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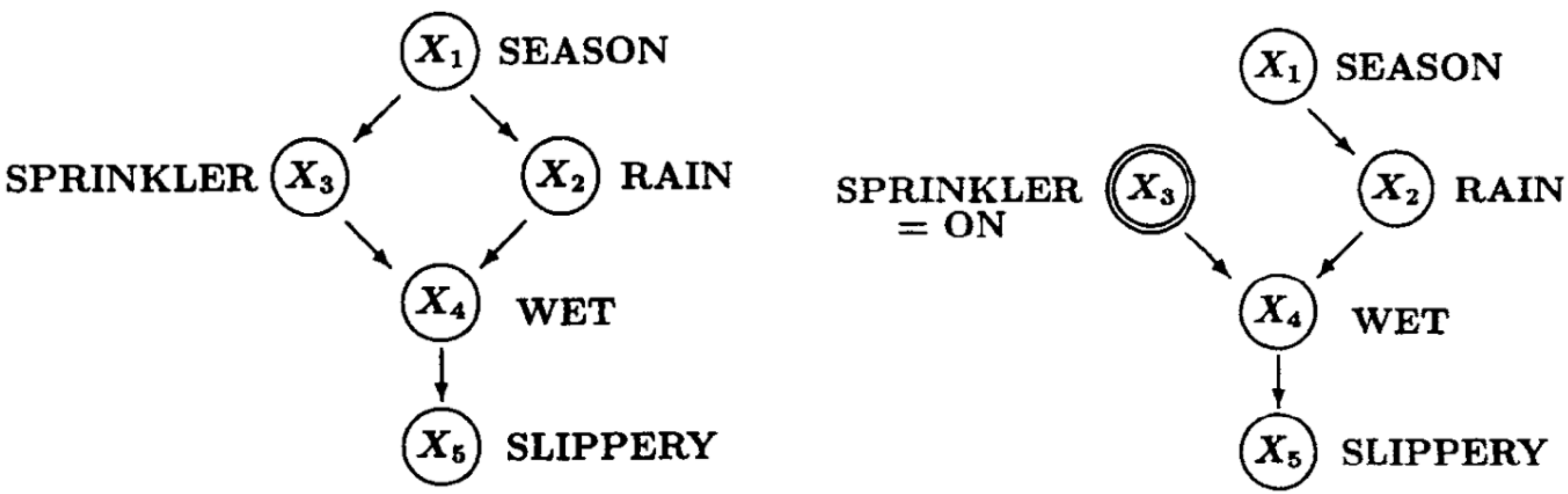
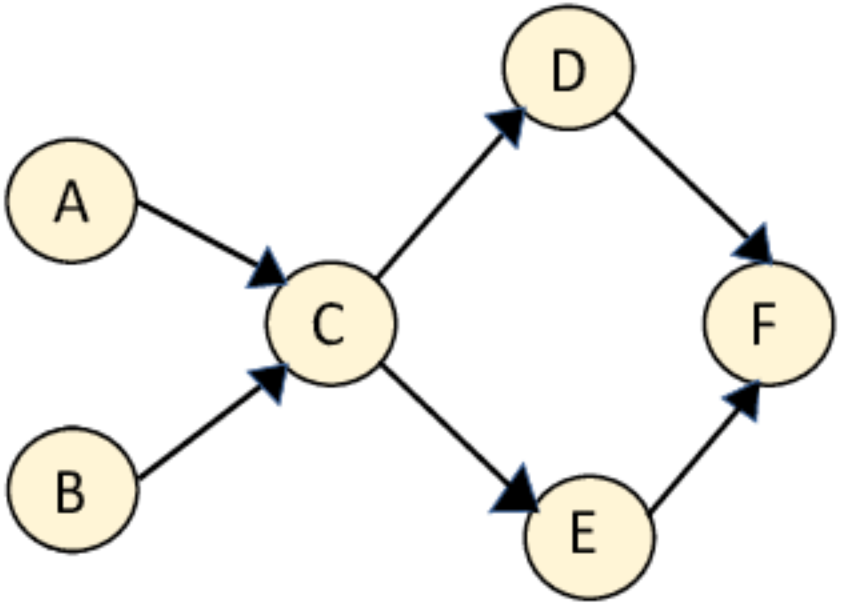
- If all three criteria hold, we can estimate causal effects

Causal Bayes Nets and interventions as "graph surgery"

- If V can be organized into a causal Bayes Net G, then the relationship between the base joint distribution (no interventions) and the set of interventional distributions can be characterized succinctly.
- To find $P(V|\mathrm{Do}(X = x))$, simply "cut" all the links in G between each variable in X and its parents to create a new graph G', and then do ordinary probabilistic conditioning $P(V|X = x)$ within G'.
- This is sometimes called "graph surgery" (Spirtes et al., 1993)



Conditional exchangeability in graphical causal models



- You have your **observational** dataset...but you might be interested in estimating a **causal** quantity, e.g.:

$$P(F \mid \mathrm{Do}(D = d))$$

- Under what circumstances can we do this?

The **back-door criterion**

- A set of variables Z satisfies the BACK-DOOR CRITERION relative to an ordered pair of variables $\langle X, Y \rangle$ if:
  - no node in Z is a descendent of X; and
  - Z blocks (i.e. *d*-separates) every path between X and Y starting with an arrow into X

A node set C d-separates A and B if for every path between A and B, either:

1. there is some node N on the path whose arrows do not converge and which *is* in C; or
2. there is some node N on the path with converging arrows, and neither N nor any of its descendants is in C.

- If Z fulfills the back-door criterion relative to $\langle X, Y \rangle$, then we have **conditional exchangeability** and the causal effect of X on Y is identifiable:

$$P(Y = y \mid do(X = x)) = \sum_{z \in Z} P(Y = y \mid X = x, Z = z) P(Z = z)$$

(Pearl, 2009)