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Correlation vs causation examples in real life

When I first started blogging about correlation and causation (literally my third and fourth post ever), I asserted that there were three possibilities whenever two variables were correlated. Now that I'm older and wiser, I've expanded my list to six: Thing A caused Thing B (causality) Thing B caused Thing A (reversed causality) Thing A causes Thing B which then makes Thing A worse (bidirectional causality) Thing A causes Thing X causes Thing Y which ends up causing Thing B (indirect causality) Some other Thing C is causing both A and B (common cause) It's due to chance (spurious or coincidental) The obvious conclusion is that years spent blogging about statistics directly correlates to the number of possible ways of confusing correlation and causation you recognize. Anyway, I've talked about this a lot over the years, and this lesson is pretty fundamental in any statistics class…though options #3 and #4 up there aren't often covered at all. It's easily forgotten, so I wanted to use this post to pull together an interesting example of each type. Smoking cigarettes cause lung cancer (Thing A causes Thing B): This is an example I use in my Intro to Internet Science talk I give to high school students. Despite my continued pleading to be skeptical of various claims, I like to point out that sometimes disbelieving a true claim also has consequences. For years tobacco companies tried to cast doubt on the link between smoking and lung cancer, often using "correlation is not causation!" type propaganda. Weight gain in pregnancy and pre-eclampsia (Thing B causes Thing A): This is an interesting case of reversed causation that I blogged about a few years ago. Back in the 1930s or so, doctors had noticed that women who got pre-eclampsia (a potentially life threatening condition) also had rapid weight gain. They assumed the weight gain was causing the pre-eclampsia, and thus told women to severely restrict their weight gain. Unfortunately it was actually the pre-eclampsia causing the weight gain, and it is pretty likely the weight restrictions did more harm than good. Dating and desperation (Thing A causes Thing B which makes Thing A worse): We've all had that friend. The one who strikes out with everyone they try to date, and then promptly doubles down on their WORST behaviors. This is the guy who stops showering before he takes girls out because "what's the point". Or the girl who gets dumped after bringing up marriage on the third date, so she brings it up on the first date instead. This is known as "bidirectional causality" and is less formally known as "a vicious cycle". In nature this can cause some really amusing graph behavior, as in the case of predators and prey. An increase in prey can cause an increase in predators, but an increase in predators will cause a decrease in prey. Thus, predator and prey populations can be both positively AND negatively correlated, depending on where you are in the cycle. Vending machines in Schools and obesity (Thing A causes Thing X causes Thing Y which then causes Thing B): One obvious cause of obesity is eating extra junk food. One obvious source of extra junk food is vending machines. One obvious place to find vending machines is in many schools. So remove vending machines from schools and reduce obesity, right? No, sadly, not that easy. In a longitudinal study that surprised even the authors, it was found that kids who moved from schools without vending machines to those with vending machines don't gain weight. What's interesting is that you can find a correlation between kids who were overweight and eating food from vending machines, but it turns out the causal relationship is convoluted enough that removing the vending machines doesn't actually fix the original end point. Vitamins and better health (Some other Thing C is causing Thing A and Thing B):This one is similar to #4, but I consider it more applicable when it turns out Thing A and Thing B weren't even really connected at all. Eating a bag of chips out of a vending machine every day CAN cause you to gain weight, even if removing the vending machine doesn't help you lose it again. With many vitamin supplements on the other hand, initial correlations are often completely misleading. Many people who get high levels of certain vitamins (Thing A) are actually just those who pay attention to their health (Thing C), and those people tend to have better health outcomes (Thing B). Not all vitamins should be tarred with the same brush though, this awesome visualization shows where the evidence stands for 100 different supplements. Spurious Correlations (spurious or due to chance): There's a whole website of these, but my favorite is this one: Causal inference, not for the faint of heart. Posted on 22nd February 2017 by Ludwig Ruf Tutorials and Fundamentals Consciously or subconsciously, we're striving to find explanations in our surroundings about why things happen the way they happen. Let's say we want to know why I suffered from a headache yesterday, or why some genes facilitate the mutation of human cells into cancer cells. Finding the real cause that triggers an outcome is important for three main reasons. It enables us to 1) explain the current situation, 2) predict future outcomes, and 3) to create interventions targeting the cause to change the outcome. Now obviously the difficult task is to find the