Correlation and Causation

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12 Scientific Reasoning

Acknowledgements: Bill Bechtel

Review: two types of correlational studies

1. when same items have values on two score variables, correlate the scores on one with the scores on the other
   - Measure degree of correlation in terms of Pearson coefficient r
   - Predict value on one variable from that on the other using the regression line: $y = ax + b$
2. when one nominal variable divides a population into two or more sub-populations, compare the two populations on another (score) variable in terms of their central tendencies
   - If the means are different, predict the value on the score variable depending on the value of the nominal variable.

Review

In both types of correlational studies, one commonly makes inferences from a sample to an actual (total) population.

- Does what is found in the sample apply to the actual population?
- addressed in terms of statistical significance:
    - Is the result in the sample one that would be unlikely to happen by chance if there weren't a correlation or a difference in the actual population?
    - The *p*-value specifies the likelihood of the result in the sample happening by chance (in drawing the sample). (E.g., $p < 0.05$ indicates there is less than 5% chance of the result happening by chance)

Review

- In testing a claim about differences in the means of two sub-populations, one tests the null hypothesis, hypothesis that there is no difference in the means.

⇒ The strategy is to try to reject the null hypothesis in terms of the results in the sample:

  - If the differences in means in the sample are statistically significant (at a choosen level), one infers that the null hypothesis is false.

    ⇒ Therefore, the means differ in the real populations.

  - If the differences in means in the sample are not statistically significant (at the choosen level), one cannot reject the null hypothesis.

    ⇒ Whatever differences there might be, they will not have been detected.

Note

Note

No significant difference does not mean there is no difference: There may well be a difference, but one that has not been detected given the tests employed. All we can say is that we have not detected any difference.

Contrast:

- We have not found the person who killed the Prime Minister.
- No one killed the Prime Minister.

Review: two types of error

- Type 1 error: concluding that there is a difference between the two groups in the population when there is no difference.
- Type 2 error: concluding that there is no (detectable) difference between the two groups in the population when there is a difference
- To reduce Type 1 error: demand a higher *p*-value before accepting that there really is a difference
- To reduce Type 2 error: use a larger sample size, which is more likely to produce a statistically significant difference if there really is a difference in the two groups

The logic of correlational research

- To confirm or falsify a correlational claim based on a sample, we use *modus tollens*. The first premise in each case, though, is different.
- Confirming a correlational claim:

  (1) If there is no difference between means in the population, then there will not be a statistically significant difference (p $<$?) in my sample.
  (2) There is a statistically significant difference (p $<$?) in means in my sample.

  $\therefore$ *There is a difference between means in the population.*

- We pick the level of significance in the first premise according to how great a risk of error we can accept.

Avoid Affirming the Consequent!

What about this argument?

(1) If there is a difference between means in the population, then there will be a statistically significant difference (p $<$?) in my sample.
(2) There is a statistically significant difference (p $<$?) in means in my sample.

$\therefore$ *There is a difference between means in the population.*

This is invalid!

The logic of correlational research

- Falsifying a correlational claim:

  (1) If there is a detectable difference between means in the population, then there will be a statistically significant difference (p $<?$) in my sample.
  (2) There is no statistically significant difference (p $<?$) in means in my sample.

  $\therefore$ There is no detectable difference between means in the population.

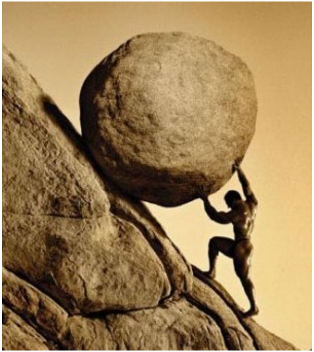
- The truth of the first premise depends upon using a large enough sample.
- (Note: the conclusion refers to detectable differences.)

Quest for finding causes

When something happens, we ask ‘Why?’; we want to know what caused the event. But why are we interested in what caused the event?

- knowing the causes frequently provides understanding
- knowing causes empowers us to intervene
- these two tend to go together:
  - Why do these barrels produce better beer?
    - learning the reason is more hops provides understanding
    - and a procedure for making better beer
  - How does HIV cause AIDS?
    - knowing about protease inhibitors explains
    - and tells us a good place to intervene

What is a cause?



The roots of appeal of causation lie in our doing something to produce and effect:

- We want to move a rock, so we push it.
- We want to see a friend so we walk to her apartment.
- We want to stay warm so we put on a jacket.

Definition (Cause)

Independent of our own action, a cause is something which brings about or increases the likelihood *of an effect.*

Example: the cause of the explosion was the spark from the generator

Correlation and causation

- A major reason people are interested in correlations is that they might be indicative of causation.
- Correlations per se only allow you to predict:
    - The correlation of unprotected sex with having a baby nine months later allows you to predict that if you engage in unprotected sex, you are more likely to have a baby nine months later.
- Causation tells you how to change the effect:
    - Knowing that unprotected sex causes (increases the likelihood of) having a baby nine months later allows you to take action to have or not have a baby.

