# Methods for Causal Inference
# Lecture 11

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# Common errors for assignment 1

The sum of the probabilities of all events equals to one:

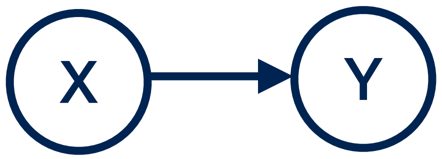
$$p(X = 1|Y = 1) + p(X = 0|Y = 1) = 1$$ ✓

It is **not** the case that: $p(X = 1|Y = 1) + p(X = 1|Y = 0) = 1$ ✗

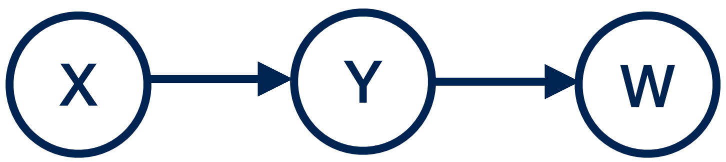
Total law of probability:

$$p(X = 1|Y = 1)p(Y = 1) + p(X = 1|Y = 0)p(Y = 0) = p(X = 1)$$ ✓

# Common errors for assignment 1




$$p(X|Y) \neq P(X)$$




$$p(X|W) \neq P(X)$$

$p(X, Y, Z) = P(X)P(Y|X)P(W|Y)$ for the chain above

Note than we can always write: $p(X, Y, W) = P(X)P(Y|X)P(W|Y, X)$ (By product rule). The simplified equation uses the information, from the graph, that conditioning on Y, d-separates X and W.

# Common errors for assignment 1

Estimator vs ground truth

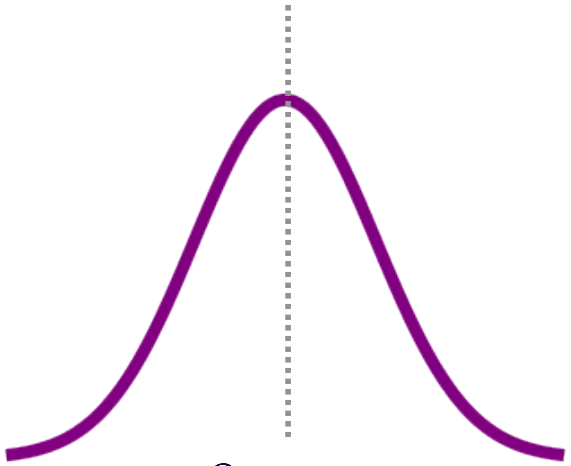
$Y = 2X + \epsilon$

Here coefficient of X, $\beta = 2$ , is the ground truth value of $\beta$

However, when we regress Y over X, we obtain a finite sample estimate of $\beta$ , referred to as $\hat{\beta}$

(or better notation: $\hat{\beta}_n$, where $n$ represents the number of data points)

