

# Causal Diagrams

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# Motivation

Before going into all the technicalities of causality, we need to understand *why* we should worry so much about causality: **many interesting research questions are causal in nature.**

## Examples: Economic research questions

- We don't want to know if countries with higher minimum wages have less poverty, we want to know if raising the minimum wage reduces poverty.
- We don't want to know if people who take a popular common-cold-shortening medicine get better, we want to know if the medicine made them get better more quickly.
- We don't want to know if the central bank cutting interest rates was shortly followed by a recession, we want to know if the interest rate cut caused the recession.

# So what is causality?

## Definition: Causality

We say that  $X$  causes  $Y$  when we interfere and change the value of  $X$  without changing anything else, then the distribution of  $Y$  would also change as a result.

# Causality – Examples

## Examples: a few causal relationships

Obvious ones:

- A light switch being set to on causes the light to be on
- Setting off fireworks raises the noise level

Less obvious ones:

- Getting a college degree increases your earnings
- Tariffs reduce the amount of trade

# Causality

## Correlation does not imply causality.

Often we observe non-zero correlations that do not reflect causal relationships (or may be causal in the wrong direction!)

### Examples: Causality vs. correlation

Obvious ones:

- People tend to wear shorts on days when ice cream trucks are out
- Rooster crowing sounds are followed closely by sunrise

Less obvious ones:

- Colds tend to clear up a few days after you take Emergen-C
- The performance of the economy tends to be lower or higher depending on the president's political party

# Causality

Not all  $Y$  must be due to  $X$ : we still say  $X$  causes  $Y$  even if changing  $X$  does not always change  $Y$ , but just changes the distribution of  $Y$ : the **probability** that  $Y$  occurs.

## Example: Switches and bulbs

Flipping a light switch (  $X$  ) on alters the distribution of the light coming on (  $Y$  ), but not that it happens for certain:

- The bulb may be broken
- The bulb may be loose
- There may be no electricity

# Weasel words

There are lots of words that are generally taken to imply causality, as well as words that describe relationships *without* implying causality.

There are also some “weasel words” that don’t technically say anything about causality but clearly want you to hear it.

What are some of these words?

We can say  $X$  causes  $Y$  by saying:

- $X$  causes  $Y$
- $X$  affects  $Y$
- The effect of  $X$  on  $Y$
- $X$  influences  $Y$

# Why are Weasel words important?

- Knowing these terms can help interpreting what scientific studies are really saying, and when someone might be trying to be misleading:

Weasel terms are problematic because they convey that there is a relation between  $X$  and  $Y$  (from  $X$  to  $Y$ ), without literally claiming a causal relationship.

- Clearly non-causal terms do not even specify which of  $X$  and  $Y$  goes first! They just talk about these two variables and how they work together.
- Causal phrases always have a clear direction. They further tell us *what*  $X$  is doing to  $Y$ .

The key is that all the weasel phrases are equally true if you swap the positions of  $X$  and  $Y$ , even though swapping them would really change how we'd interpret the claim. "Aspirin is linked to headaches" is no more or less true than "Headaches are linked to aspirin." You can hear the notion that aspirin causes your headache in the first one, which is false. You can get away with it without technically lying because it's true that they're "linked."



# Causal diagrams

Causal diagrams were developed in the mid-1990s by the computer scientist Judea Pearl<sup>1</sup> who was trying to develop a way for artificial intelligence to think about causality.

## Definition: Causal diagram

A causal diagram is a graphical representation of a data generating process (DGP). Variables in the DGP are represented by nodes. The causal relationships in the DGP, each represented by an arrow from the cause variable to the caused variable.

<sup>1</sup> Pearl, Judea. 2009. Causality. 2nd ed. Cambridge, MA: Cambridge University Press.

# Causal diagrams

## Example: Flipping coins for cake

Two people A and B flip a coin. If they get head, then person A gets a slice of cake. If they get tail, then person B gets the slice.

We have...

