

11.3 Estimating Causal Effects

11.3.1 The intuition behind the back-door criterion (Chapter 3, p. 79)

Question to author:

In the definition of the back-door condition (p. 79, Definition 3.3.1), the exclusion of X 's descendants (Condition (i)) seems to be introduced as an after fact, just because we get into trouble if we don't. Why can't we get it from first principles; first define sufficiency of Z in terms of the goal of removing bias and then, show that, to achieve this goal, we neither want nor need descendants of X in Z .

Author answer:

The exclusion of descendants from the back-door criterion is based indeed on first principles, in terms of the goal of removing bias. The principles are as follows: We wish to measure a certain quantity (causal effect) and, instead, we measure a dependency $P(y|x)$ that results from all the paths in the diagram, some are spurious (the back-door paths) and some are genuinely causal (the directed paths from X to Y). Thus, to remove bias, we need to modify the measured dependency and make it equal to the desired quantity. To do this systematically, we condition on a set Z of variables while ensuring that:

1. We block all spurious paths from X to Y ,
2. We leave all directed paths unperturbed
3. We create no new spurious paths

Principles 1 and 2 are accomplished by blocking all back-door paths and only those paths, as articulated in condition (ii). Principle 3 requires that we do not condition on descendants of X , even those that do not block directed paths, because such descendants may create new spurious paths between X and Y . To see why, consider the graph

$$X \longrightarrow S_1 \longrightarrow S_2 \longrightarrow S_3 \longrightarrow Y$$

The intermediate variables, $S_1, S_2, \dots$, (as well as Y) are affected by noise factors $e_0, e_1, e_2, \dots$ which are not shown explicitly in the diagram. However, under magnification, the chain unfolds into the graph in Figure 11.4:

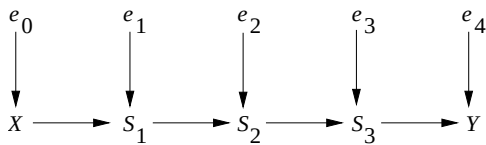


Figure 11.4: Showing the noise factors on the path from X to Y .

Now imagine that we condition on a descendant Z of S_1 as shown in Figure 11.5. Since S_1 is a collider, this creates dependency between X and e_1 which is equivalent to a back-door path

$$X \leftrightarrow e_1 \longrightarrow S_1 \longrightarrow S_2 \longrightarrow S_3 \longrightarrow Y$$

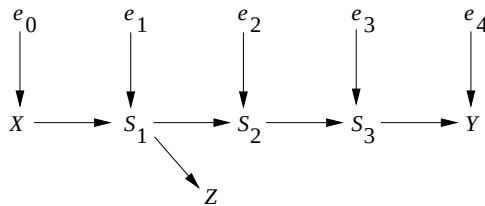


Figure 11.5: Conditioning on Z creates dependence between X and e_1 , which biases the estimated effect of X on Y .

By principle 3, such paths should not be created, for it introduces spurious dependence between X and Y .

Note that a descendant Z of X that is not also a descendant of some S_i escapes this exclusion; it can safely be conditioned on without introducing bias. (Though it may decrease the efficiency of the associated estimator of the causal effect of X on Y .) Section 11.3.3 provides an alternative proof of the back-door criterion where the need to exclude descendants of X is even more transparent.

Further questions from Reader:

This explanation for excluding descendants of X is reasonable, but it has two shortcomings:

1. It does not address cases such as

$$X \leftarrow C \rightarrow Y \rightarrow F$$

which occur frequently in epidemiology, and where tradition permits the adjustment for $Z = \{C, F\}$

2. The explanation seems to redefine confounding and sufficiency to represent something different than what they have meant to epidemiologists in the past few decades. Can we find something in graph theory that is closer to their traditional meaning?

Author's Answer

1. Epidemiological tradition permits the adjustment for $Z = (C, F)$ for the task of testing whether X has a causal effect on Y , but not for estimating the magnitude of that effect. In the former case, while conditioning on F creates a spurious path between C and the noise factor affecting Y , that path is blocked upon conditioning on C . Thus, conditioning on $Z = \{C, F\}$ leaves X and Y independent. If we happen to measure such dependence in any stratum of Z , it must be that the model is wrong, i.e., either there is a direct causal effect of X on Y , or some other paths exist that are not shown in the graph.

Thus, if we wish to test the (null) hypothesis that there is no causal effect of X on Y , adjusting for $Z = \{C, F\}$ is perfectly legitimate, and the graph shows it (i.e., C and F are non-descendant of X). However, adjusting for Z is not a legitimate for assessing the causal effect of X on Y when such effect is suspected, because the graph applicable for this task is given in Figure 11.6; F becomes a descendant of X , and is excluded by the back-door criterion.

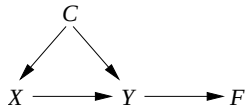


Figure 11.6: Graph applicable for accessing the effect of X on Y .

2. If the explanation of confounding and sufficiency sounds at variance with traditional epidemiology, it is only because traditional epidemiologists did not have proper means of expressing the operations of blocking or creating dependencies. They might have had a healthy intuition about dependencies, but graphs translates this intuition into a formal system of closing and opening paths.

We should also note that before 1985, causal analysis in epidemiology was in a state of confusion, because the healthy intuitions of leading epidemiologists had to be expressed in the language of associations – an impossible task. Even the idea that confounding stands for “bias,” namely, a “difference between two dependencies, one that we wish to measure, the other that we do measure” was resisted by many (see Chapter 6), because they could not express the former mathematically.³

Therefore, instead of finding “something in graph language that is closer to traditional meaning,” we can do better: explicate what that “traditional meaning” ought to have been.

In other words, traditional meaning was informal and occasionally misguided, while graphical criteria are formal and mathematically proven.

Chapter 6 (pp. 183, 194) records a long history of epidemiological intuitions, some by prominent epidemiologists, that have gone astray when confronted with questions of confounding and adjustment (see Greenland and Robins 1986; Wickramaratne and Holford 1987; Weinberg 1993;). Although most leading epidemiologists today are keenly attuned to modern developments in causal analysis, textbooks in epidemiology are still permeated with traditional intuitions that are highly suspect. (See Section 6.5.2.)

In summary, graphical criteria, as well as principles 1-3 above, give us a sensible, friendly and unambiguous interpretation of the “traditional meaning of epidemiological concepts.”

³Recall, Greenland and Robins (1986) were a lone beacon of truth for many years and, even they, had to resort to the language of “exchangeability” to define “bias,” which discouraged intuitive interpretations of confounding (see Section 6.5.3). Indeed, it took epidemiologists another six years (Weinberg 1993) to discover that adjusting for factors affected by the exposure (as in Figure 11.5) would introduce bias.