For a consistent estimator $\hat{\beta}_n \to \beta$ as $n \to \infty$



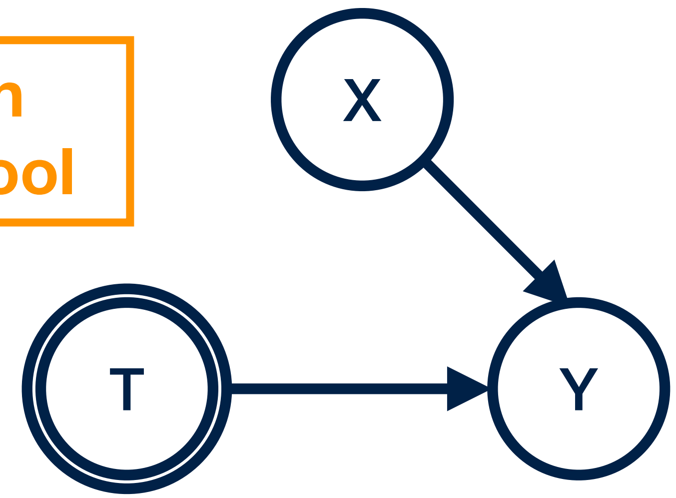
$\beta = 2$

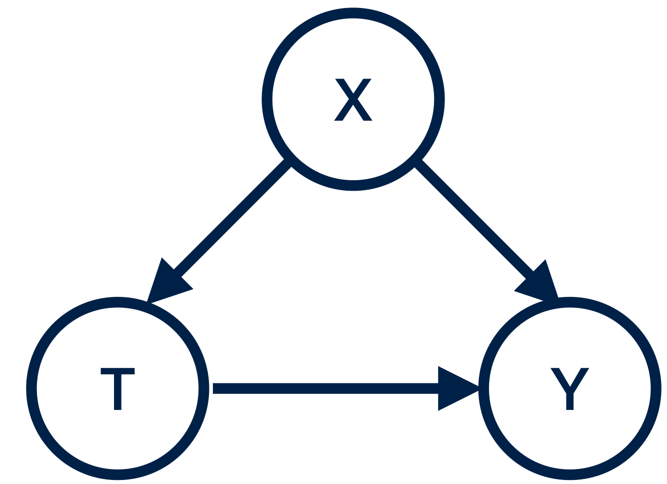
The width here is a reflection of how much data we have used to estimate $\beta$

# The adjustment formula

T: Drug usage
X: Gender
Y: Recovery

**Use Pm as an intermediate tool**




To know how effective the drugs is in the population, compare the **hypothetical interventions** by which

(i) the drug is administered uniformly to the entire population do(T=1) **vs**

(ii) complement, i.e., everyone is prevented from taking the drug do(T=0)

**Aim:** Estimate the difference (**Average Causal Effect ACE, aka ATE**)

$$\boxed{p(Y=1|do(T=1)) - p(Y=1|do(T=0))}$$

Pearl, Causal Inference in Statistics (2016)

# The Backdoor Criterion

Under what conditions does a causal model permit computing the causal effect of one variable on another, from **data** obtained from **passive observations**, with **no intervention**?

i.e.,

Under what conditions is the structure of a causal graph sufficient of computing a causal effect from a given data set? **Identifiability**

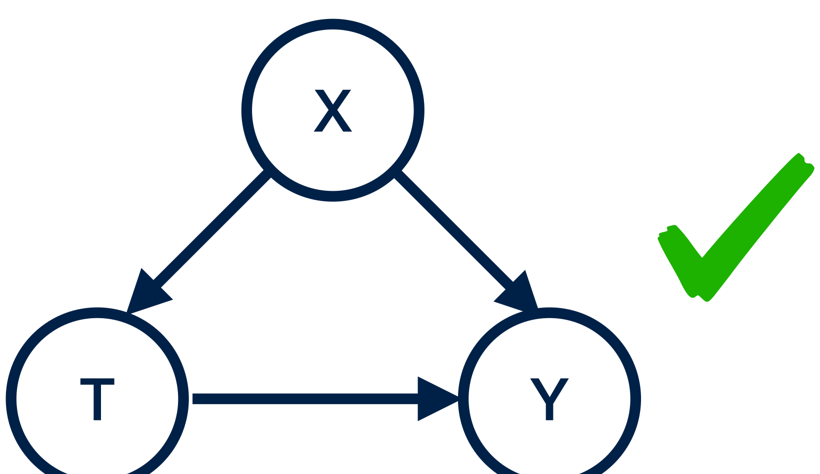
**Backdoor Criterion:** Given an ordered pair of variables (T,Y) in a DAG G, a set of variables X satisfies the backdoor criterion relative to (T,Y) if:

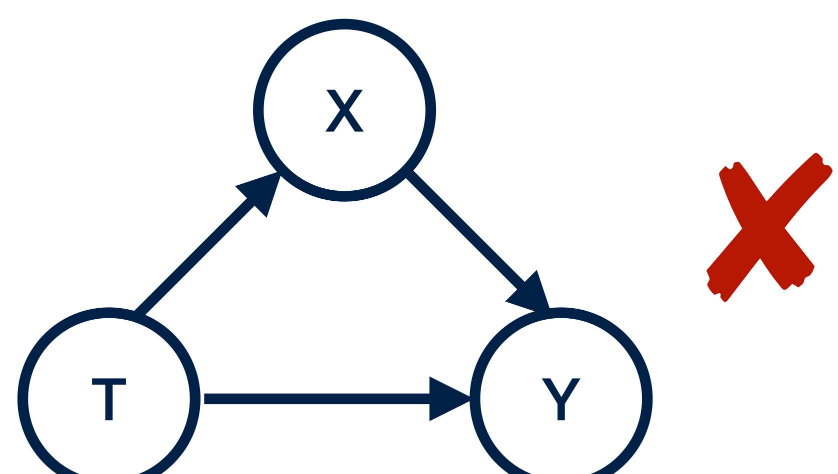
(i) no node in X is a descendent of T

(ii) X block every path between T and Y that contains an arrow into T

If X satisfies the backdoor criterion then the causal effect of T on Y is given by:

$$p(Y=y|do(T=t)) = \sum_x p(Y=y|T=t, X=x)p(X=x)$$

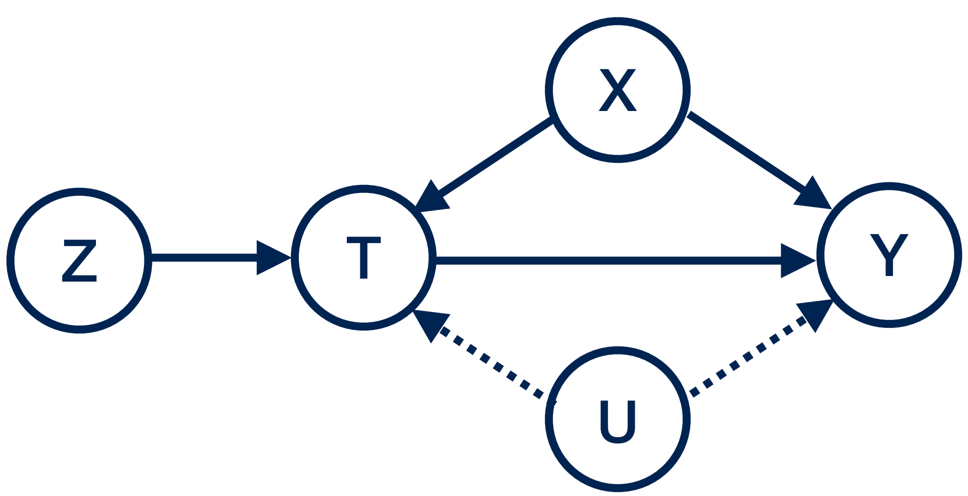



Pearl, Causal Inference in Statistics (2016)

# Pearl's Front-Door Criterion

- Backdoor does not exhaust all ways of estimating causal effects from a graph
- Front-door criterion can still be used for patterns that do not satisfy the backdoor criterion
- Example: Smoking and lung cancer (1970), industry argued to prevent antismoking regulation by suggesting that the correlation could be explained by a carcinogenic genotype that induces a craving for nicotine
- Recall sensitivity analysis
- Recall instrumental variable approach




Pearl, Causal Inference in Statistics (2016)

# Instrumental Variable assumptions

- **SUTVA**: Potential outcomes for each individual i are unrelated to the treatment status of other individuals:

$$Y^{(i)}(\mathbf{Z},\mathbf{T}) = Y^{(i)}(Z^{(i)},T^{(i)}) \ , \ |\mathbf{Z}| = |\mathbf{T}| = N \text{ individuals}$$

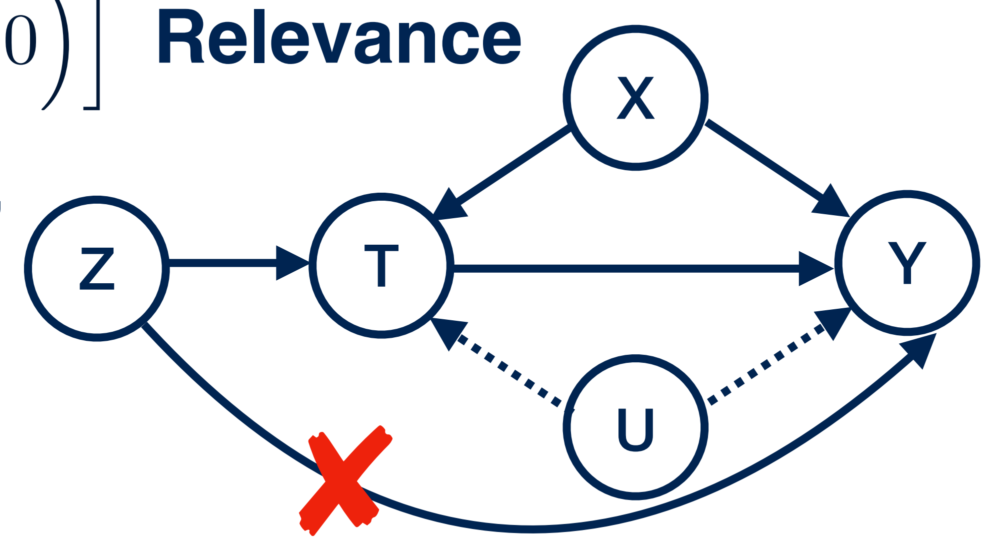
- Treatment assignment Z associated with the treatment is random:

- **Exclusion Restriction**: Any effect of Z on Y is via an effect of Z on T, i.e., Z should not affect Y when T is held constant $\left(Y^{(i)}|z=1,t\right) = \left(Y^{(i)}|z=0,t\right)$

- **Non-zero Average:** $\mathbb{E}\left[\left(T^{(i)}|z=1\right) - \left(T^{(i)}|z=0\right)\right]$ **Relevance**

- **Monotonicity** (increasing encouragement "dose" increases probability of treatment, no defiers)**:**

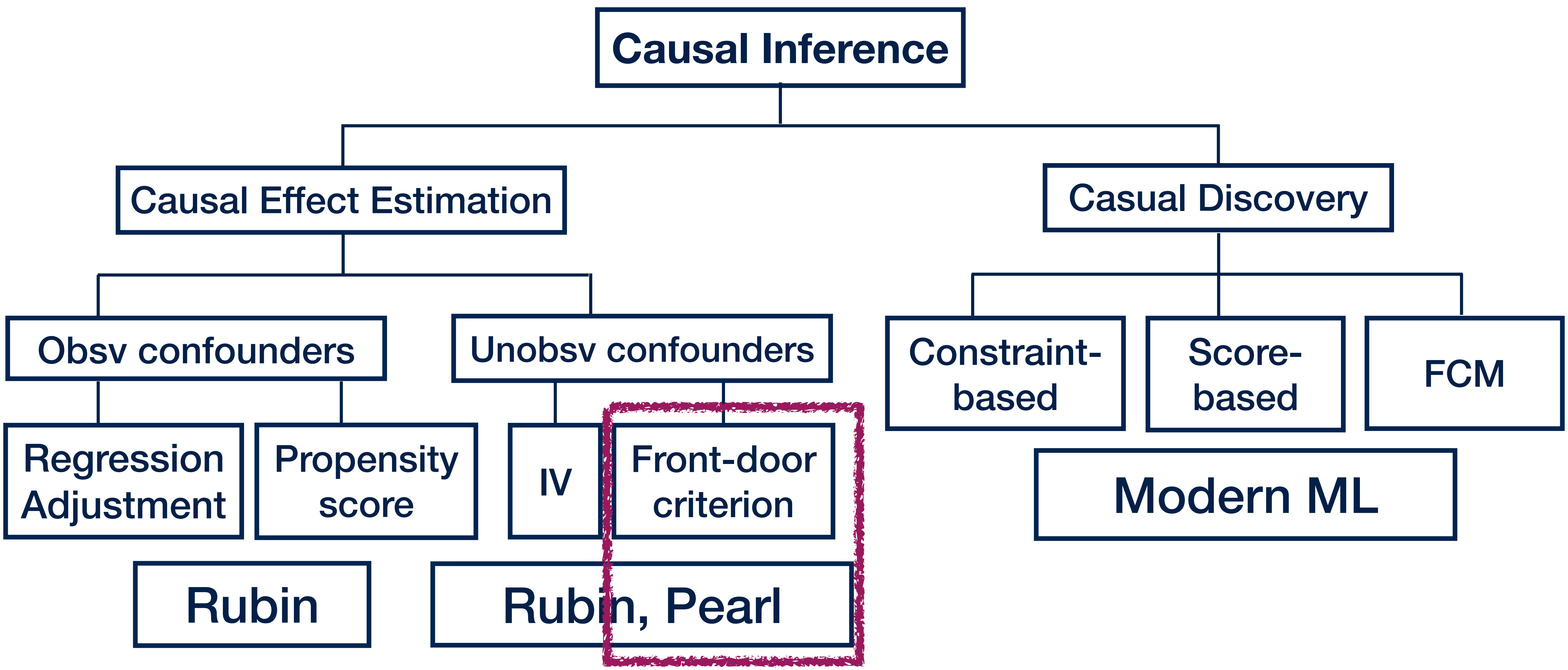
$$\left(T^{(i)}|z=1\right) \geq \left(T^{(i)}|z=0\right)$$




Rubin 1996

# So far …

- **Lecture 1**: Introduction & motivation, why do we care about causality?
- **Lecture 2**: Recap of probability theory, e.g., variables, events, conditional probabilities, independence, law of total probability, Bayes' rule
- **Lecture 3**: Recap of regression, multiple regression, graphs, SCM
- **Lectures 4-20**:



# Pearl’s Front-Door Criterion: An example

- Fig (a): The graph does not satisfy the backdoor, since the quantity we need to condition on to block the path, i.e. the genotype, is unobserved
- Fig (b): Additional measurement available: tar deposits in patients lungs
- Fig (b) still does not satisfy the backdoor criterion but we can determine the causal effect:

$$p(Y = y|do(X = x))$$

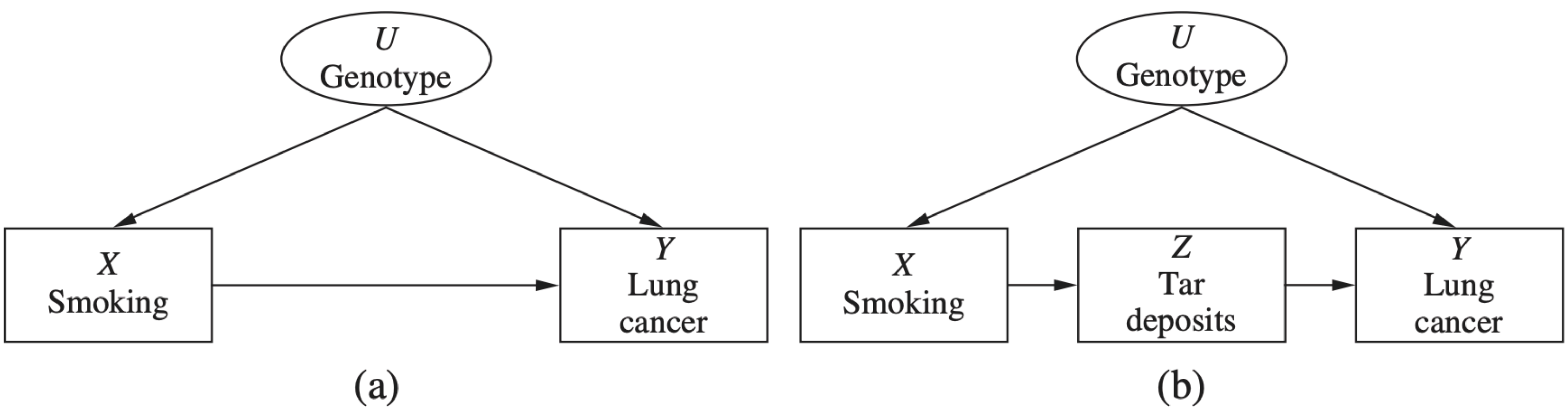



**Figure 3.10** A graphical model representing the relationships between smoking ($X$) and lung cancer ($Y$), with unobserved confounder ($U$) and a mediating variable $Z$

Pearl, Causal Inference in Statistics (2016)

# Pearl's Front-Door Criterion: A crafted example

## Interpretation 1: Tobacco industry

**Beneficial** effect of smoking:

15% of smokers have developed lung cancer vs 90.25% of non-smokers

**within tar and non-tar** subgroups, smokers have a much lower percentage of cancer than non-smokers (numbers in the table are engineered to illustrate the point that observations are not to be trusted)

**Table 3.1** A hypothetical data set of randomly selected samples showing the percentage of cancer cases for smokers and nonsmokers in each tar category (numbers in thousands)

| | Tar 400 | | No tar 400 | | All subjects 800 | |
|---|---|---|---|---|---|---|
| | Smokers | Nonsmokers | Smokers | Nonsmokers | Smokers | Nonsmokers |
| | *380* | *20* | *20* | *380* | *400* | *400* |
| No cancer | 323 (85%) | 1 (5%) | 18 (90%) | 38 (10%) | 341 (85%) | 39 (9.75%) |
| Cancer | 57 (15%) | 19 (95%) | 2 (10%) | 342 (90%) | 59 (15%) | 361 (90.25%) |

Pearl, Causal Inference in Statistics (2016)

# Pearl's Front-Door Criterion: A crafted example

## Interpretation 2: Anti-smoking lobbyists

Smoking **increases** the risk of lung cancer

If one chooses to smoke, then one's chances of building tar deposits are 95% (380/400) vs 5% (20/400) for the non-smokers.

To evaluate effect of tar, look at **smokers and non-smokers separately**. Tar has harmful effects in both groups: in smokers it increases risk of cancer from 10% to 15% and in non-smokers 90% to 95%. Therefore: Smoking -> tar -> cancer.

