A Brief Introduction to Causal Inference

Brady Neal

causalcourse.com

What is causal inference?

Inferring the effects of any treatment/policy/intervention/etc.

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Examples:

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- Effect of climate change policy on emissions

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- Effect of treatment on a disease
- Effect of climate change policy on emissions
- Effect of social media on mental health

What is causal inference?

Inferring the effects of any treatment/policy/intervention/etc.

Examples:

- Effect of treatment on a disease
- Effect of climate change policy on emissions
- Effect of social media on mental health
- Many more (effect of X on Y)

Motivating example: Simpson's paradox

Correlation does not imply causation

Then, what does imply causation?

Causation in observational studies

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Simpson's paradox: COVID-27

New disease: COVID-27

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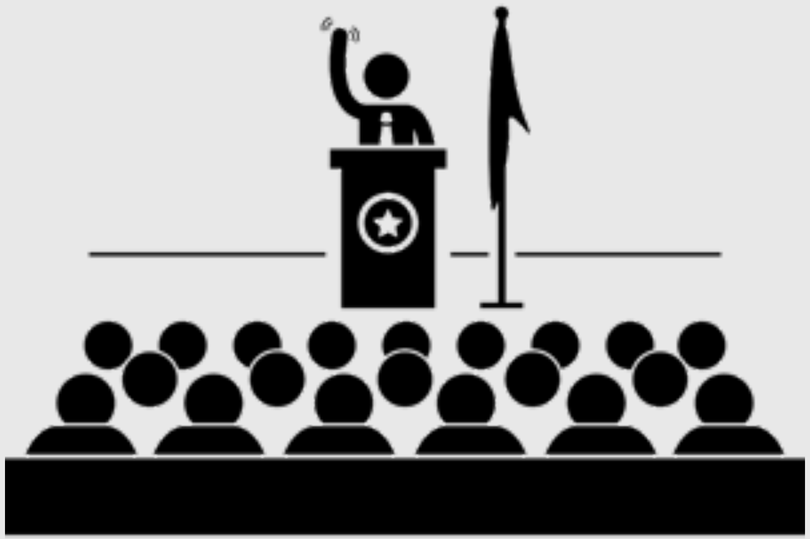
Treatment T: A (0) and B (1)

Simpson’s paradox: COVID-27

New disease: COVID-27

Treatment T: A (0) and B (1)

YOU



Simpson's paradox: COVID-27

New disease: COVID-27

Treatment T: A (0) and B (1)

Condition C: mild (0) or severe (1)

Simpson's paradox: COVID-27

New disease: COVID-27

Treatment T: A (0) and B (1)

Condition C: mild (0) or severe (1)

Outcome Y: alive (0) or dead (1)

Simpson's paradox: mortality rate table

Treatment	Total
A	**16%** (240/1500)
B	19% (105/550)
	$\mathbb{E}[Y \mid T]$

Simpson's paradox: mortality rate table

Condition

Treatment	Mild	Severe	Total
A	15% (210/1400)	30% (30/100)	**16%** (240/1500)
B	**10%** (5/50)	**20%** (100/500)	19% (105/550)
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Simpson's paradox: mortality rate table

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$$\frac{1400}{1500}(0.15) + \frac{100}{1500}(0.30) = 0.16$$

$$\frac{50}{550}(0.10) + \frac{500}{550}(0.20) = 0.19$$

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Which treatment should you choose?

Simpson's paradox: scenario 1 (treatment B)

Condition

Treatment	Mild	Severe	Total
A	15% (210/1400)	30% (30/100)	**16%** (240/1500)
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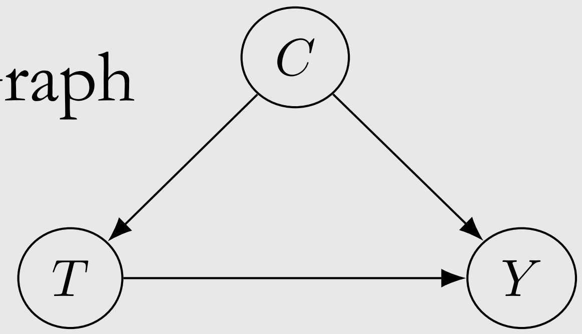
Causal Graph



Simpson's paradox: scenario 1 (treatment B)

Treatment		Condition: Mild	Condition: Severe	Condition: Total
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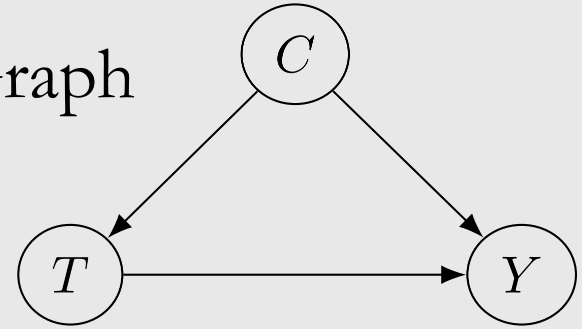