Correlations point to causation

- Statistical relations between variables that exceed what is statistically expected are typically (but not always) due to causal relations.
    - although not necessarily due to direct causal relations (e.g., there may be a common cause)
- Examples:
    - consumption of red wine and reduced heart attacks
    - books that have a green cover and books that do not sell many copies
    - good study habits and good grades

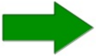
Correlation symmetrical, causation asymmetrical

- being run into in a traffic accident might be a cause for the big dent in your car
- having a big dent in your car is correlated with having a car accident, but it is not the cause of having a car accident
- causation is directional, correlation is symmetrical

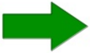
$\Rightarrow$ So when correlation points to causation, we still need to establish the direction.

Problem of directionality

Does watching violence of TV result in aggressive behaviour in children?



Or do the factors that generate aggressive behaviour cause children to watch more violence on TV?

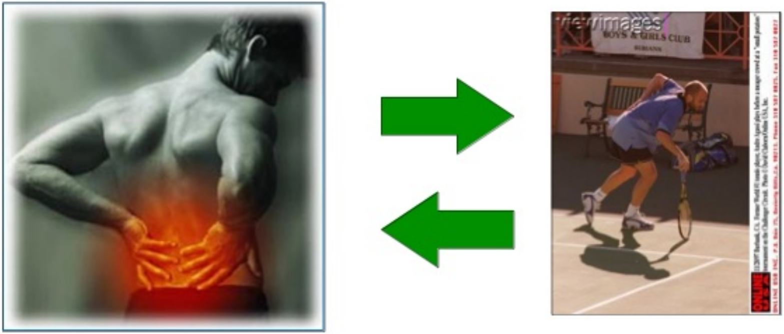


Causal loops

Sometimes X causes Y and then Y causes more X.

- The causation here is still directional, but works in both directions.

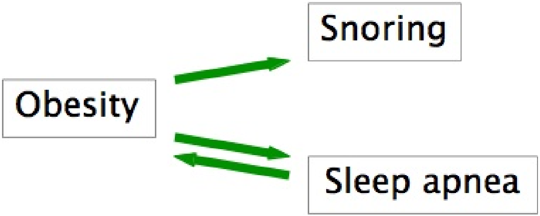
Example: back pain may be the cause of a person limping, but walking with a limp may cause further back pain.



Snoring and obesity

- There is a positive correlation between obesity and snoring.

⇒ Does obesity cause (increased) snoring?
  - Yes, via fat buildup in the back of the throat.
- But fat buildup also causes sleep apnea (sleeper stops breathing momentarily and wakes up).
- As a result of sleep apnea, sufferer is tired and avoids physical activity...
  - ... thereby getting more obese.



Relating correlation and causation

- Establishing correlation does not establish causation

  —but it is a big part of the project!

- If X causes Y, then one expects a correlation between X and Y
  - The greater the value of X (if X is a score variable), the greater the value of Y.
  - Individuals exhibiting X (if X is a nominal variable) will have greater values of Y.

Independent/dependent variables

Independent variable:

- the variable that is thought to the cause
- the variable that is altered/manipulated in an experiment
- the treatment in a clinical trial

Dependent variable:

- the variable that is thought to be the effect
- the variable that one is trying to predict/explain
- the outcome

$\Rightarrow$ The dependent variable depends on the independent variable.

Measured versus manipulated

- The strongest tests of causation claims involve manipulation of variables. $\Rightarrow$ experiments
- In some contexts, a researcher does not or cannot manipulate the independent variable.
  - immoral to assign people to categories such as having unprotected sex
  - cannot assign people to categories such as being female
- If we are nonetheless considering causes in such a case, we refer to a measured independent variable.
- When it is possible to manipulate the independent variable (conduct an experiment), we speak of a manipulated independent variable.

Measures and data

- Often causal relations are specified in general terms:

  Violence on TV causes violent behaviour in school

- The variables used to operationalize such variables are sometimes referred to as measures. The specific values on these variables are data. Consider:

  The number of gun firings on a given TV show is a good measure of violence on the show. We have related data on gun firings to data on two measures of aggressive behavior by those watching the show.

  - the measure: violence operationalized as number of gun firings
  - data on number of gun firings

Correlation without direct causation

Figure 4.3 *Confounds*

- Sometimes one variable is directly related causally to another.
- But sometimes the causation is via some other link (or the other way around...).