**Regardless of any natural craving, avoid harmful tar by not smoking.**

**Table 3.2** Reorganization of the data set of Table 3.1 showing the percentage of cancer cases in each smoking-tar category (numbers in thousands)

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| Cancer | 57 (15%) | 2 (10%) | 19 (95%) | 342 (90%) | 76 (19%) | 344 (81%) |

Pearl, Causal Inference in Statistics (2016)

# Pearl's Front-Door Criterion

X -> Z is **identifiable**, since no back path from X and Z: $X \leftarrow U \rightarrow Y \leftarrow Z$

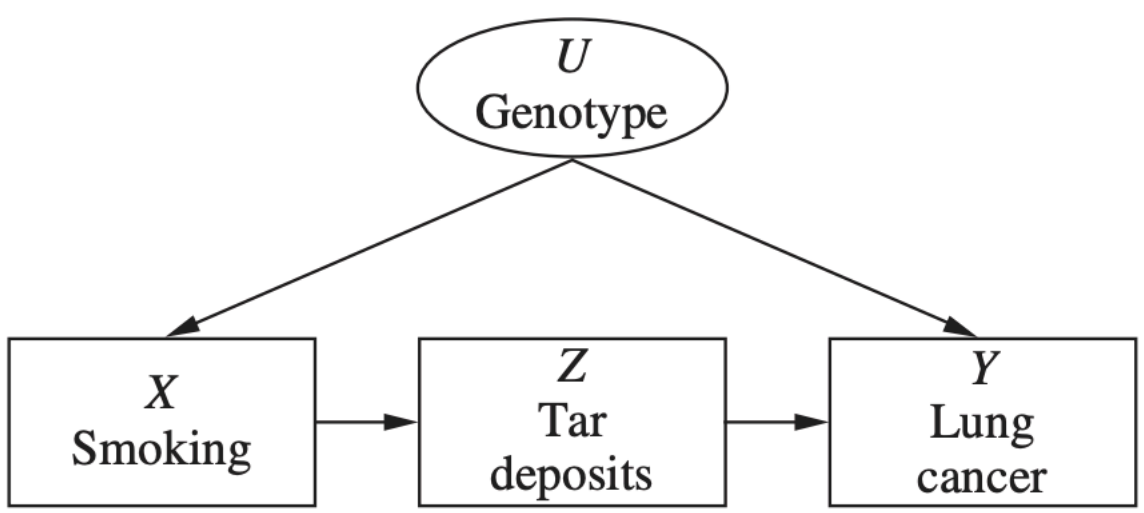
$$p(Z = z|do(X = x)) = p(Z = z|X = x) \quad *$$

Z -> Y is **identifiable**, since backdoor from Z to Y:

$$Z \leftarrow X \leftarrow U \rightarrow Y$$

is **blocked** by conditioning on X:

$$p(Y = y|do(Z = z)) = \sum_x p(Y = y|Z = z, X = x)p(X = x) \quad **$$




Pearl, Causal Inference in Statistics (2016)

# Pearl's Front-Door Criterion

Letting z be the value Z takes when setting X=x, from the graph, we have:

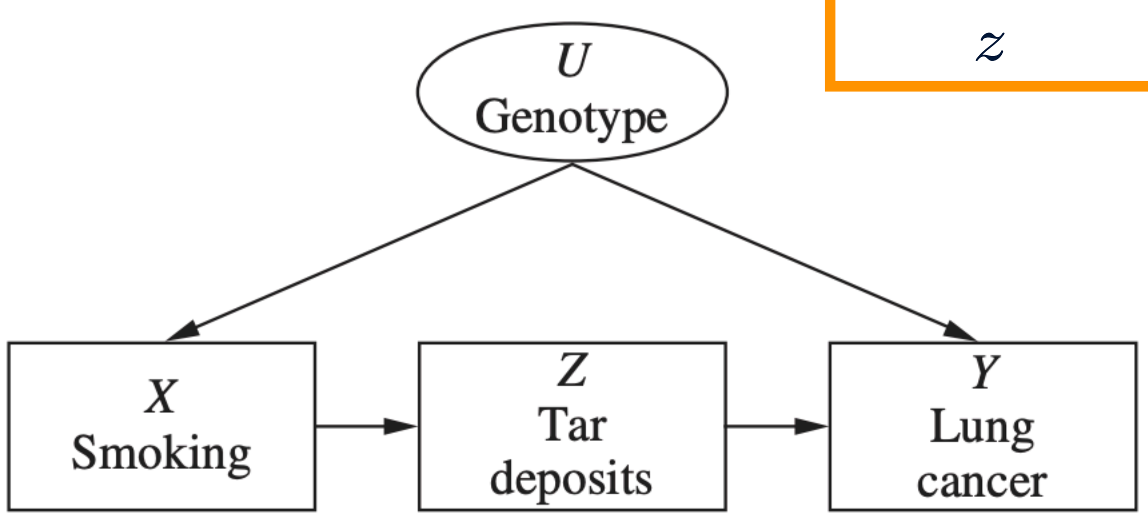
$$p(Y|do(X=x)) = p(Y|do(X=x), Z) = p(Y|do(Z=z))$$

