Is all that coffee I'm drinking hurting me?

Talking about causality in Intro Stats

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SSC 2017

The context

- Introductory statistics
- Non-mathematical
- Students from a wide variety of programs of study
- 1700 students in 6 sections
- 1 section online, 5 sections taught as inverted classrooms

Some important ideas in the course related to causal reasoning

- If two groups are similar apart from the treatment, then differences in the outcomes between the two groups can be attributed to the treatment.
- What is the purpose of randomization in experiments (and sampling)?
- Without randomization, the possibility of confounders should keep you up at night.
- *Sometimes, Always, or Never?*
  - Correlation implies causation.
  - If X causes Y and the correlation between X and Y is positive, then Y increases when X increases.

“Correlation does not imply causation”

Tufte suggested that the shortest true statement that can be made about causality and correlation is one of the following:

1. “Empirically observed covariation is a necessary but not sufficient condition for causality.”
2. “Correlation is not causation but it sure is a hint”

(https://en.wikipedia.org/wiki/Correlation_does_not_imply_causation)

Causality in introductory statistics

Summary:

- Some evidence of student misconceptions related to reasoning about causation
- Why is causal reasoning difficult?
- What can we do about it?
- Does causation matter in 2017?

Some evidence of student misconceptions related to reasoning about causation

Some evidence of misconceptions related to reasoning about causation

A classroom "clicker" question:

What conditions would need to be satisfied in order to say that a change in the variable X causes a change in the variable Y?

A. When the correlation between X and Y is close to 1 or -1
B. When an experiment shows a difference in Y between randomly assigned values of X
C. When the participants in the study are a random sample from a population of interest
D. All of the above

Some evidence of misconceptions related to reasoning about causation

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B. When an experiment shows a difference in Y between randomly assigned values of X
C. When the participants in the study are a random sample from a population of interest
D. All of the above (the most commonly chosen answer)

Some evidence of misconceptions related to reasoning about causation

From a pre-post test of conceptual understanding (CAOS):

A recent research study randomly divided participants into groups who were given different levels of Vitamin E to take daily. One group received only a placebo pill. The research study followed the participants for 8 years to see how many developed a particular type of cancer during that time period. Which of the following responses gives the best explanation as to the **purpose of randomization** in this study?

A. To increase the accuracy of the research results.

B. To ensure that all potential cancer patients had an equal chance of being selected for the study.

C. To reduce the amount of sampling error.

D. To produce treatment groups with similar characteristics.

E. To prevent skewness in the results.

Some evidence of misconceptions related to reasoning about causation

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E. To prevent skewness in the results.

- 74% of students got it wrong in both pre- and post-test
- 11% of students got it right in both pre- and post-test
- 15% of students got it wrong in pre-test, but right in post-test

Some evidence of misconceptions related to reasoning about causation

From a study on secondary school students' covariational reasoning (Gil & Gibbs, 2017)

Pre-unit activity:

- Explore relationships in Gapminder
- Our goal: assess current level of covariational and multivariable reasoning
- Common student comment: "Correlation is not causation"

Some evidence of misconceptions related to reasoning about causation

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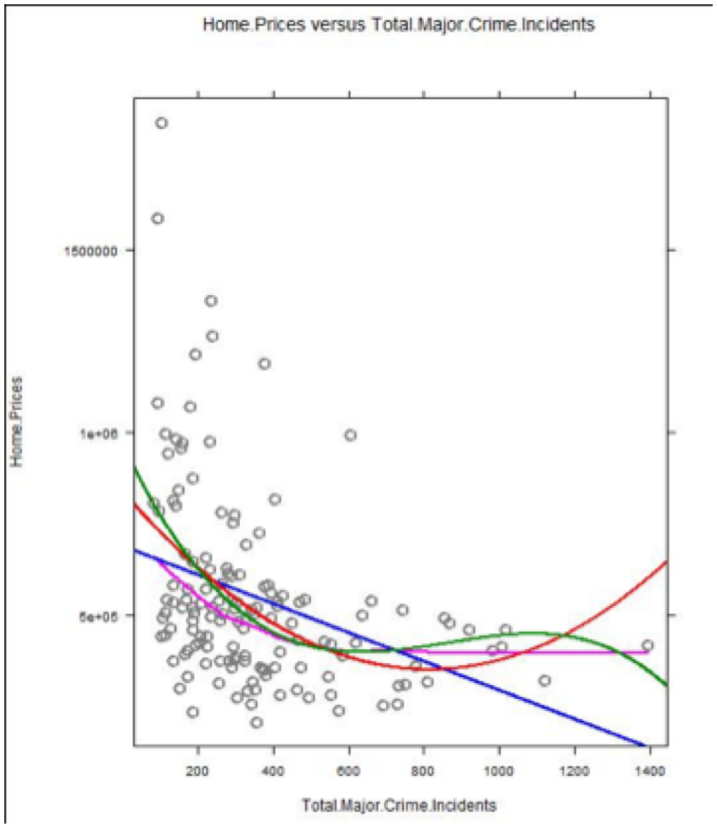
Final activity:

- Explore relationships in Wellbeing Toronto data http://map.toronto.ca/wellbeing and create a pitch to the mayor
- Conclusion? "Less crime leads to higher house prices"



Some evidence of misconceptions related to reasoning about causation

From Ontario grade 12 "Foundations for College Mathematics" course learning outcomes:

"By the end of this course, students will make conclusions from the analysis of two-variable data (e.g., ***by using a correlation to suggest a possible cause-and-effect relationship****), and judge the reasonableness of the conclusions (e.g., by assessing the strength of the correlation; by considering if there are enough data)"*

Why is causal reasoning difficult?

