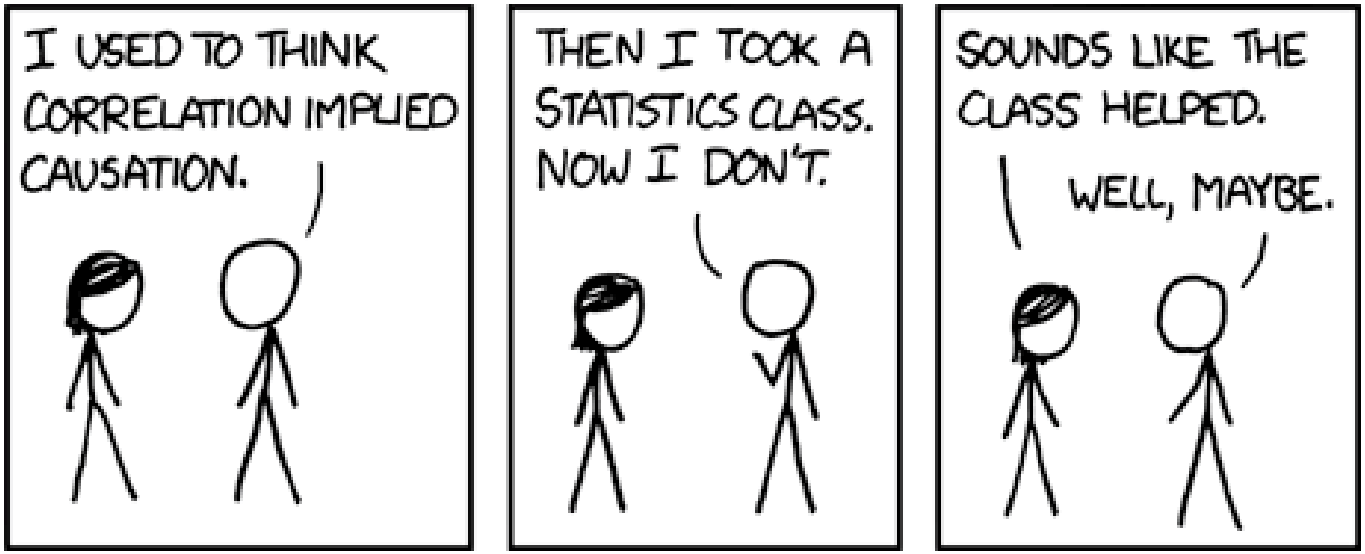
Causal Inference



https://xkcd.com/552/

SML310: Research Projects in Data Science, Fall 2019

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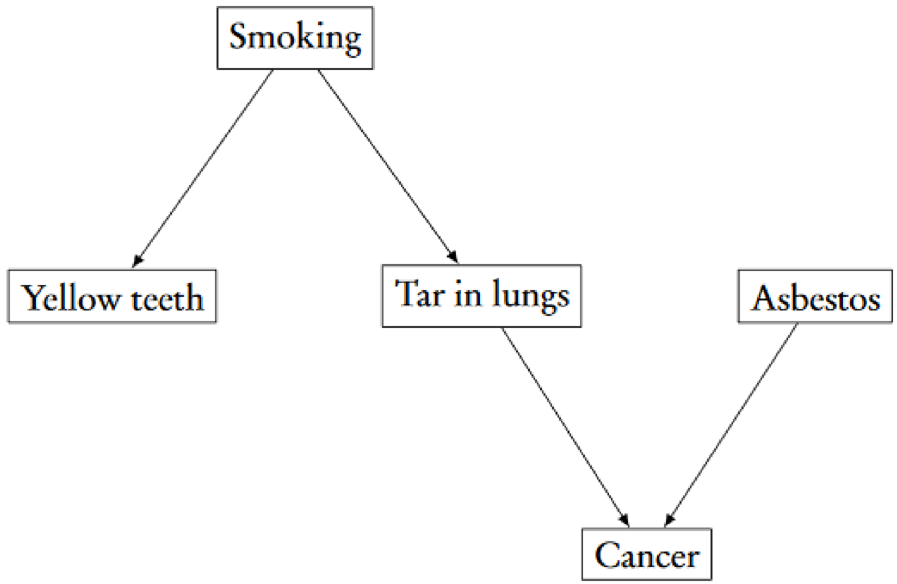
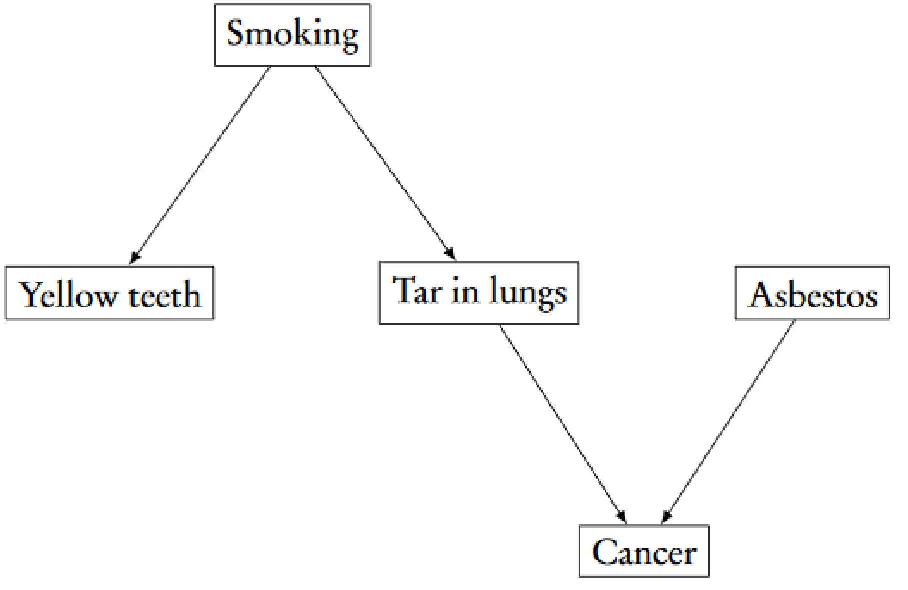
Content from Cosma Shalizi,
Advanced Data Analysis from an Elementary Point of View

Directed Acyclical Graphs (DAG) for representing causal structure