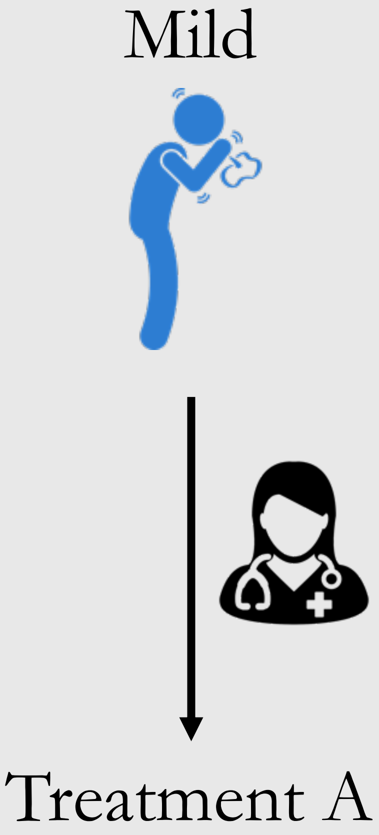

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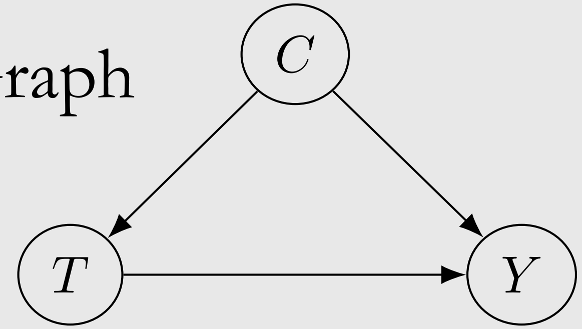

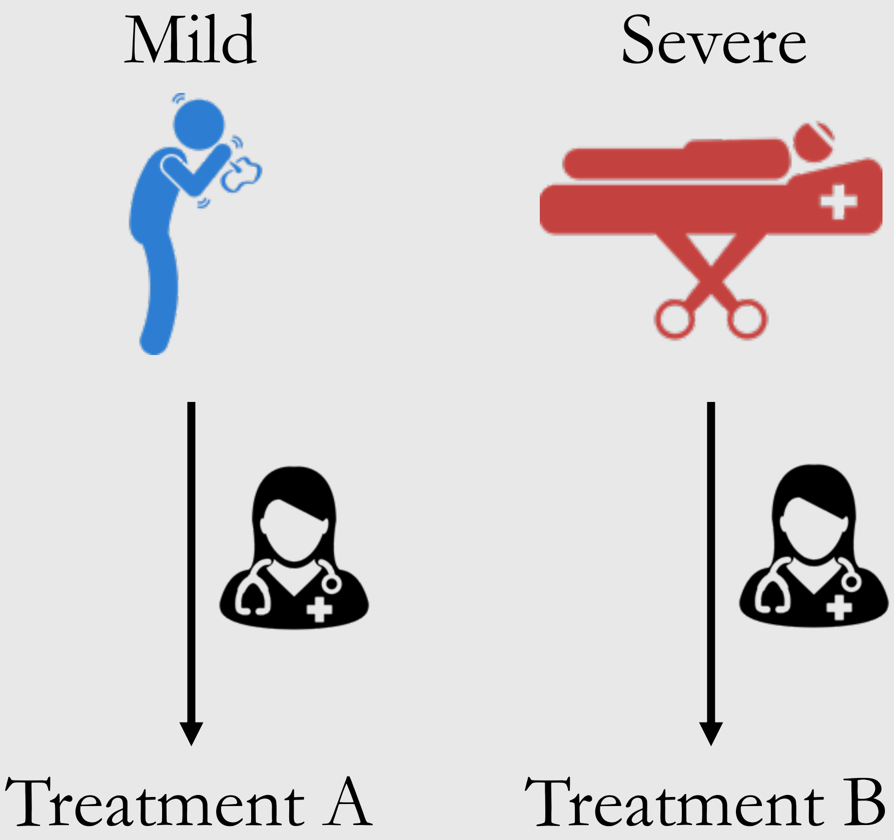

Simpson's paradox: scenario 2 (treatment A)

Condition

Treatment	Mild	Severe	Total
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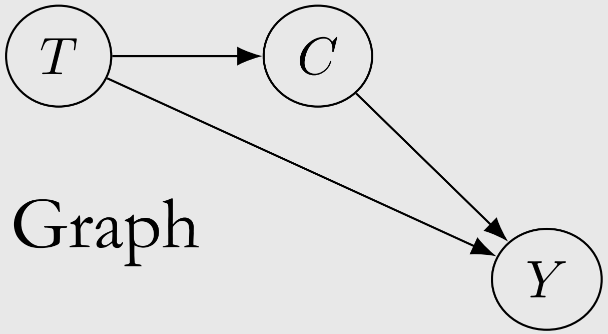

Causal Graph

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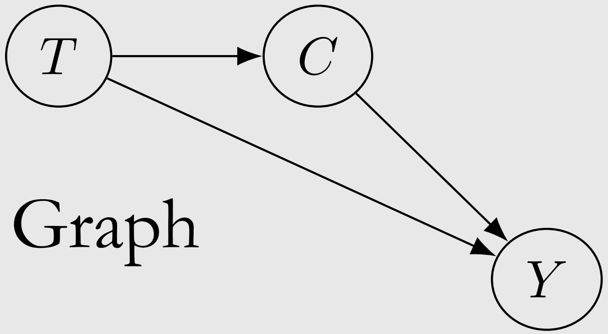