Why is causal reasoning difficult?

Reason 1: Ambiguous language

- Unfamiliar scientific vocabulary:
  - Affects students' ability to understand lectures, readings, assessments, feedback
  - Creates anxiety
  - Makes the subject appear more difficult than it is
- Words that are used differently in common conversation (e.g., association, random, control, correlation, cause, effect, etc.) can cause students to build incorrect understanding

(Kaplan et al. 2009, Dunn et al. 2016)

Why is causal reasoning difficult?

Reason 2: Belief Bias

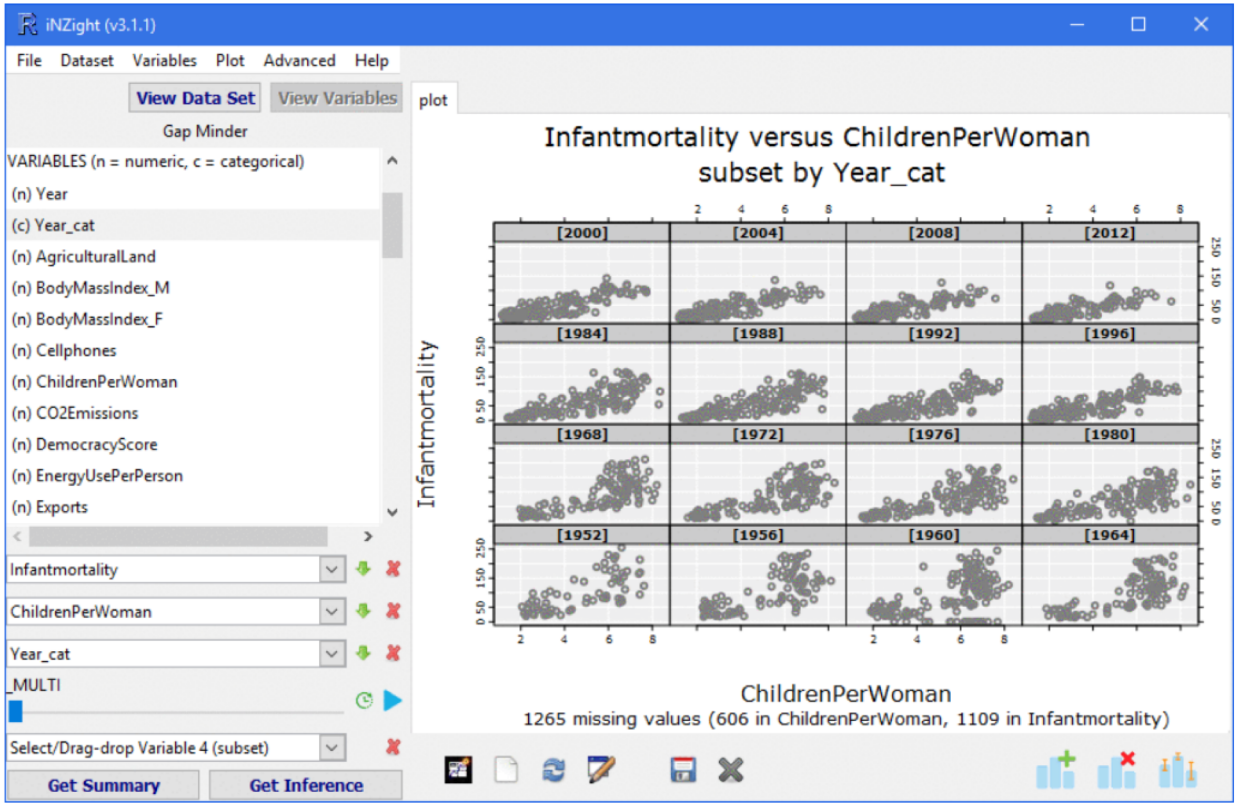
- *Belief Bias:* Students are predisposed to be influenced by prior beliefs
- A study: Students were presented with 3 studies each showing significant results and similar effect sizes, with believability rated as low, moderate, high
- For **only** the study with low believability, students:
  - questioned the design (sample size, choice of subjects)
  - criticized the size of the effect
  - asked about potential sources of bias

(Kaplan 2009)

Why is causal reasoning difficult?

Reason 3: Lack of multivariable reasoning

- Despite training, secondary school students did not choose to use multivariable visualization tools in iNZight (Gil & Gibbs 2017)



Why is causal reasoning difficult?

Reason 4: Untangling unquantifiable uncertainty from experiment-to-causation inference

- Other possible issues:
  - Data quality
  - Data validity
  - Generalizability
- Most research has focused on sample-to-population inference rather than experiment-to-causation inference

(Pfannkuch et al. 2015)

What can we do?

What can we do?

Be aware of ambiguous language and and discuss the ambiguity

urbandictionary.com

TOP DEFINITION

Random

The latest buzzword used amongst mindless teenagers as a way of showing just so utterly irreverent their predictable sense of humour is. Particularly dominant among English teens and University students, the word "random" or the act of being "random" is a desperate plea for others to recognise how totally against the grain of the norm you are and that you're really crazy and out there. Trouble is, being "random" is predictable, boring, moronic and extremely sad indeed.

Often used by an **MTVeenager**.