- two variables
  1. the outcome of coin flip (  $X$  )
  2. which person gets the cake (  $Y$  )
- one causal relationship: the outcome of the coin flip determines which person gets cake.

# Causal diagrams

Example: Flipping coins for cake

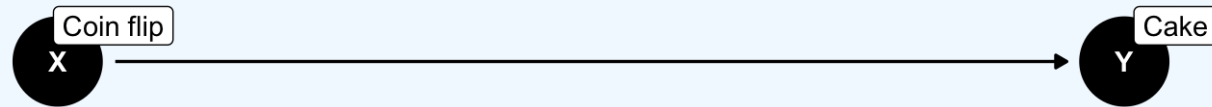


Figure 1: A simple causal diagram

# Causal diagrams

## Some points to be noted

- Each variable on the graph may take multiple values.
- The arrow just tells us that one variable causes another. It does not say anything about whether that causal effect is positive or negative.
- Other events that might effect the outcomes are ignores.
- Outcomes of outcomes are not taken into consideration.
- All (non-trivial) variables relevant to the DGP should be included, even if we cannot measure or see them.

# Causal diagrams

## Unmeasured Variables (labelled U)

Unmeasured Variables serve two purposes in causal diagrams:

- they are the key parts of the data generating process
- they can sometimes fill in for variables that we know must be there, but we have no idea what they are.

**Latent variables** (labelled L) are an example of unmeasured variables: They explain *why* two variables that are correlated but neither of them causes the other

# Causal diagrams

## Example: Ice-cream sales revisited

Ice-cream sales (X) are high when people wear shorts (Y). However, there is no causal relationship between ice-cream sales and people wearing shorts: weather (U) is latent variable causes them both.