Then summing over all states z of Z:

$$p(Y=y|do(X=x)) = \sum_z p(Y=y, z|do(X=x))$$ Total prob rule

Product rule: $$= \sum_z p(Y=y|z, do(X=x))p(z|do(X=x))$$

Line 1 $$\boxed{= \sum_z p(Y=y|do(Z=z))p(z|do(X=x))}$$




Pearl, Causal Inference in Statistics (2016)

# Pearl’s Front-Door Criterion

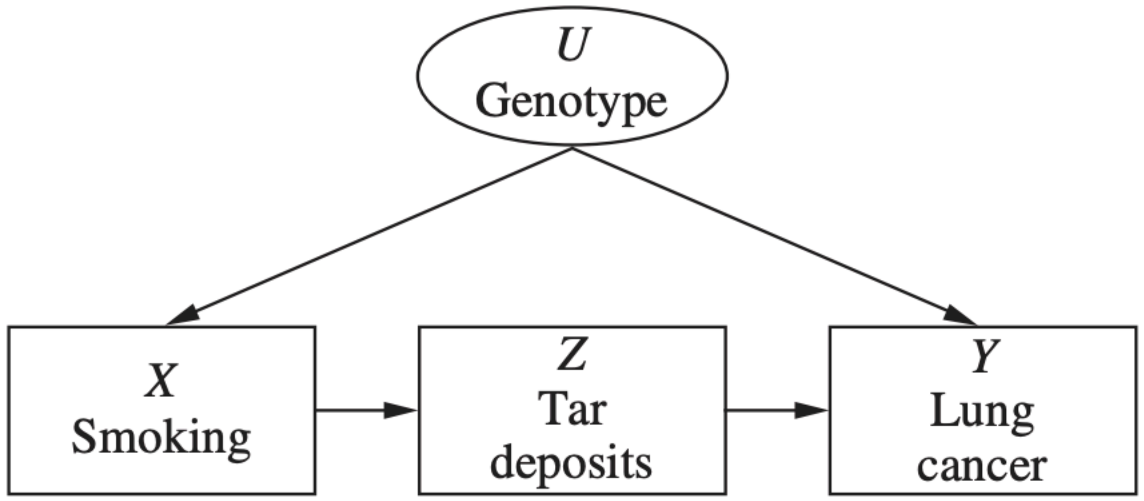
$$p(Z = z | do(X = x)) = p(Z = z | X = x) \quad \star$$

$$p(Y = y | do(Z = z)) = \sum_{x'} p(Y = y | Z = z, X = x') p(X = x') \quad \star\star$$

$$p(Y = y | do(X = x)) = \boxed{\sum_{z} p(Y = y | do(Z = z)) p(Z = z | do(X = x))}$$

Using $\star$ and $\star\star$ summing over all states z of Z:

$$p(Y = y | do(X = x)) = \sum_{z} \sum_{x'} p(Y = y | Z = z, X = x') p(X = x') p(Z = z | X = x)$$




**Front-door formula**

Pearl, Causal Inference in Statistics (2016)

# Pearl’s Front-Door Criterion: Which group is right?

$$p(Y=y|do(X=x)) = \sum_z \sum_{x'} p(Y=y|Z=z,X=x')p(X=x')p(Z=z|X=x)$$

$$\begin{aligned}
p(Y=1|do(X=1)) &= \underbrace{p(Y=1|z=0,x'=0)}_{342/380}\,p(x'=0)\,\underbrace{p(z=0|x=1)}_{20/400} \\
&+ \underbrace{p(Y=1|z=0,x'=1)}_{2/20}\,p(x'=1)\,\underbrace{p(z=0|x=1)}_{20/400} \\
&+ \underbrace{p(Y=1|z=1,x'=0)}_{19/20}\,p(x'=0)\,\underbrace{p(z=1|x=1)}_{380/400} \\
&+ \underbrace{p(Y=1|z=1,x'=1)}_{57/380}\,\underbrace{p(x'=1)}_{0.5}\,\underbrace{p(z=1|x=1)}_{380/400} \\
&= 0.5475
\end{aligned}$$

$$p(Y=1|do(X=0)) = 0.5025$$

**Average Causal Effect ACE:** $p(Y=1|do(X=1)) - p(Y=1|do(X=0)) = 0.045$

**4.5% increase**

**Table 3.2** Reorganization of the data set of Table 3.1 showing the percentage of cancer cases in each smoking-tar category (numbers in thousands)

| | Smokers 400 | | Nonsmokers 400 | | All subjects 800 | |
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$342/380$