Uni Student: "Cheese! HA HA!"
Another Uni Student: "Wow that's soooo RANDOM! Let's go and buy some trendy clothes which have meaningless and pretentious words/numbers all over to make us look random."

What can we do?

Teach design early and incorporate it throughout the course

- An overarching question for the course:

  How does how I collect my data affect my analysis and my conclusions?

- An exercise:

  How would you design a study to test whether speaking to your fetus in utero is important to the child's development?

What can we do?

Give students the language to talk about associations

The New York Times

Coffee Drinkers May Live Longer

By TARA PARKER-POPE MAY 16, 2012 5:00 PM 292

VENTURA COUNTY STAR
vcstar.com
PART OF THE USA TODAY NETWORK

Study suggests heavy coffee drinkers may die early

By Tom Kisken of the Ventura County Star

*Posted: **Sept. 01, 2013***

What can we do?

Give students the language to talk about associations

The New York Times

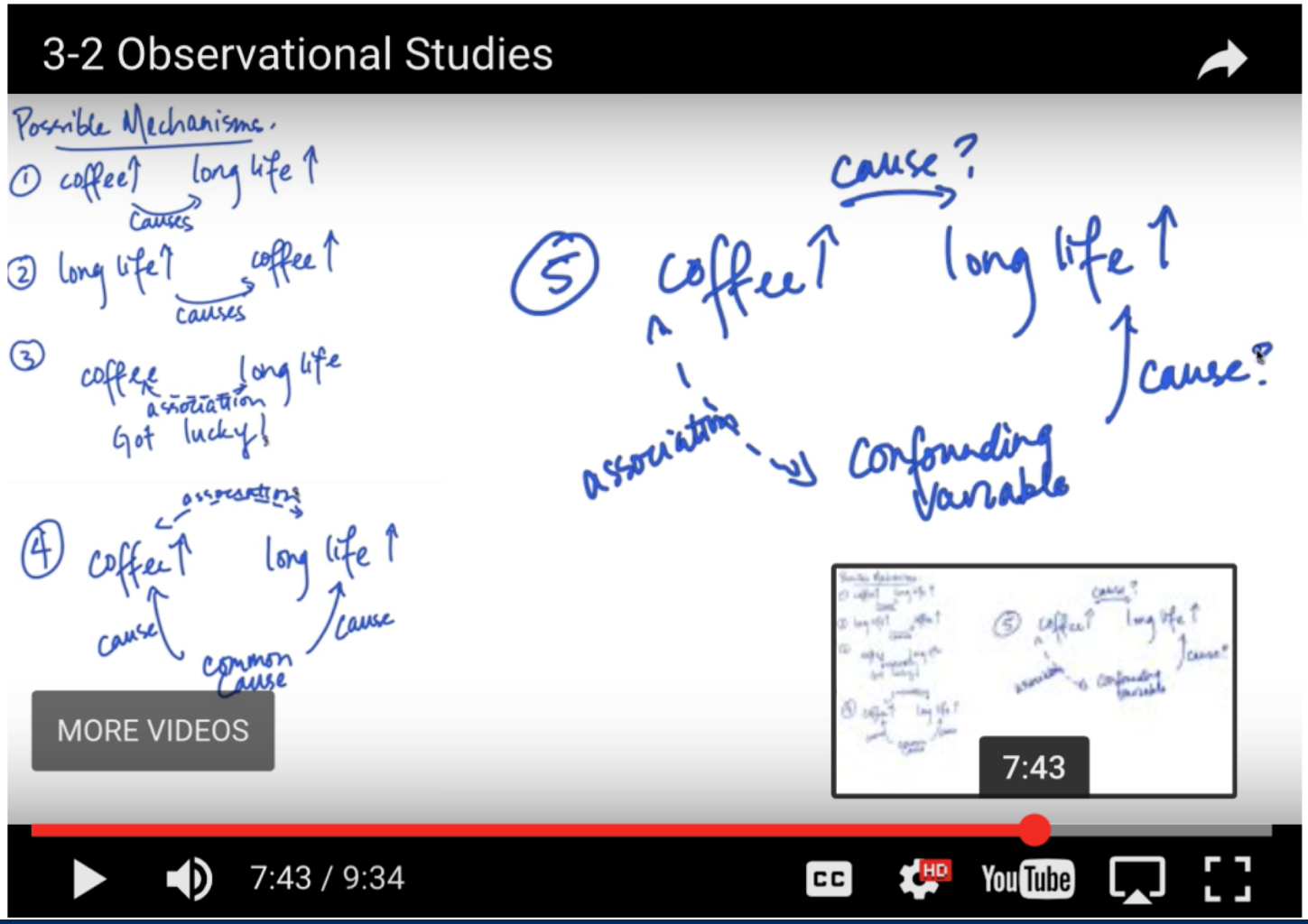
Coffee Drinkers May Live Longer

By TARA PARKER-POPE MAY 16, 2012 5:00 PM 292

- Report on study in *New England Journal of Medicine*
- Looked at association of coffee drinking and mortality
- 400,000 men and women, aged 50-71 years
- Followed from 1995 to 2008
- 52,000 died

What can we do?

Give students the language to talk about associations



1. Causation
2. Reverse causation
3. Coincidence
4. Common cause
5. Confounding variable

What can we do?