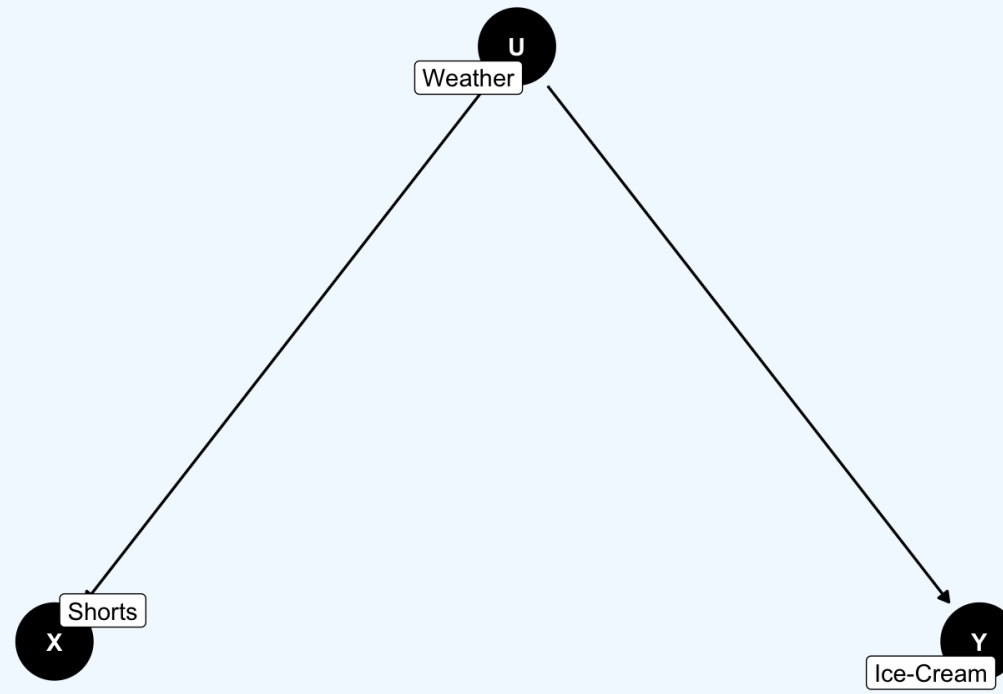


Figure 2: Unobserved variable

# Causal diagrams – the real world: on an omission mission

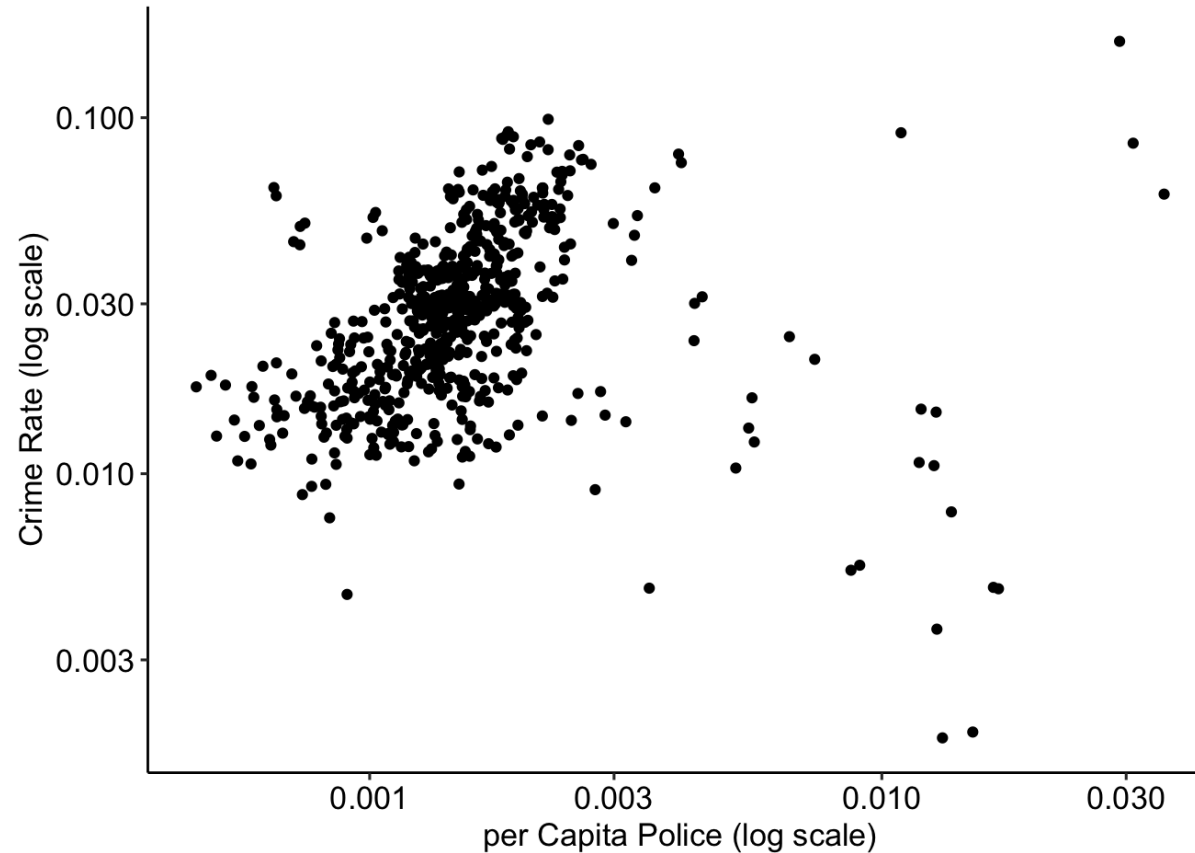


Figure 3: Police Presence and Crime Rate by County, North Carolina 1981-1987

# Causal diagrams – the real world: on an omission mission

To make a causal diagram, we think of following latent variables:

- Expected crime payout (profitability of crime w.r.t. likelihood to get caught, sentencing law severity)
- Law and order politics (how tough the political system in the local area wants to be on crime)

Some assumptions are:

- Lagged crime does not cause law and order politics
- The poverty rate is not a part of the DGP
- Lagged police per capita does not cause current police per capita
- Recent popular crime movies do not cause crime

There are arrows that are not there. These are just as important parts of a DAG!