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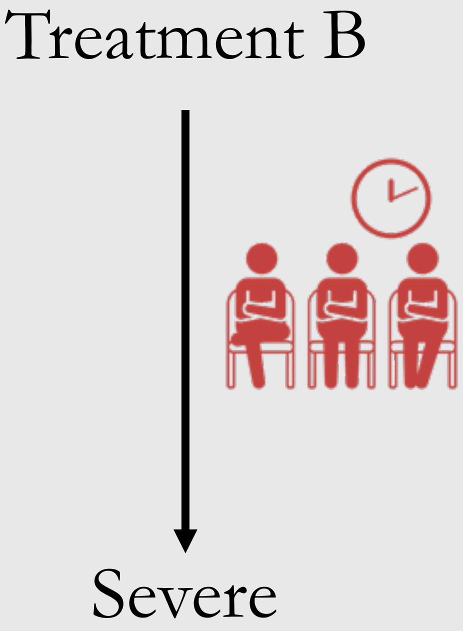

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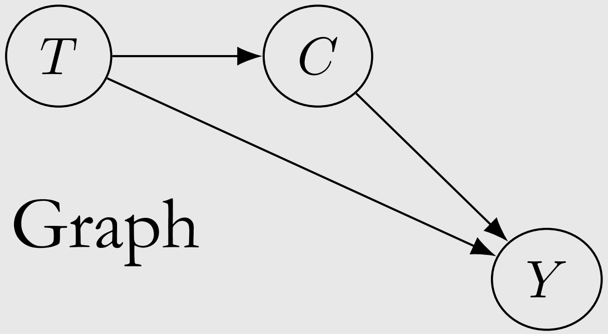

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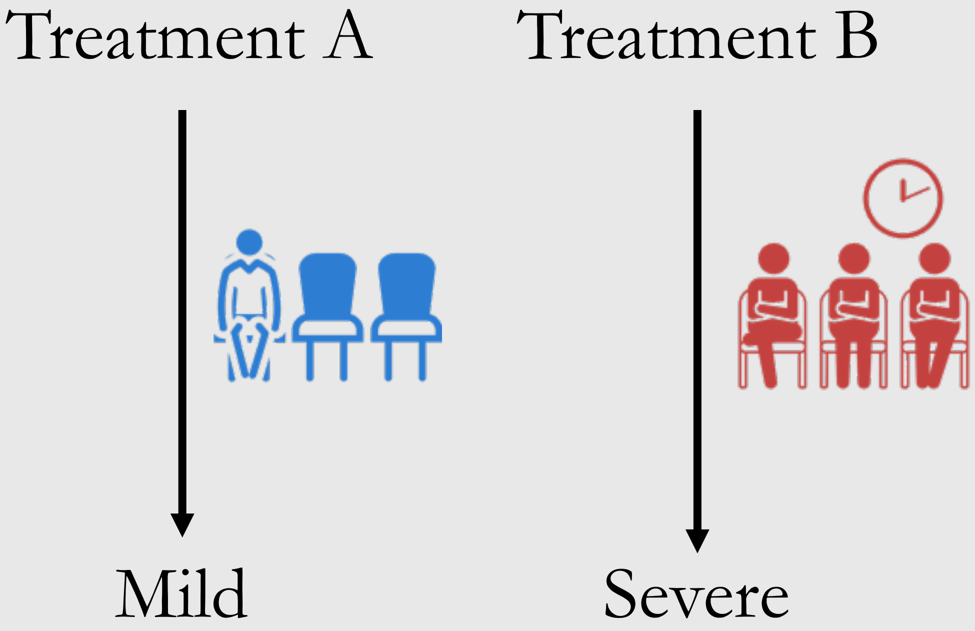
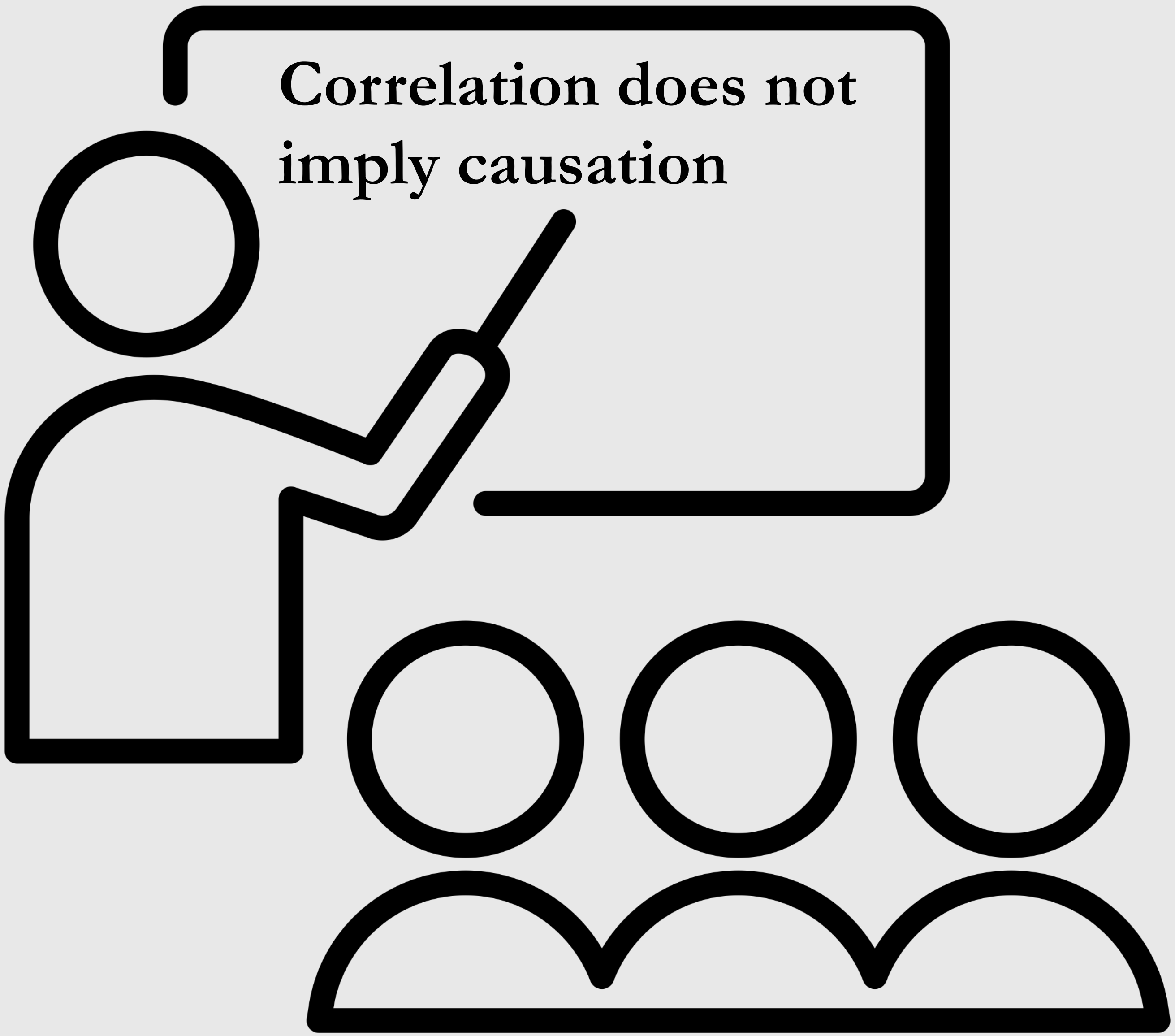