Emphasize the roles of randomization

3-3 Experiments

Randomisation in Experiments

		Assignment of treatments	
		Random	Not random
Selection of experimental units	Random	Can make causal conclusions that can be generalised to the population	Cannot make causal conclusions but results can be generalised to the population
	Not random	Can make causal conclusions about only the participating experimental units	Cannot interpret observed relationships as causal and cannot generalise beyond the participating experimental units

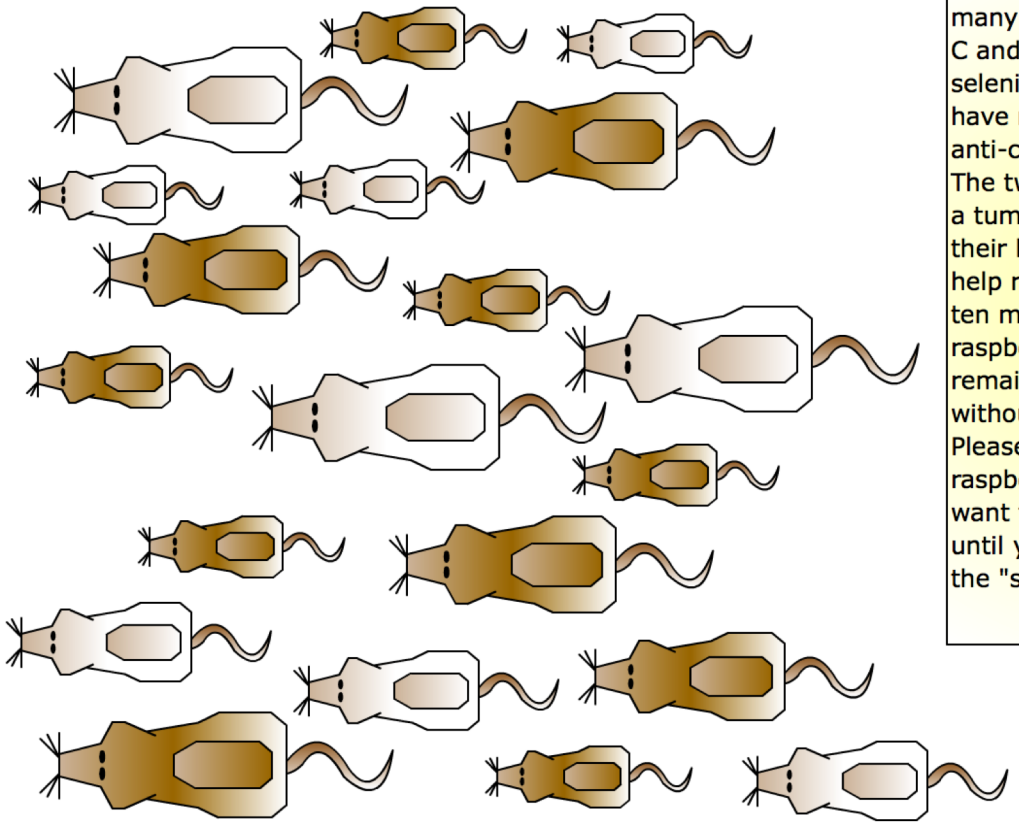
MORE VIDEOS

15:31 / 15:50

What can we do?

Demonstrate why randomization works

Please Choose 10 Mice for the Raspberry Treatment



Raspberries have a high content of many beneficial compounds like vitamins C and E, folic and ellagic acid, calcium, selenium, etc. As a result, researchers have recently been investigating their anti-cancer properties.
The twenty mice in the picture all have a tumor growing just under the skin on their backs. To test if raspberries can help reduce the growth of these tumors, ten mice will be chosen to have raspberries added in their diet and the remaining ten will eat a normal diet without the raspberries.
Please pick the ten mice to receive the raspberry diet (just click on mice you want to include in the raspberry group until you have selected ten, then click the "submit selections" button).

submit selections

0 Number of Chosen Mice

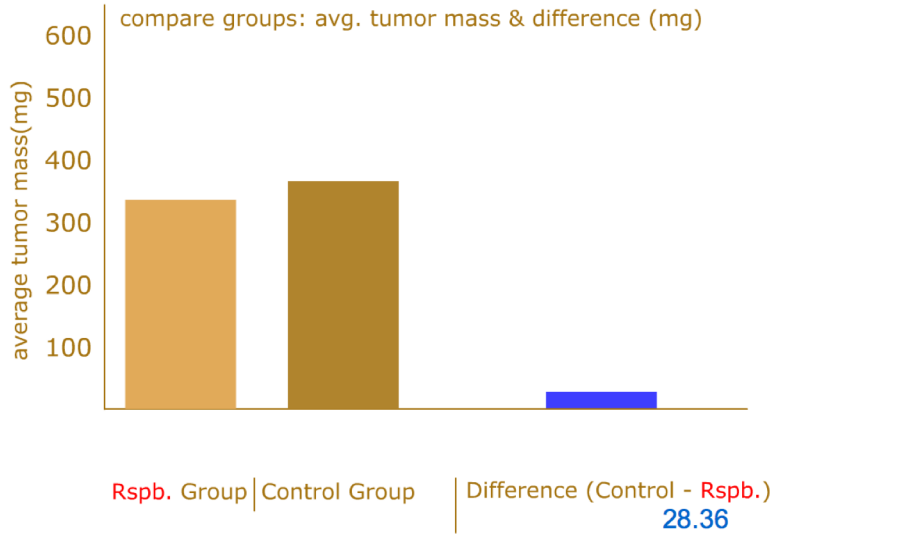
https://www.causeweb.org/cause/webinar/activity/2009-05

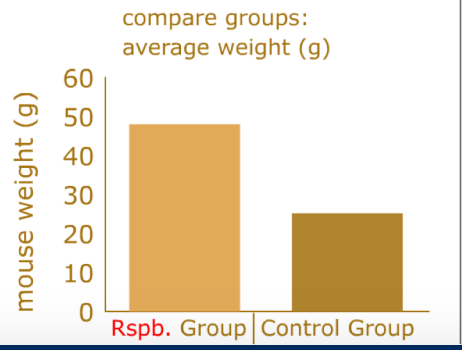
What can we do?

