Directed Acyclical Graphs (DAGs)

Introduction

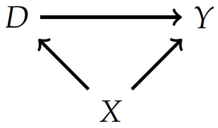
- We are going to look a little more in depth at the sort of diagrams we first saw in relation to IV.
- These types of graph are known as "Directed Acyclical Graphs", or DAGs, and were actually first developed by the inventor of IV, Phillip Wright, in the 1920's!
- Despite the complicated name, they are designed to make thinking about causality more simple and intuitive.
- This style of thinking about causality was popularised by Judea Pearl (computer scientist) in 2009 and has only very recently become more mainstream in economics (it still isn't really mainstream, but it will be in the next 5 years).

(These slides closely follow Scott Cunningham's chapter on DAGs in The Mixtape).

Introduction

- Before we do anything, what does “directed acyclical graph” even mean?
- It is a diagram which shows connections between nodes (graph), where those connections run only in one direction (directed), and there is no way to return to a node once you have passed it, i.e. there are no cycles (acyclical).
- This raises one fairly major limitation of DAGs: it is very cumbersome to model reverse causality.
- Typically, people have to resort to using multiple nodes for the same variable but with different time indexes.
- But let’s look at an example to see what’s going on.

Example



- This is simple DAG showing the relationship between three variables.
- Perhaps D is exercise, Y is health, and X is age. The arrow $D \to Y$ represents the causal effect of exercise on health. This is likely what we are interested in estimating.
- However, the fact that age affects both the amount you exercise and your overall health, causes us problems when trying to estimate the causal effect of exercise on health.

The Backdoor Path

- Despite the diagram being quite simple, it contains a lot of interesting features.
- First notice that there are two ways that D and Y are connected. The causal path $D \rightarrow Y$, and what is known as the "backdoor path" $D \leftarrow X \rightarrow Y$.
- Although the arrows don't lead in a directional way from D to Y, they nonetheless connect the two.
- But we have seen this before many times, this is simply another way to express omitted variable bias! X is the omitted variable in this case.

The Backdoor Path

- You will also see people refer to X in this situation as a “confounder”, because it confounds our ability to determine the true causal effect of D on Y.
- When you simply look at the correlation between D and Y, you pick up the causal effect **and** the backdoor path effect.
- So if we want to determine only the causal effect, we need to close off the backdoor path. All backdoor paths!
- But we already know how to do this. If we control for X, we fix it at some value and don’t allow it to change, this prevents us walking down the backdoor path.

So What's the Point?

- It seems like we haven't learnt anything that we didn't already know. So why are we bothering with all of this??
- A DAG is a means to organise yourself and your thinking. Although the above example was simple and we didn't learn anything new, this is not always the case (google "DAG for causal inference" and look at some of the complicated graphs you can get).
- The reason that DAGs can get so complicated is that they should include **all** causal relationships between the variables in question.
- When dealing with real world phenomena, there can be **many** relationships and a DAG will help you keep track of everything.

Unobserved Variables

- In the previous example, each of the variables were observable, and we could close the backdoor path (control the omitted/confounding variable) to get back causality.
- But a lot of the time, we may not have access to everything we would like:

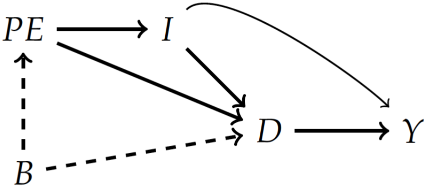
$$\begin{tikzcd}
D \arrow[rr] & & Y \\
& U \arrow[ul, dashed] \arrow[ur, dashed] &
\end{tikzcd}$$

- In this diagram, the dashed arrows represent the fact that we have no way to measure the effect along those arrows, i.e. U is unobserved.

Unobserved Variables

- For the previous diagram, we may have something like D being college education, Y being earnings, and U being innate ability.
- Since U is unobservable in our data, we cannot control for it and we say that the backdoor path is left open.
- If we simply look at the correlation between college education and earnings, we will partly pick up the effect of college students being innately higher ability than non-college students. Again, the classic problem of omitted variable bias.

A More Complex Example



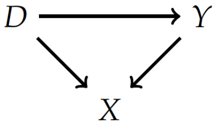
(credit: Scott Cunningham, The Mixtape)

- D is college education, Y is earnings, B is a collection of all background characteristics (including genetics), PE is parents' education, and I is parents' income.
- Let's try to decipher what this DAG is telling us...