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|---|---|---|---|---|---|---|
| | Tar | No tar | Tar | No tar | Tar | No tar |
| | *380* | *20* | *20* | *380* | *400* | *400* |
| No cancer | 323 (85%) | 18 (90%) | 1 (5%) | 38 (10%) | 324 (81%) | 56 (19%) |
| Cancer | 57 (15%) | 2 (10%) | 19 (95%) | 342 (90%) | 76 (19%) | 344 (81%) |

Pearl, Causal Inference in Statistics (2016)

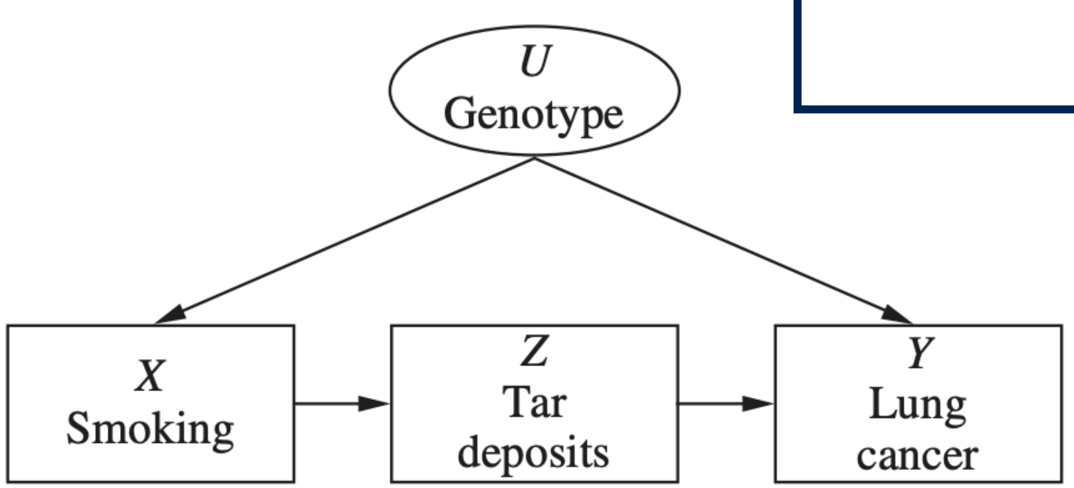
# Pearl's Front-Door Adjustment

**Front-door criterion**: A set of variables Z is said to satisfy the front-door criterion relative to (X,Y) if:

1. Z intercepts all directed paths from X to Y
2. There is no unblocked path from X to Z
3. All backdoor paths from Z to Y are blocked by X

**Front-door adjustment**: If Z satisfied the front-door criterion relative to (X,Y), and if p(x,z)>0, then the causal effect of X on Y is identifiable and is given by:

$$\boxed{p(y|do(x)) = \sum_{z} p(z|x) \sum_{x'} p(y|x', z)p(x')}$$




Pearl, Causal Inference in Statistics (2016)

# Do Calculus

- Do-calculus: Contains, as subsets:
  - Backdoor criterion
  - Front-door criterion

- Allows analysis of more intricate structure beyond back- and front-door

- Uncovers **all** causal effects that can be identified from a given causal graph

- Power of causal graphs is not just representation but towards **discovery** of causal information

# Causal Inference

- **Model** a causal inference problem with assumptions manifest in Causal Graphical Models [**Pearl]**

- **Identify** an expression for the causal effect under these assumptions ("causal estimand"), [**Pearl**]

- **Estimate** the expression using statistical methods such as matching or instrumental variables, [**Rubin**'s Potential Outcomes]

- **Verify** the validity of the estimate using a variety of robustness checks.

# DoWhy Simulations

**Simple DoWhy tutorials on my GitHub 'Causality in Biomedicine'**

**DoWhy tutorials:**
https://microsoft.github.io/dowhy/index.html

**CausalGraphicalModels Tutorials:**
https://github.com/ijmbarr/causalgraphicalmodels
**Adjusting for the wrong variable:** http://www.degeneratestate.org/posts/2018/Jul/10/causal-inference-with-python-part-2-causal-graphical-models/
**Front-door:** http://www.degeneratestate.org/posts/2018/Sep/03/causal-inference-with-python-part-3-frontdoor-adjustment/

**Also see ML extensions to DoWhy, e.g. EconML:**
https://github.com/microsoft/EconML

# Methods for Causal Inference
# Lecture 11

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