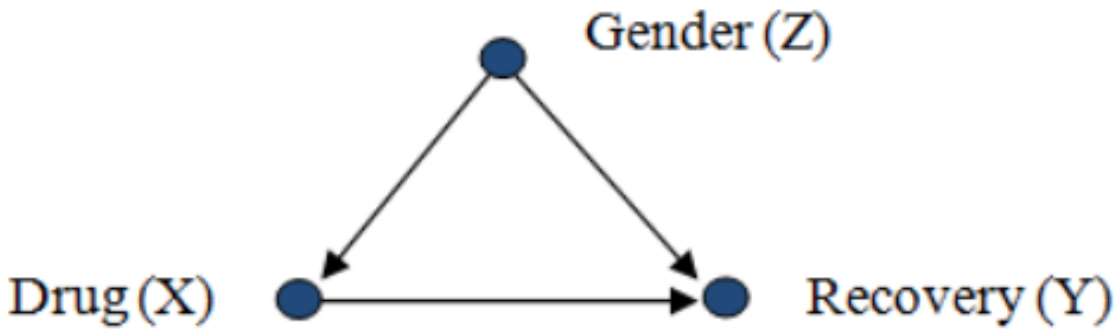
version 3.0: EdX Causal Diagrams (Draw Your Assumptions Before Your Conclusions course)

1. Causal DAGs
2. Confounding
3. Selection Bias
4. Measurement Bias and putting it all together

Wikipedia example

Control [edit | edit source]

Consider a researcher attempting to assess the effectiveness of drug X, from population data in which drug usage was a patient's choice. Data show that gender(Z) differences influence a patient's choice of drug as well as their chances of recovery (Y). In this scenario, gender Z confounds the relation between X and Y since Z is a cause of both X and Y:

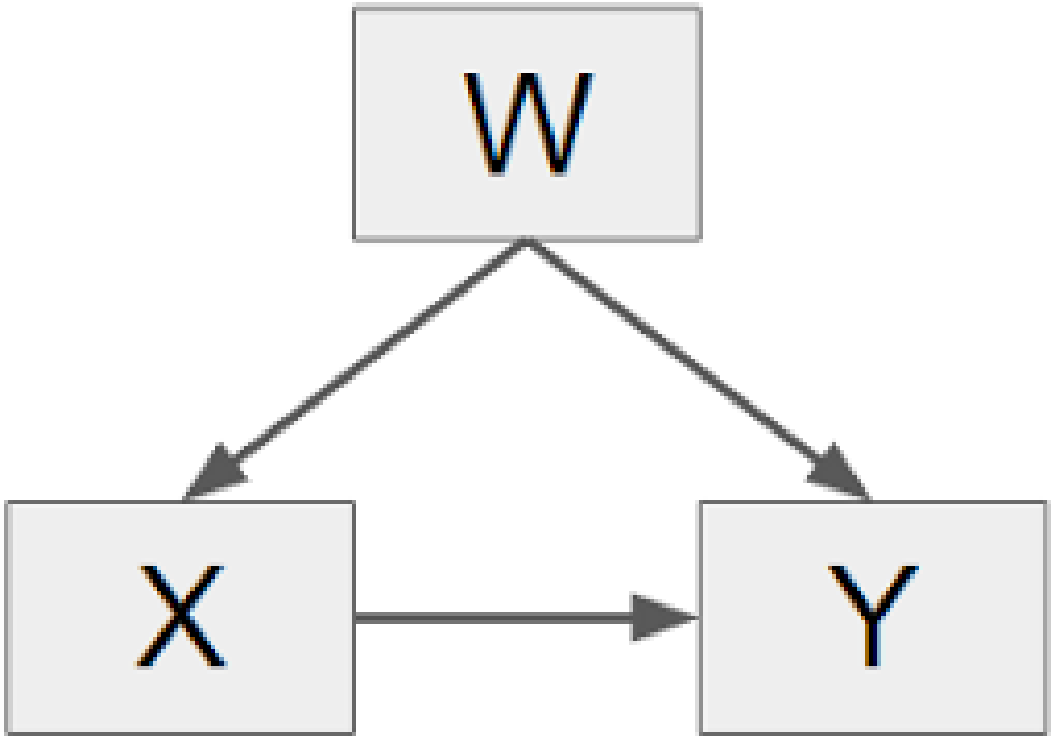


We have that

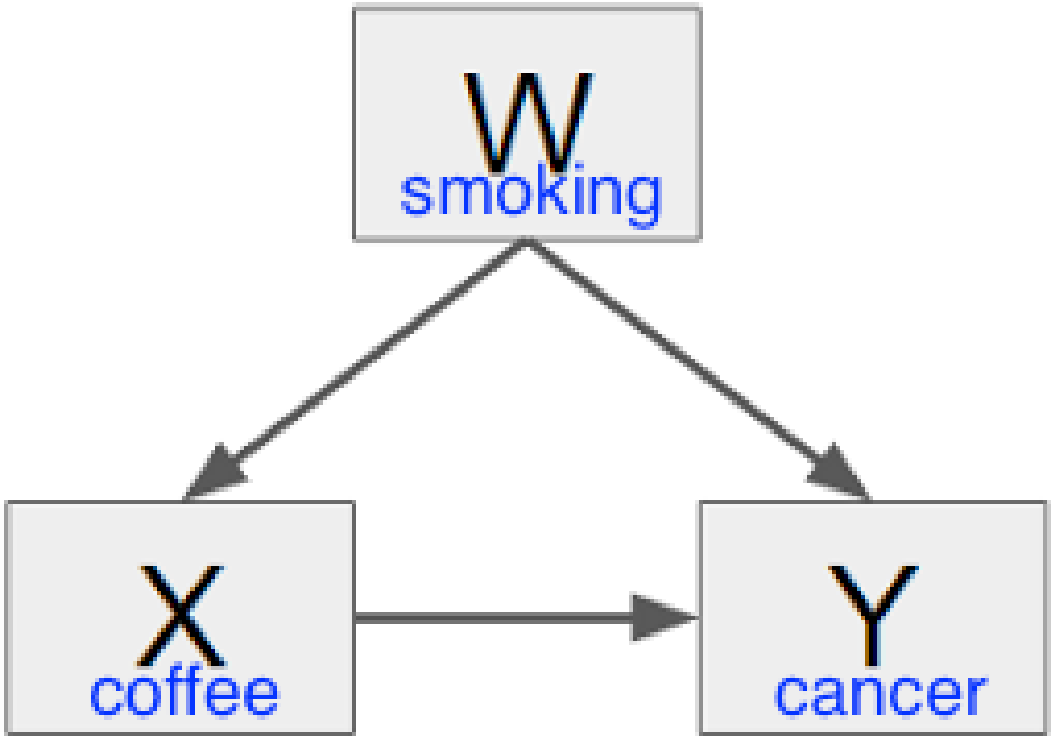
$$P(y \mid do(x)) \neq P(y \mid x) \tag{2}$$

because the observational quantity contains information about the correlation between X and Z, and the interventional quantity does not (since X is not correlated with Z in a randomized experiment). Clearly the statistician desires the unbiased estimate

Coffee (X), Cancer (Y), and Smoking (W)



Coffee (X), Cancer (Y), and Smoking (W)



Learning outcomes (EPI524 Hernan and Swanson)

At the completion of the course, you will be able to:

1. Explain why models are necessary for confounding control
2. Control for confounding using various modeling approaches
3. Identify the relative advantages and disadvantages of each modeling approach
4. Recognize and formulate well defined questions concerning causal effects

EPI524 Description (Hernan and Swanson)

EPI524 describes models for confounding control (or adjustment), their application to epidemiologic data, and the assumptions required to endow the parameter estimates with a causal interpretation. The course introduces students to two broad sets of methods for confounding control: methods that require measuring and appropriately adjusting for confounders, and methods that do not require measuring the confounders.

EPI524 Description cont. (Hernan and Swanson)

Specifically, the course introduces outcome regression, propensity score methods, the parametric g-formula, inverse probability weighting of marginal structural models, and instrumental variable methods as means for confounding control. The models described in EPI524 are for time-fixed dichotomous exposures and dichotomous, continuous, and failure time (e.g., survival) outcomes.

EPI524 Description (Hernan and Swanson)

- Pretty tough sledding
- Can we determine learning outcomes that are more accessible to a broader audience?
- Can we leverage free resources (e.g., Hernan's EdX course) to provide basic background (and free up class time?)

My proposal (intro stat)

- Include multivariate thinking as part of descriptive statistics
- Include multiple regression as part of that introduction
- Address confounding by stratification and multiple regression control
- Introduce idea of a causal graph
- (Avoid paralysis and paranoia re: "other factors")

My proposal (Stat 2)

- Extend ideas of causal graph and formalize causal inference
- Incorporate Hernan EdX course to save on class time
- Focus on what causal graphs tell us to do in terms of multiple regression, exposure to one or more other methods to address confounding

My proposal (Capstone and other courses)

- Reinforce and extend these ideas in later courses and projects

Home » Member News, People News

2017 Causality in Statistics Award Announced

1 AUGUST 2017 219 VIEWS NO COMMENT

The American Statistical Association will award the fifth Causality in Statistics I
Shpitser, John C. Malone Assistant Professor of Computer Science at The Joh
2017 Joint Statistical Meetings in Baltimore.

Making this happen

- Design and confounding are arguably the most important statistical foundation topics (after the concept of variability)
- Rich and sophisticated literature on causal inference now exists
- New curricular models and materials have been created (more needed)
- Need to rethink how we integrate this material into our courses (and promulgate the approach)

Teaching multivariate thinking and confounding

1. what are we currently teaching?
2. motivating multivariate examples
3. confounding 101 and 201
4. closing thoughts: next steps

2.6 The Question of Causation*

In many studies of the relationship between two variables, the goal is to es
tablish that changes in the explanatory variable *cause* changes in the respons
variable. Even when a strong association is present, the conclusion that thi
association is due to a causal link between the variables is often hard to find
What ties between two variables (and others lurking in the background) ca

*This section is optional.

Next steps

- focus on writing (e.g., KB talk to follow)
- focus on projects (e.g., Katherine, Jessen, and Patricia talks)
- focus on visualization (e.g., Vetria's talk)
- rethink our key topics for introductory and intermediate courses

Closing thought: need to avoid paralysis

- Ensure that students don't get stuck (conclude they can't make any headway if data don't arise from a randomized trial)
- Teach (modern) design early and often
- Reinforce key aspects (observational data vs. randomized trials) when we teach inference
- Teach techniques to move beyond two-sample t-test (stratification and multiple regression)
- Make room by simplifying (what if all datasets were $n > 100$? what if p-values were de-emphasized?)

Multivariate thinking and the introductory statistics and data science course: preparing students to make sense of observational data

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Amherst College, Amherst, MA, USA

JSM, July 31, 2018

nhorton@amherst.edu
https://www.github.com/Amherst-Statistics/JSM2018