A More Complex Example

- Aside from the main story, there are a couple of things worth mentioning:
- Background characteristic effect the child's earnings only through schooling. But what about non-academic skills (persuasiveness, charm, etc.)? This is a strong assumption!
- There are three backdoor paths, only two of which can be closed (the third cannot because B is unobserved):
  - $D \leftarrow I \rightarrow Y$ (backdoor path 1)
  - $D \leftarrow PE \rightarrow I \rightarrow Y$ (backdoor path 2)
  - $D \leftarrow B \rightarrow PE \rightarrow I \rightarrow Y$ (backdoor path 3)

Colliders



- The X variable in the DAG above is known as a "collider" since there are paths from D and Y which collide at X.
- This is very similar to the first simple DAG we saw, but now the arrow between X and Y has changed direction.
- There are still two paths connecting D and Y, but now the backdoor path $D \rightarrow X \leftarrow Y$ is said to contain a collider.
- Whenever the backdoor path contains a collider, the backdoor is closed as long as we **don't** control for it!
- This seems a bit counterintuitive... some examples will help make sense of this.

Collider Example 1

- Suppose D is a dummy for being female, Y is intelligence, and X is whether you are a professor.
- My guess would be that the causal effect of being female on intelligence is zero, i.e. men and women are equally capable.
- Furthermore, if we simply looked at the correlation between intelligence and being female, I think it would come out to be zero.
- But what would happen if the sample we analysed was restricted to professors. This is equivalent to controlling for being a professor.

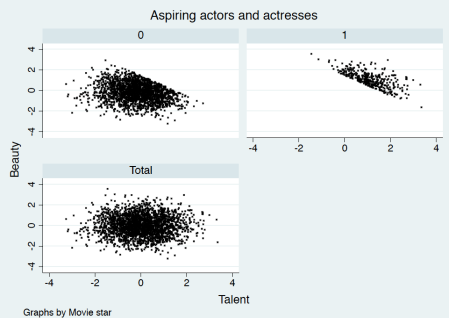
Collider Example 1

- Since there is still discrimination against women in the workplace, in order to become a professor as a woman, you have to be that little bit better than if you were a man.
- So for male professors, there will be some brilliant ones, and some not so brilliant ones (yes, I see you looking at me!).
- But for female professors, there are very few "not so brilliant" ones; they wouldn't have been able to become a professor if so.
- What this creates is a seeming positive causal effect of being a woman on being smart (when you restrict yourself to only professors).
- So controlling for the collider has caused bias in our causal analysis.
- If we had simply looked at the whole population, we would not have reached this incorrect conclusion.

Collider Example 2

- Of course, this is not unique to professors, or intelligence.
- Consider actors (male or female). To become a successful actor it is helpful to be both talented and good looking.
- In fact, there may even be some trade-off a producer/director is willing to make regarding looks and talent.
- If you're a superb actor, I don't care what you look like (Steve Buscemi comes to mind... sorry!), but if you're not a great actor, you better look damn good!
- So if you only look at actors, it looks like beauty and talent are negatively correlated. Those who are good are ugly, and those who are bad are good looking.

Collider Example 2



(credit: Scott Cunningham, The Mixtape)

- The is simulated data representing the story on the last slide.
- The bottom plot is of all aspiring actors. The top plots split these people out by whether they are successful and in big films/tv (on the right) or whether they are unsuccessful.
- We can see that in both subpopulations, there is a negative correlation between beauty and talent.

Collider Example 3

- Final example. This is one I only realised quite recently and have probably fallen prey to myself.
- Most people like to date someone who is good looking and nice.
- Let's make things simple and say these are the only things you care about.
- As with the director/producer, you will have some (probably unconscious) weighing up and trading off between these two things.
- I'm thinking this sort of thing: "He's a bit of an arse but he's gorgeous!"

Collider Example 3

- Now the people you date are also the people who you get to know better than almost anyone else.
- So when someone asks you if you think good-looking people tend to be more horrible (or dumb/mean/any other negative trait), you'll tend to think through the people you've dated.
- But what you've now done is conditioned on a collider (whether you dated the person).
- And you'll (rightly) conclude that for people you've dated, there is a negative relationship between beauty and kindness.
- Then you'll (mistakenly) conclude that this is true for the whole population. (Of course, you won't make such a mistake now!).

When do we Have a Causal Effect

- So, when can we be sure that we have found a causal effect?
- If you have created a realistic DAG which accurately portrays all of the relationships between the pertinent variables, then you must simply check whether all backdoor paths have been closed.
- A backdoor path can be closed in one of two ways:
  - Control for each confounding variable along the backdoor path.
  - If a collider is present along the path, do not control for it.

Summary

- We have seen a new way to think about causality using directed acyclical graphs.
- These graphs give us a nice way to organise our thoughts when it comes to messy relationships between several different variables.
- We have seen that confounding variables are just omitted variables, and must be controlled for if we want to obtain a true causal effect.
- We have seen a new type of variable called a collider. And have discussed how it can cause bias in our thinking if we control for it.