Motivating example: Simpson's paradox

Correlation does not imply causation

Then, what does imply causation?

Causation in observational studies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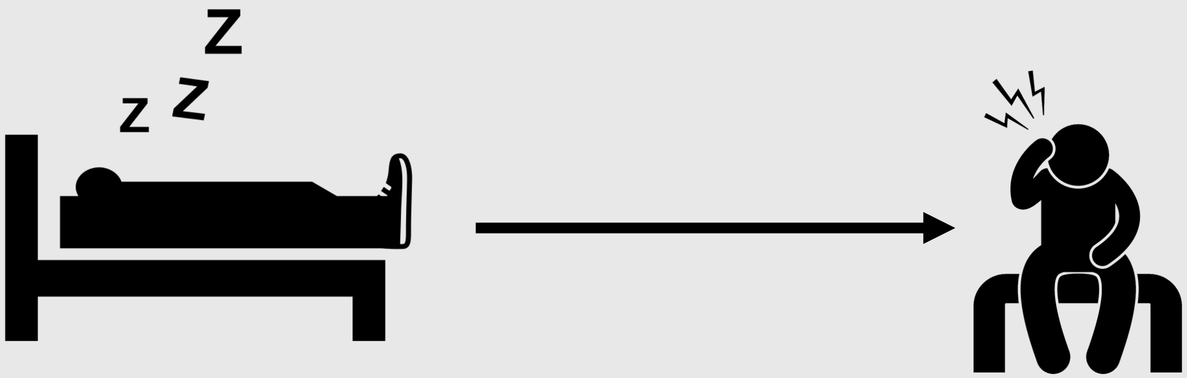
Correlation does not imply causation

Sleeping with shoes on is strongly correlated with waking up with a headache



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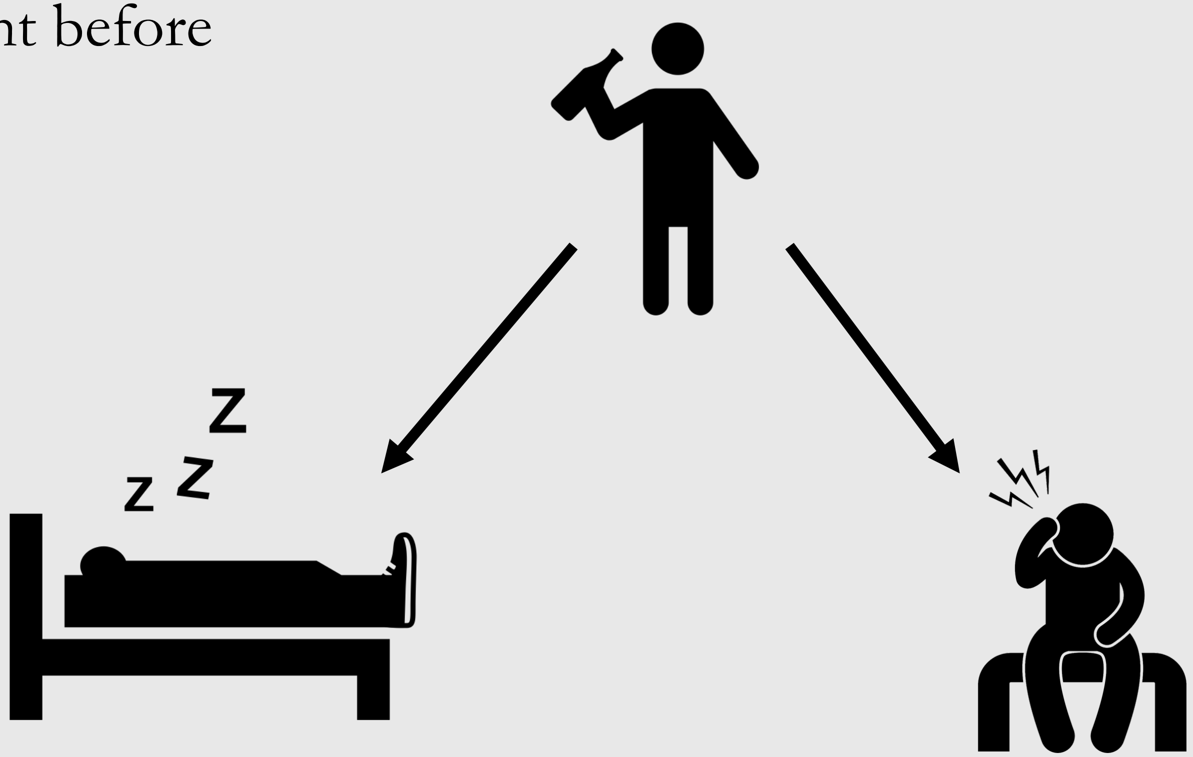
Common cause: drinking the night before