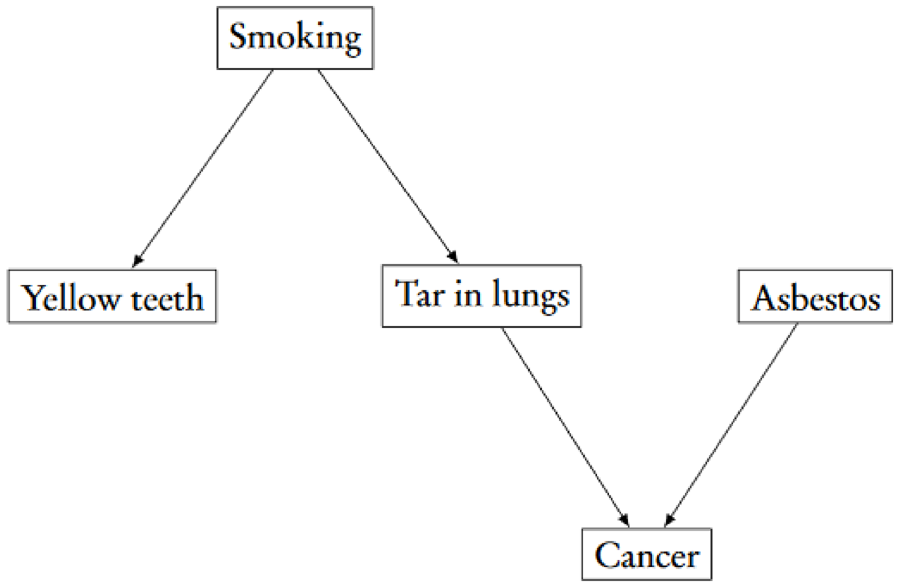
- If we know the value of *Smoking (0 or 1)*, we can generate the value of *Yellow teeth* and *Tar in lungs*
- If we know the value of *Tar in lungs* and *Asbestos*, we can generate the value of *Cancer*
- A datapoint is generated by first generating *Smoking* and *Asbestos,* then *Yellow teeth* and *Asbestos*, then *Cancer*