It's a balancing act — omitting movies is okay, omitting the poverty rate likely is not!



# Causal diagrams – the real world: on an omission mission

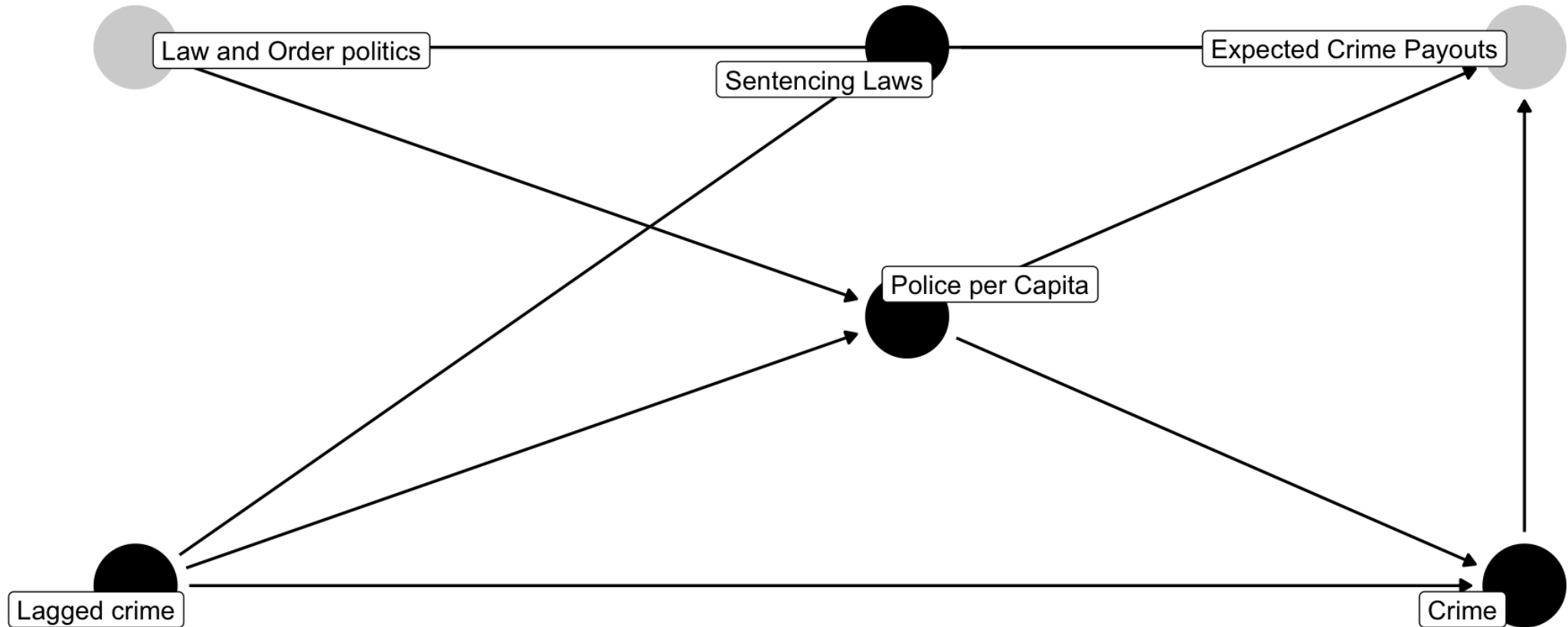


Figure 4: Police presence and crime rate

# Causal diagrams and research questions

## Does additional police presence reduce crime?

The causal diagram can be used to figure out how to identify the answer to our research question.

We may identify parts of the diagram that indicate how police per capita to causes crime)

- Police per capita → Crime (direct effect)
- Expected crime payout → Crime (indirect effect)

The variation in our data that answers our research question thus relates to police per capita causing crime, and to police per capita causing expected crime payout, which *then* affects crime.

To get our answer, we have to dig out *that* part of the variation in crime and block out the alternative explanations (e.g. lagged crime causes both).

