Chapter 6: Graphical Representation of Causal Effects

A DAG is a representation of causal knowledge and/or belief. It is an indispensable tool in observational epidemiology. It clarifies the structure of relationships between variables. Using a DAG, you can infer (somewhat intuitively), betwen any two variables

- if there is a direct causal relationship
- if there is any association between them
- if part of that relationship can be broken through conditioning on a third variable
- if a relationship can be induced by conditioning on a third variable

DAG are not full statistical models but they set important ground rules, This is covered in Technical point 6.1 but it's implications are hard to see without a grounding in the rules of probability

When you draw a DAG, you should include the variables you measured and any common causes, even if unmeasured. The real opinion that comes into a DAG is in the direction of arrows, whether effects are directed or from common causes and the absence of an arrow between nodes.

Some kind of association is present between A and Y if there is at least one of these

(a) direct causation of A on Y: A-> Y
(b) a common cause of L of A and Y : A <- L -> Y
(c) conditioning of a collider, L: A -> L <- Y

Note in (c), A and Y are not associated. A collider does not allow association to flow. But conditioning on it, opens a path.

Sec 6.3, tries to motivate the probabilistic idea of conditional independence. Two variables which share a common cause have an association from that. That association can be “broken” by “holding” their common ascestor “constant”. That could include restriction, stratification or adjustment.

Sec 6.4 gives positivity and consistency as necessary conditions for using DAGs.

Positivity is not a natural criterion in DAGs. It is best seen when we attempt to adjust for confounding. We need to assume that all the levels of the confounder are represented in treated and untreated groups.

Consistency is the caution that we should be careful about using DAGs with exposure variables. They cite the example of "exercise" as an exposure. It is an ill defined intervention because it's effect may vary in its type or intensity.

Fine point 6.1 covers d-separation. Two nodes in a graph are d-separated if all back door pathways have been blocked.

- Blocked if there is no conditioning and two nodes are connected by at least 1 collider

- Blocked if you condition on a non-collider in the path

- Open if there you condition on a collider in the path

- Blocked if you condition on a collider in the path and also on a variable downstream from the collider

d-separation implies conditional independence between the two nodes by anything that is conditioned on in the above.

The text mentions faithfulness. It is worrying about if there could be causation in a DAG which is hidden because two variables have no correlation. They cite the example of effects which run in opposite directions.

Sect 6.5 elaborates of the 3 ways nodes in a DAG can be associated and emphasized that the ones which are not directly causal are sources of bias

Confounding. The exposure and outcome share common causes.

Collider. We have conditioned on common effect of the exposure and outcome (a collider). This is also known as selection bias.

Sec 6.6 discusses effect modification and I find it an awkward fit for the chapter. Effect modification is not well shown by DAGs. Effect modification is very model dependent and DAGs are model independent and can't predict whether an interaction could be present, let alone strong. They make the point that if there is effect modification it could be because of a causal effect modification or that the effect modifier is a surrogate for something that causes effect modification.

Chapter 7: Confounding

We want to isolate the causal effect of A on Y.

This means dealing with the ubiquitous threat of confounding. A concept I am confident you are familiar with.

To isolate causal effects, we need exchangeability (which requires some kind of randomization) or conditional exchangeability. That means we identify a set of variables L such that $Y^a \perp A \mid L$. We'll discuss how this assumption animates methods for causal inference soon.

Our mission to identify what set(s) of variables L would satisfy this based on our DAG. The important thing is that there may be more than 1 set of variables that can do that.

The answer is that we need to use the backdoor criteria to find all the L which can d-separate A and L. That means dealing with the two sources of bias discussed in Ch 6

The chapter spends a bit of time demonstrating the incoherence that results with informal definitions of confounding "anything associated with A and Y". That was the definition I learned and it is elegantly debunked in Graph 7.4.

The more rigorous you get, the more slippery terms like confounding and confounder get. They settle on "confounding is any bias which would be eliminated by randomization" and a confounder is "any variables which could be used to de-confound".

SWIGs are introduced to give a more clear connection to counterfactual but I don't see them changing any of the things we do with graphs.

DAGs are not objective truth. But they are a huge advance. They have clarified threats to causal inference and given a framework to act on them. It allows an analyst to act in a way consistent with their beliefs and allows for a clear and principled disagreement by experts who see the causal system differently. Debates about "what do adjust for" didn't have a clear way to disagree before graphs clarified confounding.