Directed Acyclical Graphs (DAG) for representing causal structure



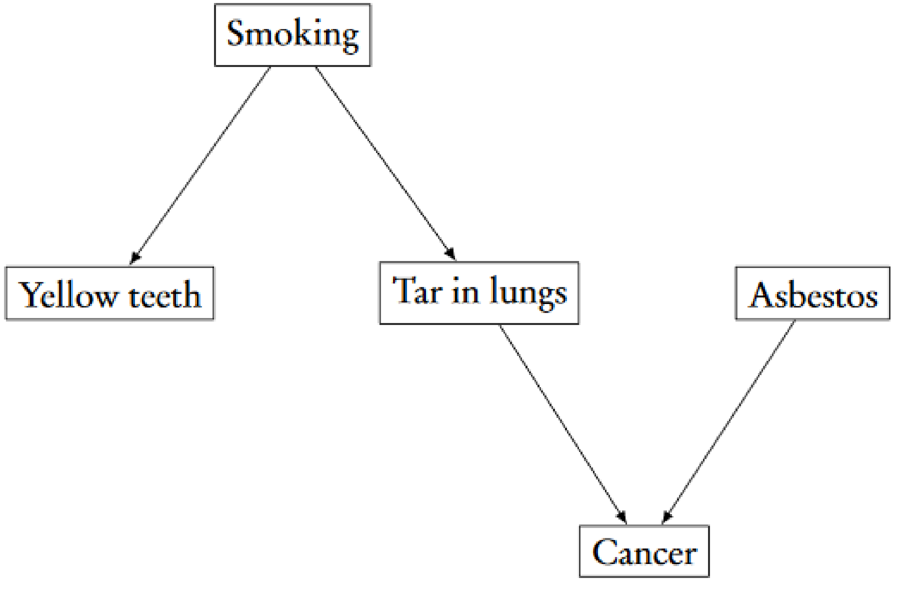
- The graph encodes our knowledge (or assumptions) about the causal structure of the data
- Can help with inferences

Directed Acyclical Graphs (DAG) for representing causal structure



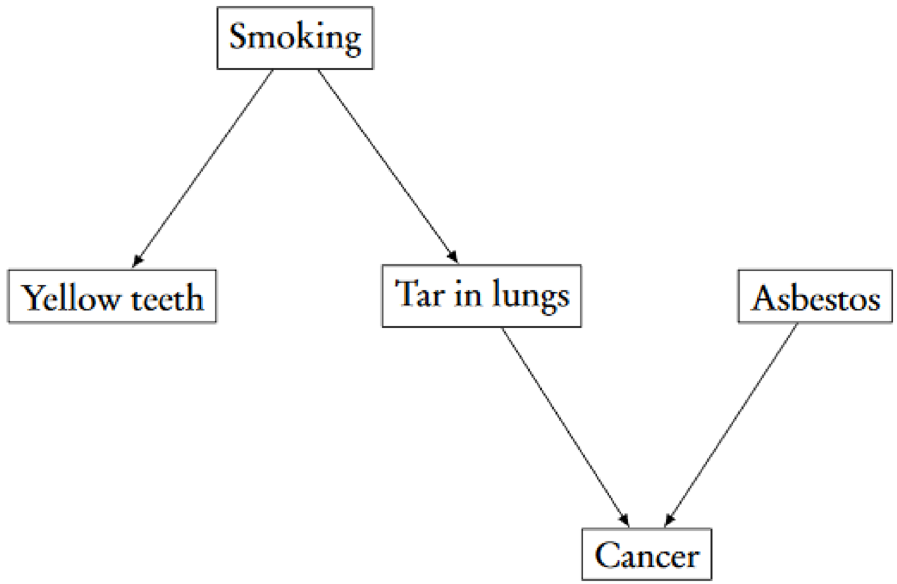
- *Tar* is independent of *Asbestos*
  - They are independently generated
- *Tar* is *not* independent of *Asbestos* given *Cancer*
  - Intuition: if $Cancer = 1$ and $Asbestos = 1$, then $Tar = 1$ is less likely than otherwise, since the cancer is already explained
    - This called “Explaining away”