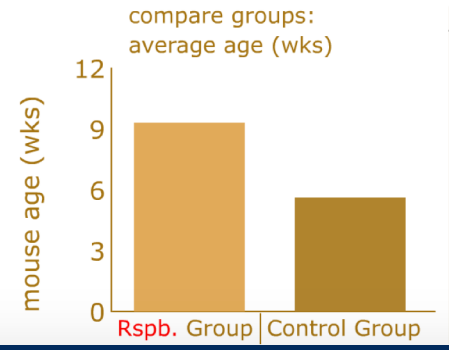
Demonstrate why randomization works

Summary of Data for Raspberry and Control Groups

	total selected	average wt. (g)	average age (wks.)	average tumor mass (mg)	proportion female	proportion brown
Rspb. Group	10	48	9.3	335.74	6 / 10	6 / 10
Control Group	10	25.1	5.6	364.1	4 / 10	5 / 10







random mouse selection

hand-selected mice summary

back to hand-selected mice

restart activity

use raw data

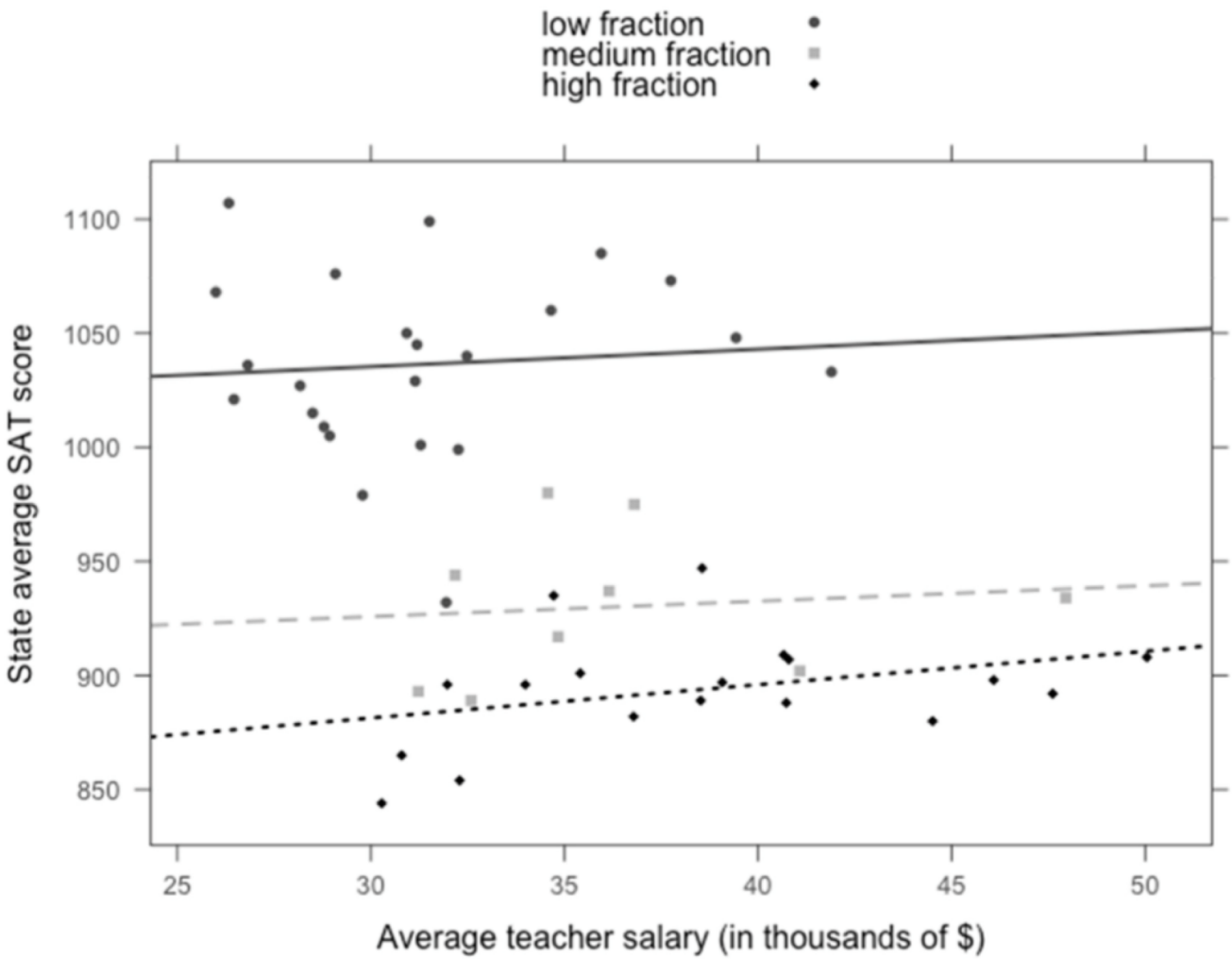
What can we do?