cause. Difficulty in establishing cause arises because behaviour and physiological processes are often the result of complex interactions between a multitude of factors. However, when things become complex, we try to break them down into the smallest units, investigate the relationships between them and put everything again together in order to draw general conclusions. In research, this is typically done by correlating the variables of interest with each other. That is, by looking to see whether, as one variable increases, another variable also increases (a positive correlation) or decreases (a negative correlation). Example 1: Chocolate consumption & Nobel Prize winners Say, for example, a study found that chocolate consumption per capita is positively correlated with the number of Nobel Prize winners per 10 million residents, with the higher the chocolate consumption, the more Nobel Prize winners (Messerli, 2012). Beware: the interpretation of the nature of this correlation is not straightforward. The study does not provide clear evidence about the direction of the effect. So it's impossible to make a causal interpretation such as 'eating more chocolate causes more Nobel Prizes' or that 'winning more Nobel Prizes makes you eat more chocolate'. In other words, we can say nothing about whether eating more chocolate will increase the likelihood of winning a Nobel Prize or vice versa. It is worth noting in this case that correlations simply show a pattern, without proving the nature of this pattern. It could be that this correlation simply occurs by chance. This is known as a spurious correlation (i.e. where 2 or more events are not causally related but may appear to be, either by coincidence or because they are caused by some unknown factor). Click here to discover moreÂ spurious correlations. Example 2: Antibiotic exposure during first year of life & weight gain in early childhood Let's examine a second example: the potential association between antibiotic exposure within the first year of life and weight gain during early childhood. Research indicates that receiving more antibiotic orders increases the risk of being overweight at later ages during childhood (e.g. Bailey et al., 2014). It might seem logical to conclude that consuming antibiotics in the first year of life causes excessive weight gain during early childhood. However, again, this type of research only shows a correlation. It does not examine the cause for these children becoming overweight compared to those children receiving less or no exposure to antibiotics. The follow-up question has to be: What is the exact underlying physiological mechanism behind this connection? While this research is helpful in first place, we should only take it as a starting point to discover the true mechanisms (if there are any). Without doing that, our interventions will be less effective because we are not targeting the actual cause. Bailey et al. (2014). These figures show increased risk of obesity with greater antibiotic use, particularly for children with 4 or more exposures to antibiotics. Example 3. Increased BMI and increased risk of cancers Lastly, let's consider a third example. Increased BMI seems to be associated with an increased risk of several cancers in adults (Renehan et al., 2008). Again, we might be misled by this. It would be erroneous to conclude that simply being overweight causes cancers. Instead, we need to consider other potential variables that might explain the relationship between increased BMI and increased risk of cancers. For instance, it can be argued that people with lower socioeconomic status are less educated about potential risk factors, can't afford good healthcare service (e.g. preventive measures to reduce the risk of cancers) or simply have a lifestyle facilitating the development of certain diseases (e.g. less physical activity, diet and so so). In fact, socioeconomic status seems to be associated with BMI in British women aged between 37 and 73 years (Tyrrell et al., 2016). These 3 examples illustrate some common pitfalls one can make when drawing conclusions from correlation studies. Although being aware of these pitfalls, it can be difficult to avoid them. Nevertheless, I would recommend asking yourself the following questions while dealing with correlations: Is there scientific evidence, or even plausible logic, regarding the direction of the effect? (see the chocolate example). Are there intermediate variables that can explain the correlation? e.g. a biological mechanism that could explain the relationship (see the antibiotic example). Are there unmeasured variables that could explain the correlation? e.g. a third factor which could explain the relationship (see the cancer example). To conclude, observing correlations between variables can be relatively straightforward, but establishing that one thing causes another is difficult. When reading articles or scientific papers, make sure to be critical. Question whether the claimed correlation between two variables can be treated as having a causal relationship. So what is needed for the future? I think we need to develop the big picture of the interconnected relationships, rather than finding isolated associations between individual variables. But before we have better answers regarding the complex interaction of correlations, it might be a good excuse to go for that bite of chocolate. You never know. References
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