Directed Acyclical Graphs (DAG) for representing causal structure



- *Yellow teeth* is not indep. of *Tar*
  - Both caused by *Smoking*
- *Yellow teeth* is indep. of *Tar* conditioned on *Smoking*

Directed Acyclical Graphs (DAG) for representing causal structure



- The right way to think of the arrows: *Tar might* cause *Cancer*, or have no effect
- *Smoking* is *definitely* independent of *Asbestos*

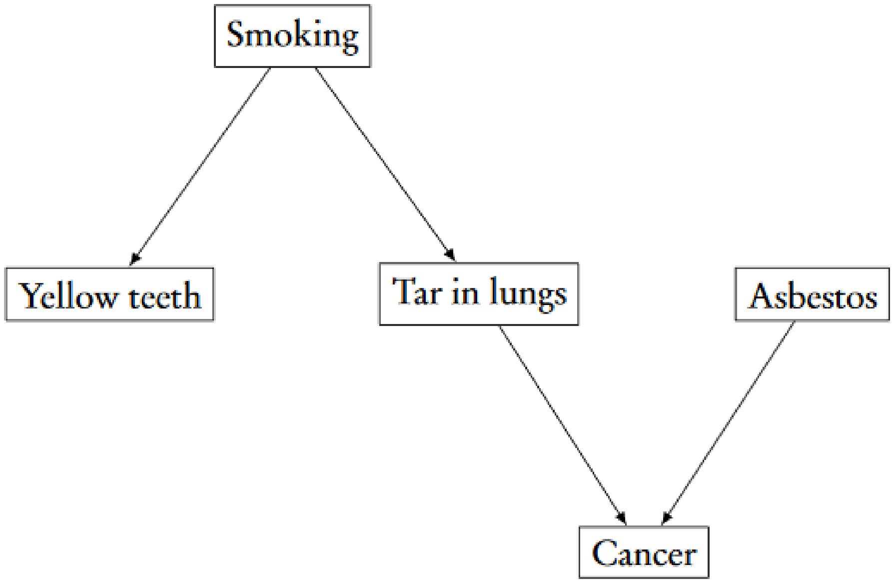
Causation

- Define “A caused B”

Causation

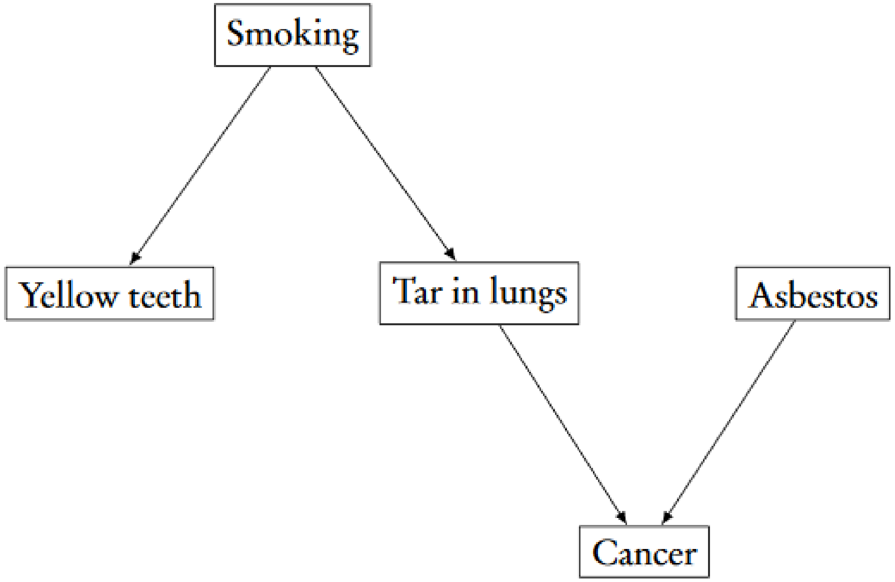
- Counterfactual: we say that *A* causes *B* if *B would not have happened* if *A* had not happened
- Causal inference: trying to answer causal questions from empirical data
  - Difficult to derive counter-factual conclusions from factual premises