Demonstrate multivariable thinking

- Simpson's paradox
  - If you can reverse the association, can it be causal?
- Guidelines for Assessment and Instruction in Statistics Education (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.
  5. Use technology to explore concepts and analyze data.
  6. Use assessments to improve and evaluate student learning.

What can we do?

Demonstrate multivariable thinking



What can we do?

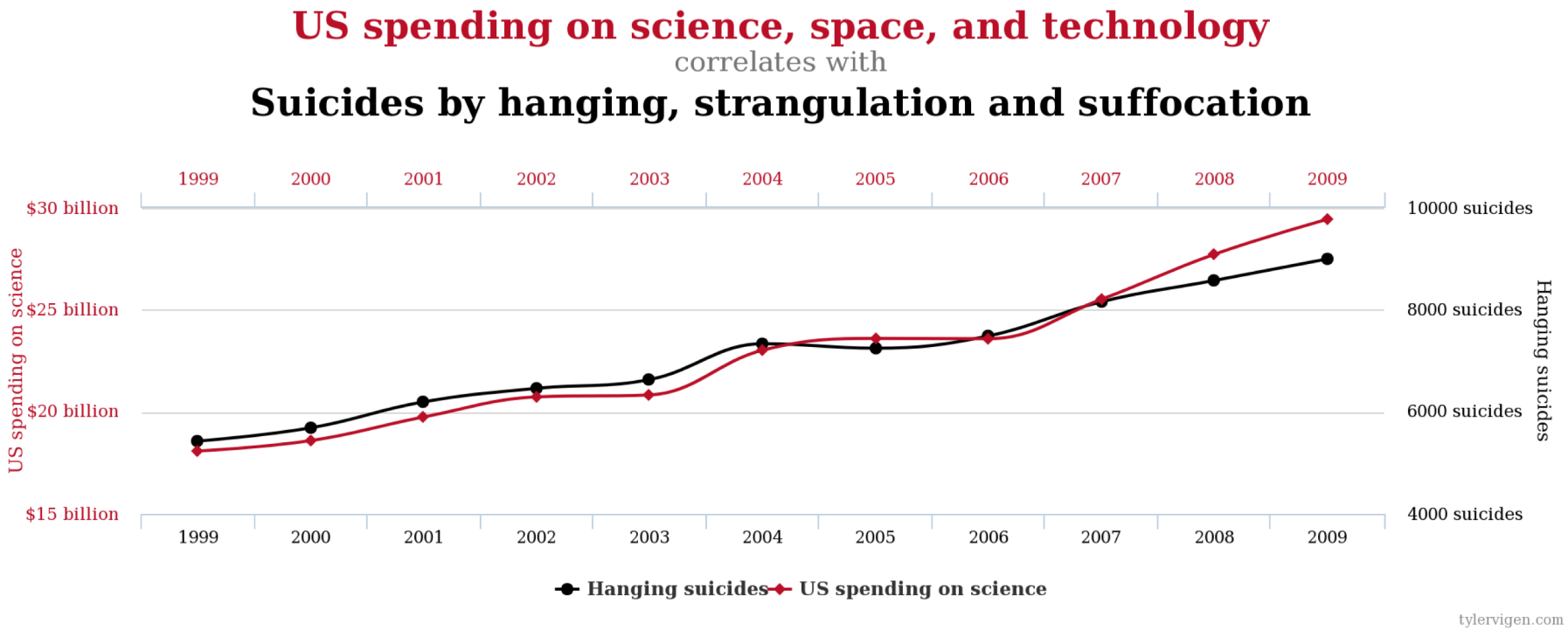
Tell stories

- Stories facilitate the following cognitive processes:
  - *Concretizing:* Provide tangible, concrete examples for abstract or complex idea
  - *Assimilation:* Integrate new information with previous understanding
  - *Structurizing:* Support the ability to apply concepts in new situations

  (Evans and Evans, 1989)
- Include stories where cause can be inferred, and when it can't, and when the causation is plausible, and when it's not

What can we do?
Tell stories

- Spurious correlations:
  - 1870s: Willian Stanley Jevons claimed to show sunspot activity affected business cycles (and was mocked) (Stigler 2005)
  - http://www.tylervigen.com/spurious-correlations