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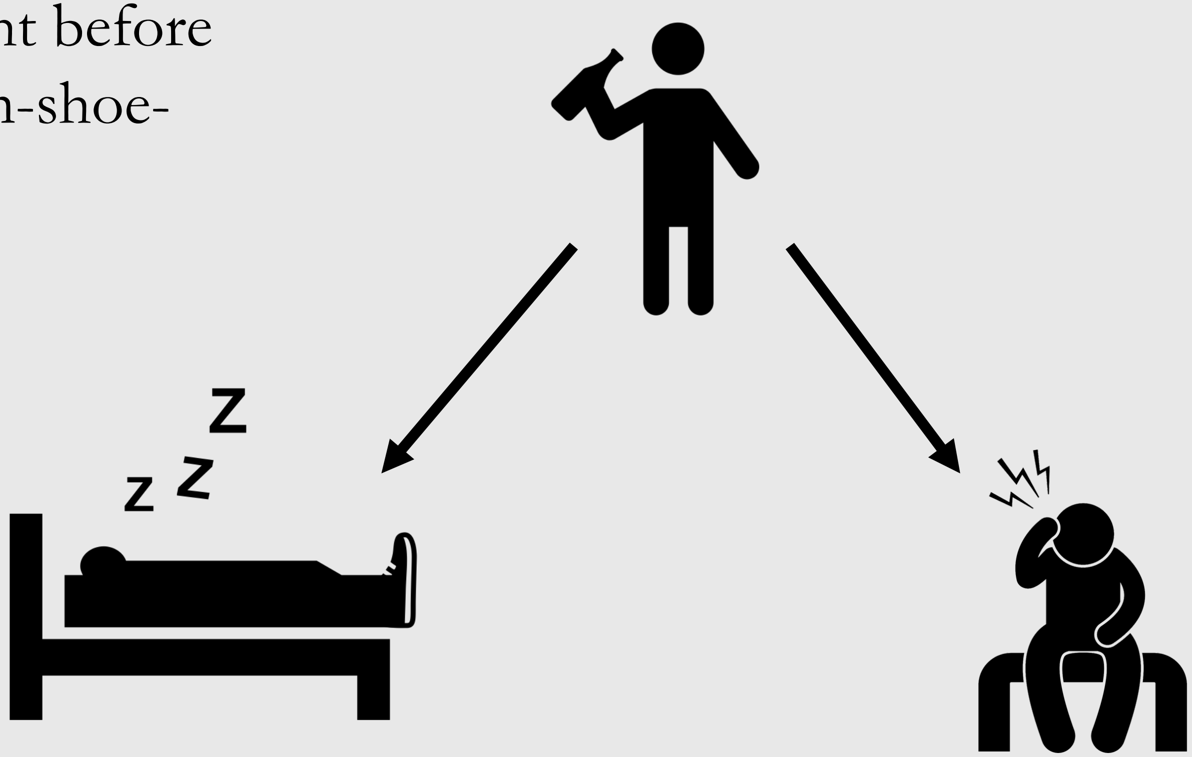
1. Shoe-sleepers differ from non-shoe-sleepers in a key way