# Causal diagrams: Moderators

- $X \rightarrow Y$  and  $Z \rightarrow Y$
- However, this could be consistent with any of the following DGPs
  1.  $Y = .2X + .3Z$
  2.  $Y = 2X + 3XZ$...and infinitely many more!
- We say that  $Z$  has a *moderating influence* on the effect of  $X$  on  $Y$  in DGP 2

# Causal diagrams: Moderators

## Definition: Moderators in causal diagrams

Moderators are variables that do not necessarily cause another variable (although they might do that too). Instead, they *moderate the effect of one variable on another*.

# Causal diagrams: Moderators

Moderator effects are *not* shown in the causal diagram.

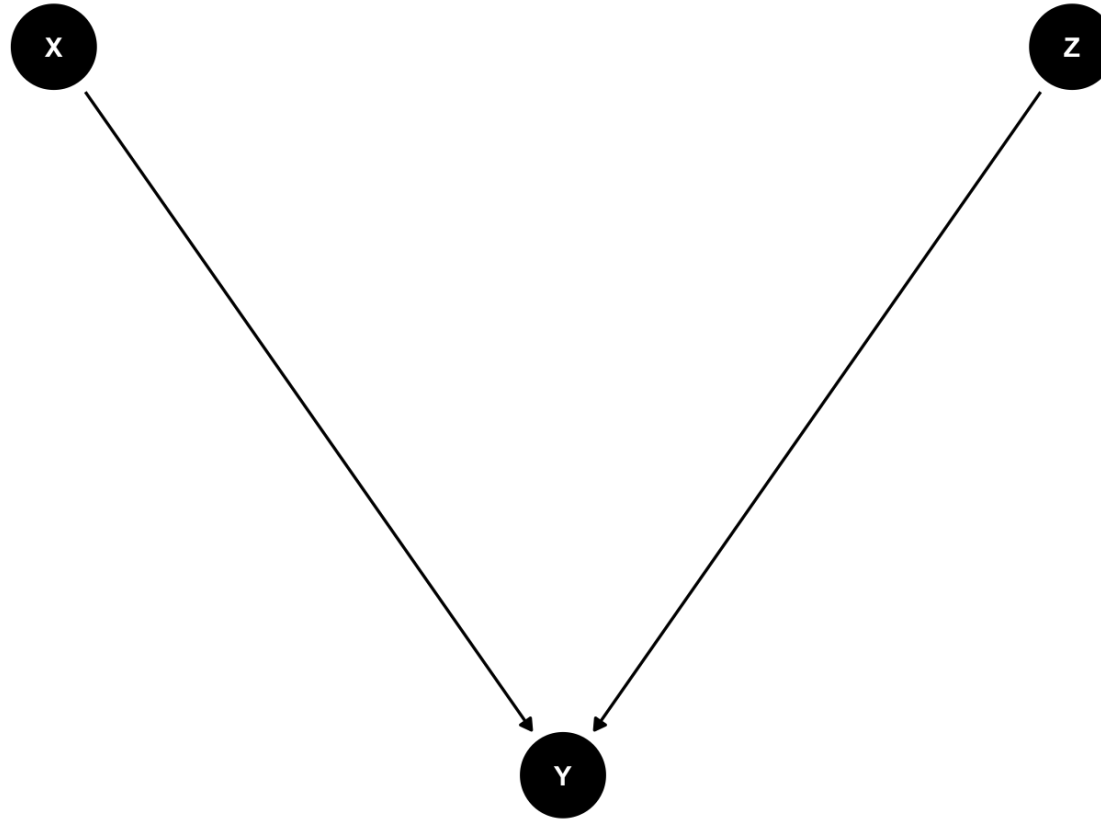


Figure 5: Z moderates X

# Causal diagrams: Moderators

## Example: Fertility drug

Consider the effect of a fertility drug (X) on the chances of getting pregnant (Y). The effect is *moderated* by the variable "having a uterus" (Z). If you don't have a uterus, the drug cannot do much for you! But if you do have a uterus, it can increase your chances of conceiving.