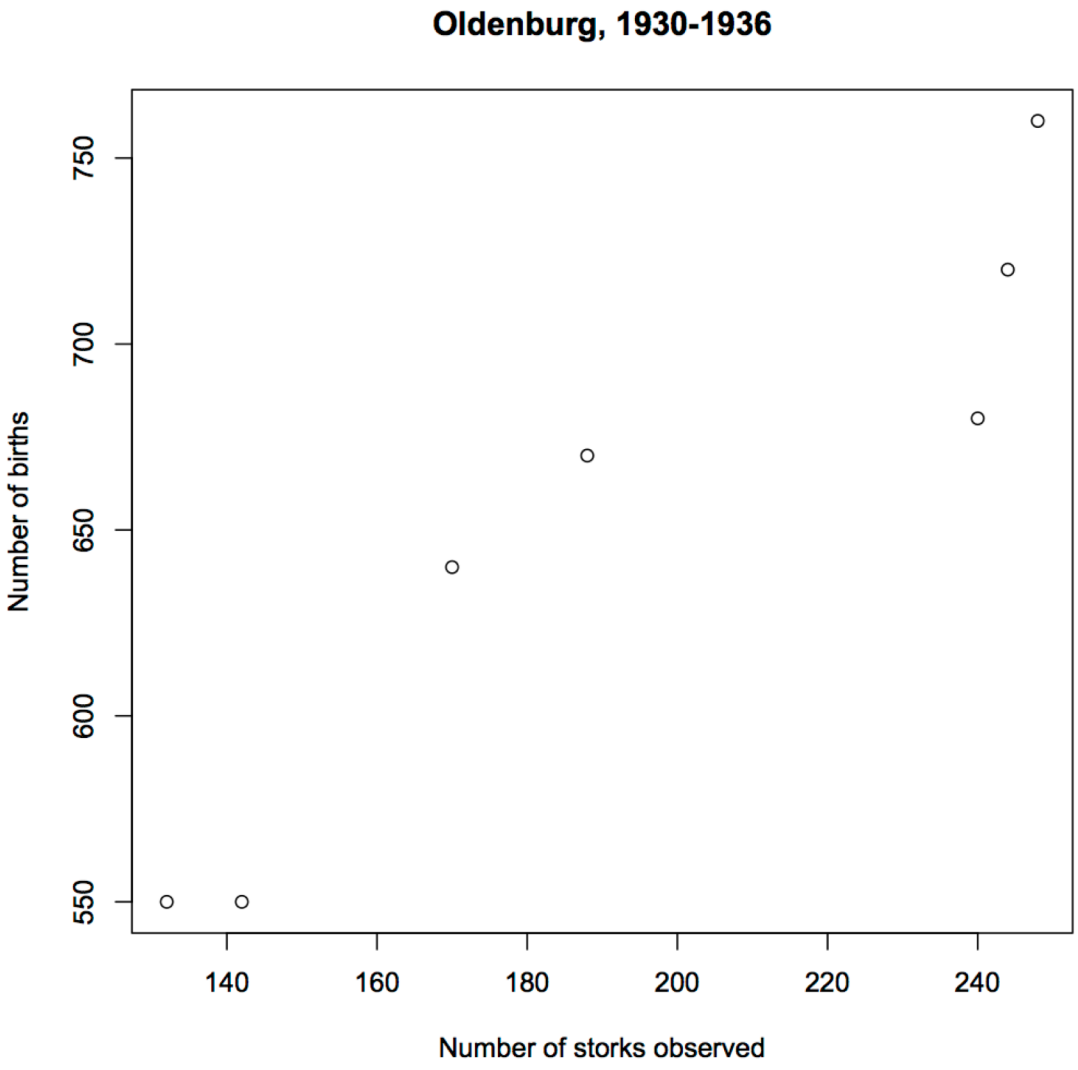
What can we do?
Tell stories

Where do babies come from?

- As is well known, storks bring newborns.
- Here's my evidence:

  The correlation between the number of births and number of storks observed is 0.94.

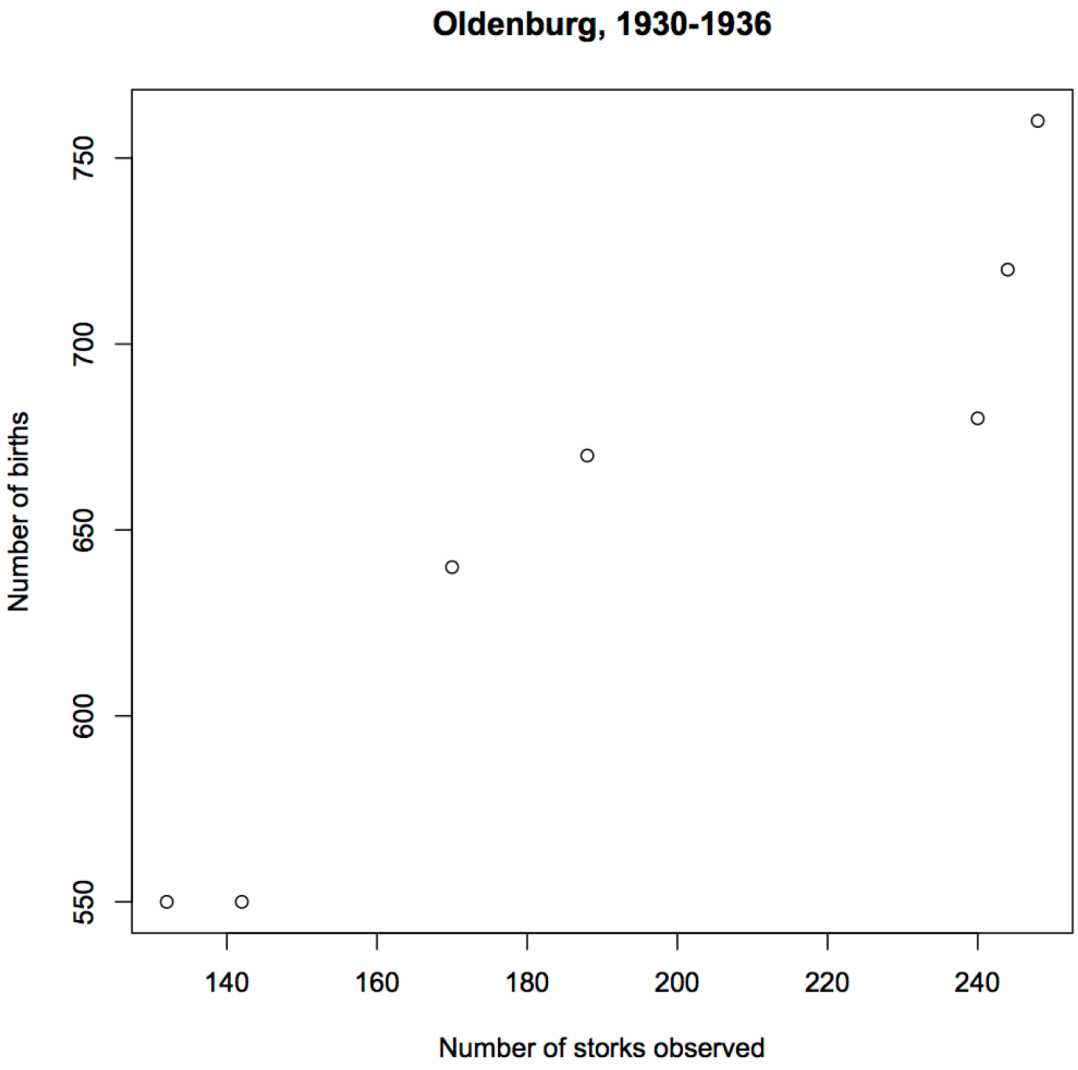
Data adapted by Box, Hunter, and Hunter from G. Fischer, *Ornithologische Monatsberichte*, vol. 44, no. 2, Jahrgang, 1936, Berlin and vol. 48, No. 1, Jahrgang, 1940, Berlin, and *Statistiches Jahrbuch Deutscher Gemeinden*, 27-33, Jahrgang, 1932-1938.