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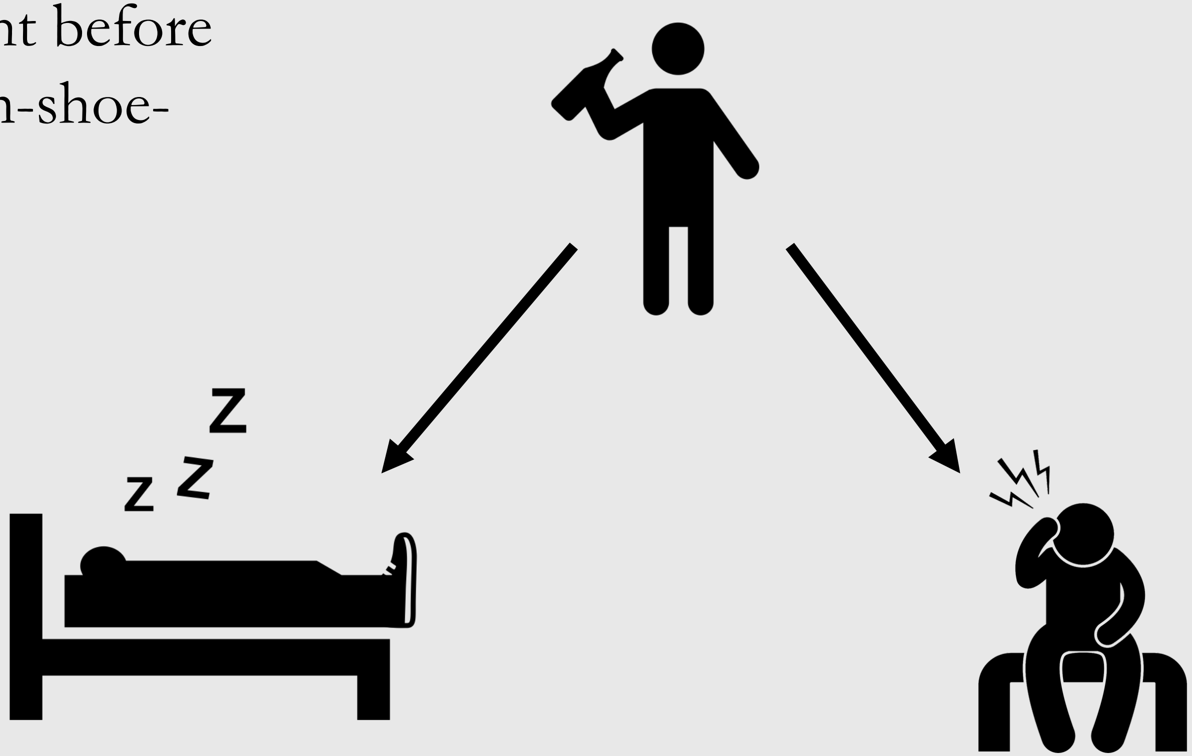

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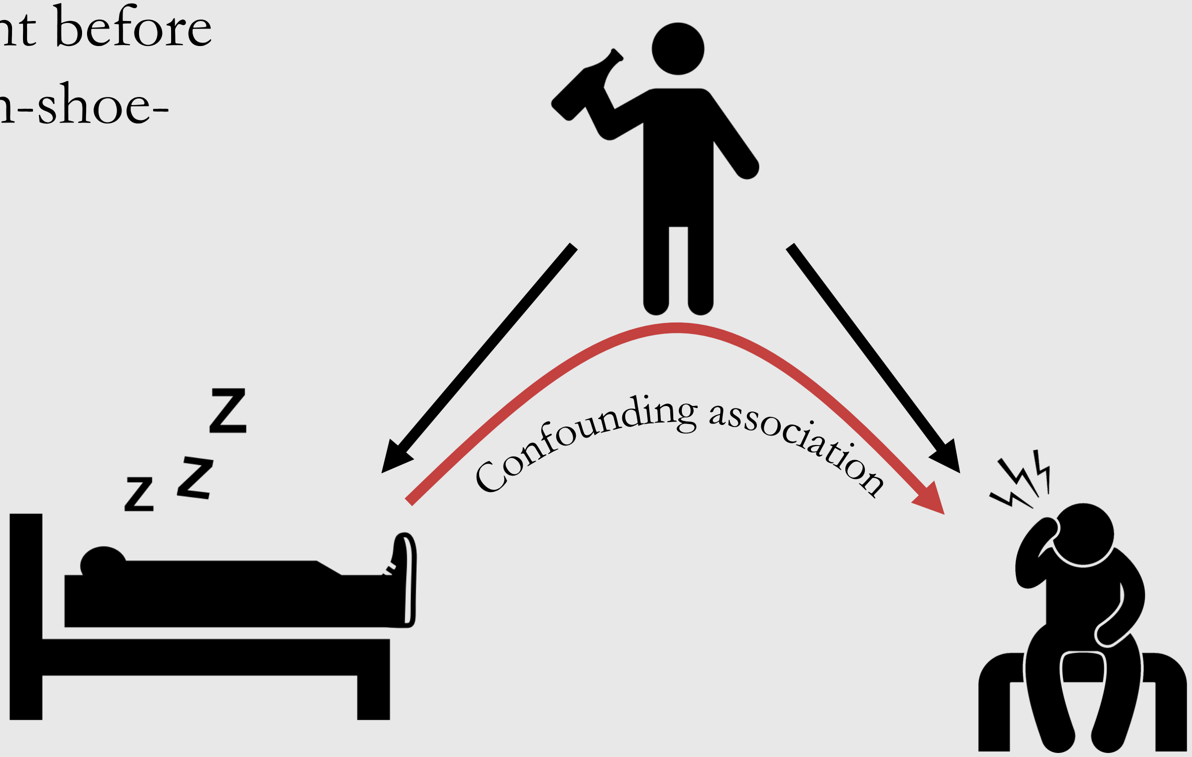