Effect of causes



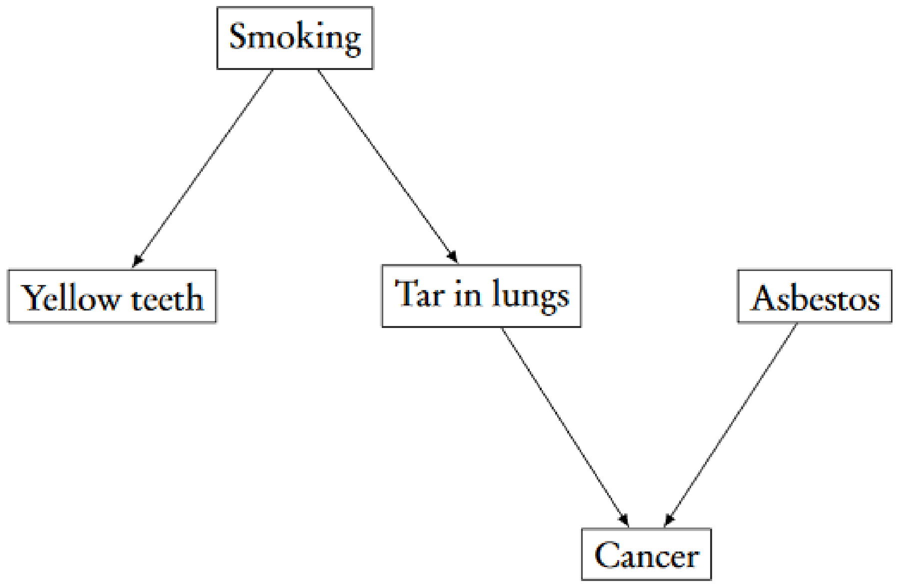
- *What is the causal relationship between exposure to asbestos and yellow teeth?*
  - There is none!
  - $Yellow$ and $Asbestos$ are not indep. conditioned on Cancer
    - Explaining away phenomenon
    - $Yellow \sim Asbestos + Cancer$ will have significant coefficients for a large dataset

Effect of causes



- *What is the causal relationship between exposure to asbestos and yellow teeth?*
  - Want to know what to control for and not to control for