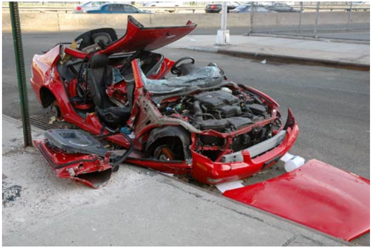
Correlations without direct causation

- ice cream sales and the number of shark attacks on swimmers are correlated
- SAT scores and college grades are correlated
- hemline and stock prices are highly correlated (as stock prices go up, so does the hemline)
- number of cavities in elementary school children and vocabulary size have strong positive correlation
- sea level in Venice and bread prices in Britain strongly correlated
- finally: sleeping with one's shoes on is strongly correlated with waking up with a headache...

When causation suspected

- Driving red cars is positively correlated with having traffic accidents

When causation suspected



- Driving red cars is positively correlated with having traffic accidents
- Why? Several possible causal scenarios:
    - accident-prone drivers prefer red
    - people become more aggressive when driving red cars
    - more dangerous cars tend to be painted red (sports cars)
    - the color red is harder to see and is more likely to be involved in a 2-car accident

Extraneous variables

- Given the number of possible variables to consider, in any given sample some will be correlated with the dependent variable of interest.
- If these are not the variables we are focusing on, we term them extraneous.
- But:
  - What we term extraneous may in fact be the causally relevant variable.
  - So, care must be taken to rule out any causal link between these extraneous variables and the dependent variable.

Limits of correlation

- Fluoride in water is correlated with lower rate of tooth decay.
- But why? Some candidates:
  - Fluoride reduces cavities.
  - People in cities with fluoride enjoy better diets.
  - People in cities with fluoride practice better dental hygiene.
  - People in cities with fluoride have better genetics.
  - Water in cities with fluoride contains other minerals (calcium) that help prevent tooth decay.
- These additional variables are extraneous from the point of view of the first hypothesis, but they might be the true causes.

Telling causal stories can be fun

Correlation: Amount of ice cream sold correlates with increased deaths by drowning...

> *Increases in nuclear power generator accidents (Chernobyl, Three Mile Island...) have resulted in greenhouse gas increases, ozone layer reduction, average world temperature rise and increases in the fraction of heavy water in rain. Concerns about nuclear catastrophe have resulted in increases in eating disorders, especially among those with a genetic predisposition to obesity. Heavy water in rain has resulted in an increase in the specific gravity of cream produced by cows, while the increasing world temperature has resulted in an increasing attendance at beach resorts, coupled with increased consumption of ice cream. The increased weight of fat worried people whose centre of gravity has been lowered by a rising consumption of heavy ice cream has caused an increased number of deaths by drowning. (Paul Gardner, Monash University, Australia)*

Another example

Correlation: Number of fire trucks and amount of fire damage...

> *While this could be another case of intentionally starting fires in effort to attract the fire people, this seems highly unlikely. Firefighter salaries are modest. The only logical explanation is that the community just feels so darn safe knowing that there are more fire trucks around, that they simply are not as careful and concerned with fire safety. They feel so confident that a truck would rescue them in an instant, before a fire could spread very far, so they are just careless. With this inappropriate assumption and subsequent increase in fires, the firefighters are even less able to arrive at a scene on time. Thus, more damage occurs. (Katie Brandt, Purdue University Indianapolis)*

Beyond causal story telling

- If a causal relation exists between two variables, then if we can directly manipulate values on one (the independent variable), we should affect values on the other (the dependent variable).
- An experiment is precisely an attempt to demonstrate causal relations by manipulating the independent variable and measuring the effect on the dependent variable.

The logic of causal research

- To confirm or falsify a causal claim based on a correlation, we use *modus tollens*. The first premise in each case, though, is different.
- Confirming a causal claim:

> *(1) If X is not a cause of Y [and there is no alternative plausible hypothesis], then there will not be a statistically significant difference in Y when X is present.*
> *(2) There is a statistically significant difference in Y when X is present [and there is no alternative plausible hypothesis].*
>
> ---
>
> $\therefore$ *X is the cause of Y.*

- Whether the first premise is true depends critically on how we set up the test of the causal hypothesis—whether we make it very unlikely that anything else could produce a difference in Y.

Avoid Affirming the Consequent!

Don't use this argument:

> *(1) If X is a cause of Y, then there will be a statistically significant difference in Y when X is present.*
> *(2) There is a statistically significant difference in Y when X is present.*
>
> ---
>
> $\therefore$ *X is the cause of Y.*

XXXXX

This is invalid!

The logic of causal research

- Falsifying a causal claim:

  (1) If X were the cause of Y [and auxiliary assumptions are true and the experimental set up is adequate], then there would be a statistically significant difference in Y when X is present.
  (2) There is no statistically significant difference in Y when X is present [and auxiliary assumptions are true and the experimental set up is adequate].

  $\therefore$ *X is not the cause of Y.*

- The truth of the first premise depends critically on how we set up the test of the causal claim.