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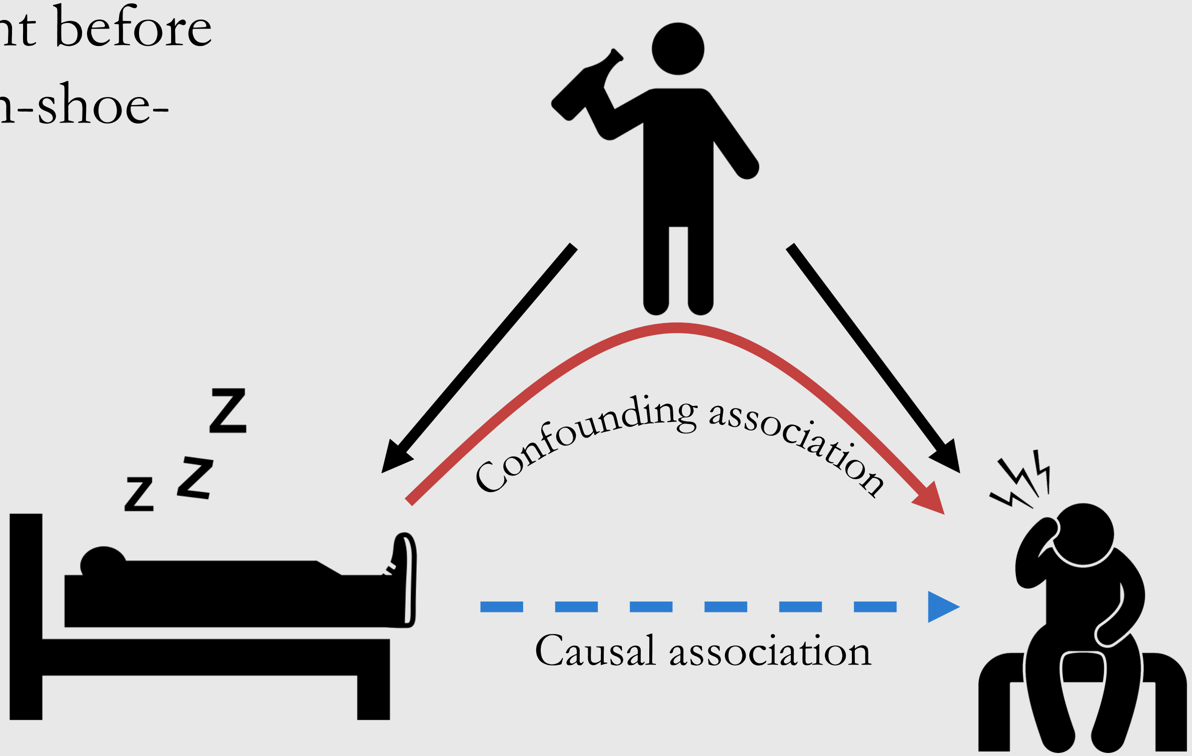

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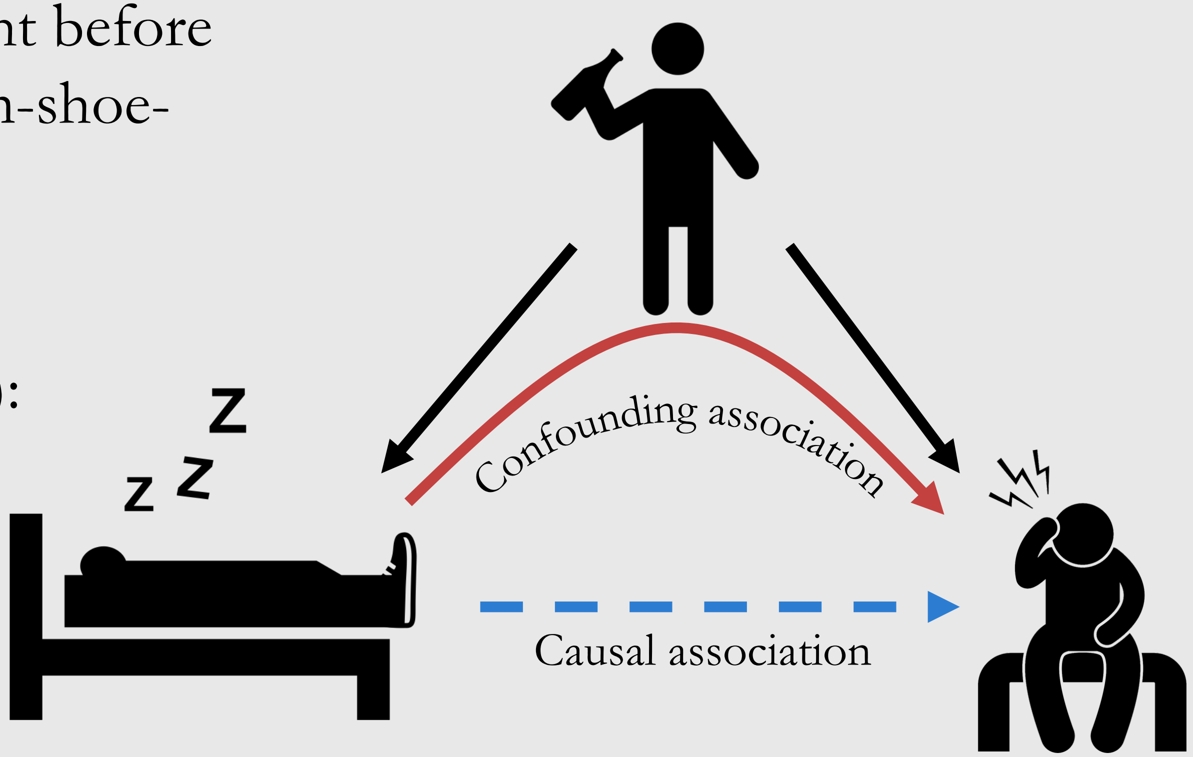
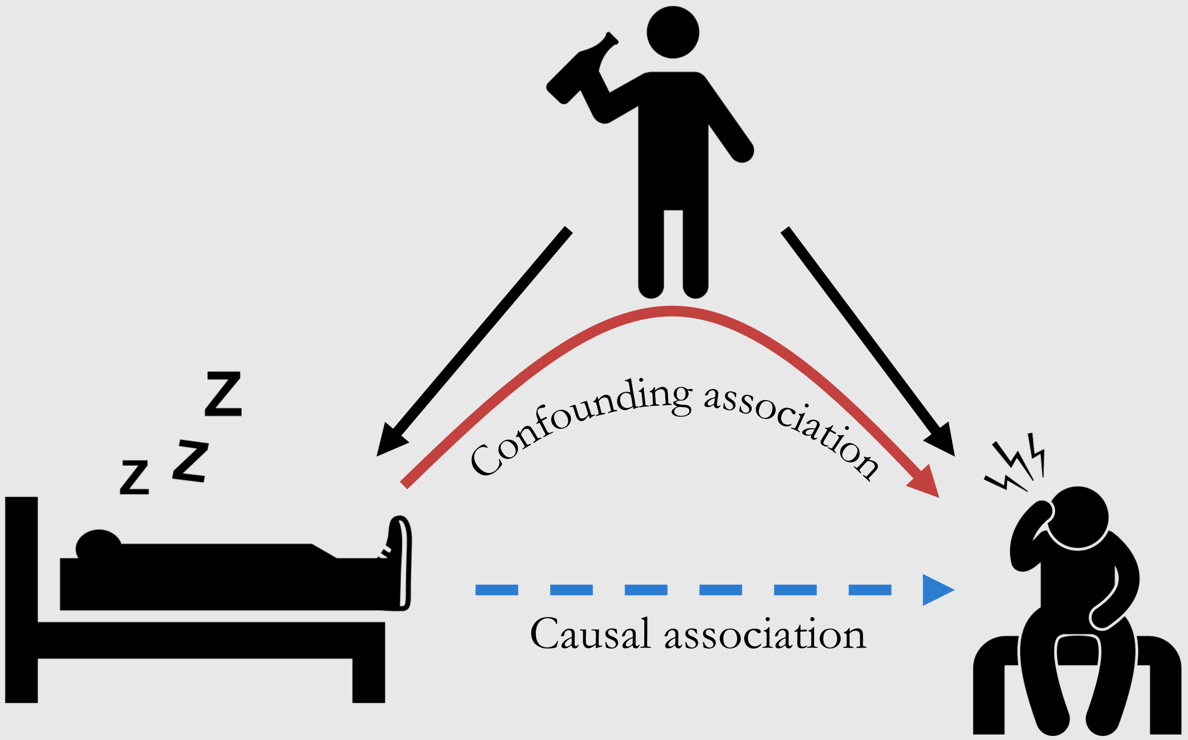
Total association (e.g. correlation): mixture of causal and confounding association