Effect of causes

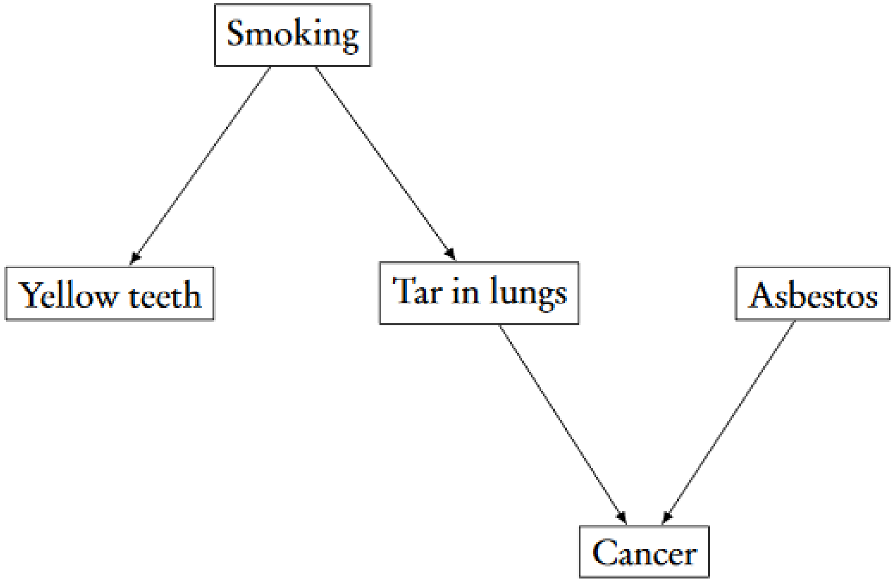


- A way of thinking about this:

$$P(Yellow|Asbestos = 1, Cancer) \neq P(Yellow)$$
$$P(Yellow|do(Asbestos), Cancer) = P(Yellow)$$

- $do(Asbestos)$ sets $Asbestos$ to 1, and changes the causal graph eliminating the mechanism that generates *Asbestos*