What can we do?

Tell stories

- The population of Oldenburg grew steadily in the 1930's.
- As the population increased, there was more building construction, providing more nesting places for storks.
- As the population increased, there were more people to have babies.



What can we do?

Tell stories

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Does drinking cow's milk help children grow taller?

Nutrition team finds 3-year-olds consuming alternative milks were 1.5 cm shorter on average

By Amina Zafar, CBC News Posted: Jun 07, 2017 4:44 PM ET | Last Updated: Jun 07, 2017 10:12 PM ET

Everest Frenke, 2, drinks some fortified soy milk. The Toronto toddler's mother sometimes adds flax oil, peanut butter or hemp seeds to ensure her daughter is getting important nutrients. (CBC)

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What can we do?

Tell stories

TECH & SCIENCE

IS PLANT MILK GOOD FOR YOU? CHILDREN WHO DRINK COW DAIRY ARE TALLER, STUDY SHOWS

BY JESSICA WAPNER ON 6/7/17 AT 2:10 PM

What can we do?

Tell stories

"To consult the statistician after an experiment is finished is often merely to ask him to conduct a post mortem examination. He can perhaps say what the experiment died of."

- Ronald Fisher, Presidential Address to the First Indian Statistical Congress, 1938

What can we do?

Don't ignore practical realities

- Experiments can be expensive, unrealistic, unethical
- Missing data messes up randomization
  - People who drop out of clinical trials are more likely to have bad results
  - Visualize missing data

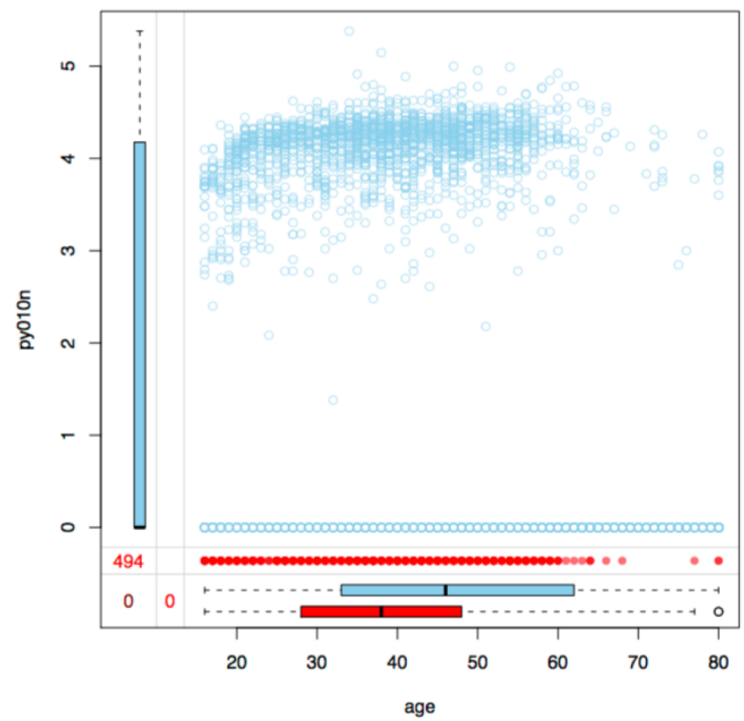

Figure 8: Scatterplot of *age* and transformed *py010n* (employee cash or near cash income) with information about missing values in the plot margins.

Does causation matter?

Does causation matter?

Next year I'm teaching a new introductory statistics course:

- First year
- For students who will go on to study statistics
- Course title:

  "An Introduction to Statistical Reasoning and **Data Science**"

Does causation matter?

With Big Data, is causality dead?

"Petabytes allow us to say: 'Correlation is enough.' "

– Chris Anderson, *Wired Magazine*, June 23, 2008

When does causation matter?

- Description, prediction, or explanation?
- Can action be taken based on a finding of correlation?
- If we want to change policy, we want to be confident change in outcomes will result.
- Is correlation good enough when the goal is to market possible purchases to online shoppers?

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