Effect of causes

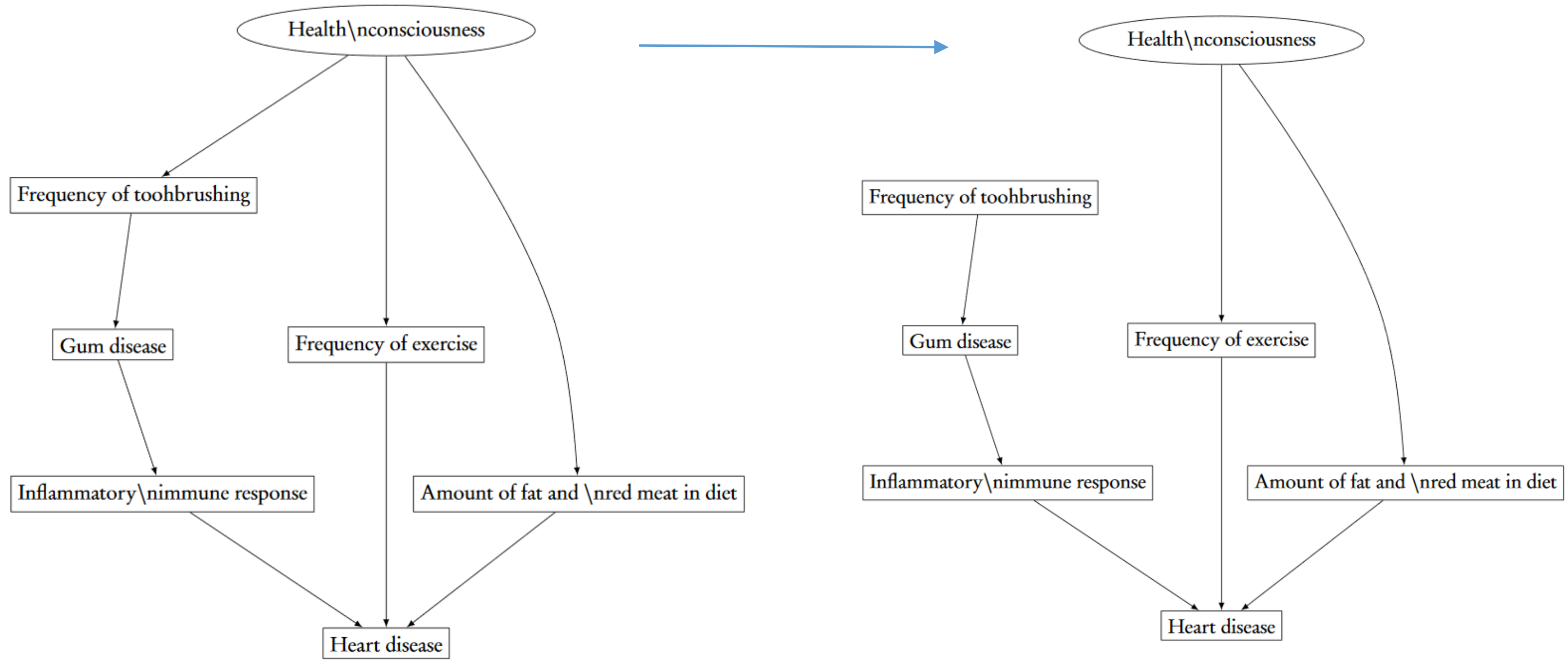


- To do causal inference, compare $P(Yellow|do(Asbestos = 1))$ and $P(Yellow|do(Asbestos = 0))$ (and verify the model says they are the same)
- A logistic regression would give a significant coefficient for $Asbestos$ ("keeping the cancer diagnosis constant, exposure to Asbestos increases the log-odds of yellow teeth by 0.1")

Causal inference: Take a step back

- $P(Yellow|do(Asbestos = 1))$ is computable *if* we know how to generate the dataset
  - This is difficult!
  - Possible *if* we know the mechanisms that generate the data *and* if we study each step in the mechanism
    - On the whiteboard

do(brushing)



Again, $\mathrm{P}(Heart\ disease|Brushing = b) \neq \mathrm{P}(Heart\ disease|do(Brushing = b))$

Identifying Causal Effects from Observations

- The most straightforward way to compute $P(Y|do(X = x))$ is to manipulate x physically and see what happens to Y
  - Run an experiment
    - Hold all other variables constant

      Or
    - Randomize all other variables

Identification

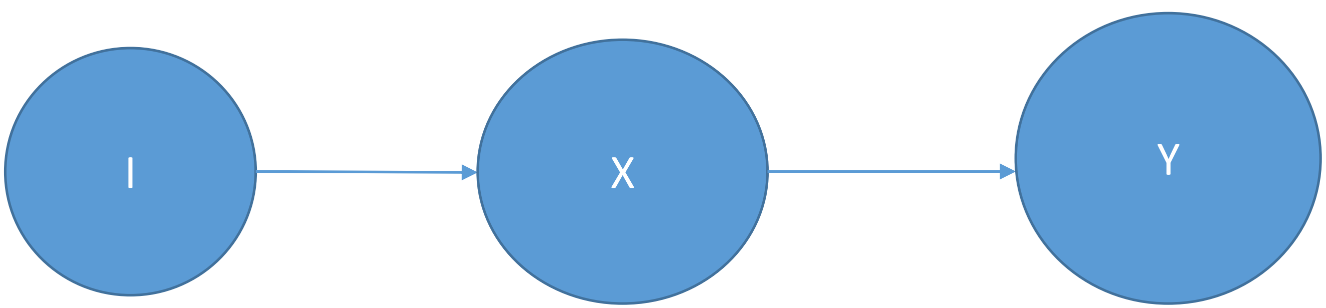
- Want to calculate the causal effect of X on Y (i.e., $P(Y|do(X = x))$, but can't run an experiment.
- Can do this if we have the causal graph and observe all the variables
  - Saw this before
- Can *sometimes* do this if not all variables are observed
  - Need to carefully look at the graph

Identification

- Do regression right
  - Control for variables which so that all the “explaining away” phenomena are eliminated
- Find all causal paths, and figure out exactly how they work
- Instrumental variables

Example of Instrumental Variables

- X: smoking
- I: cigarette taxes
- Y: health



I can be "manipulated" (maybe) by looking at different states with different taxes. We can then claim to be doing causal inference

Causal inference with Matching

- Match “like” objects which differ only on X
  - Lots of techniques

Summary

- Causal inference from observational data is sometimes possible when we can figure out the causal graph
  - This is very difficult in general
- Correlation really doesn't imply causation
  - Often the best you can do is say "An increase in X is associated with an increase in Y"