"Correlation = Causation" is a cognitive bias[1]



[1] The illusion of causality: A cognitive bias underlying pseudoscience (Blanco & Matute, 2018)

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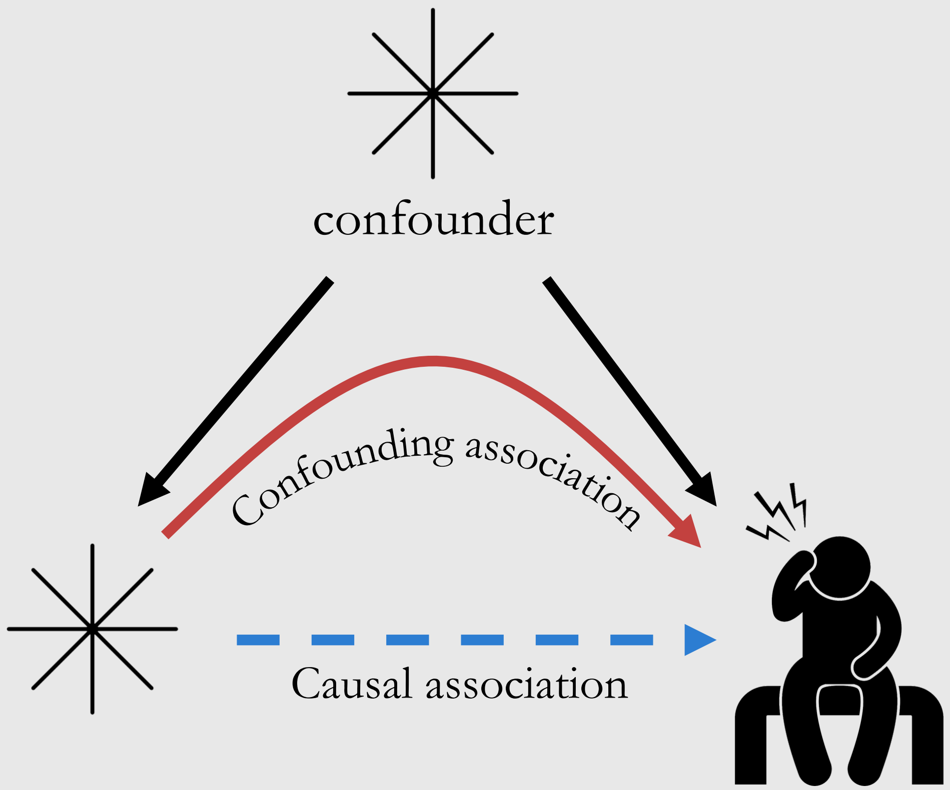

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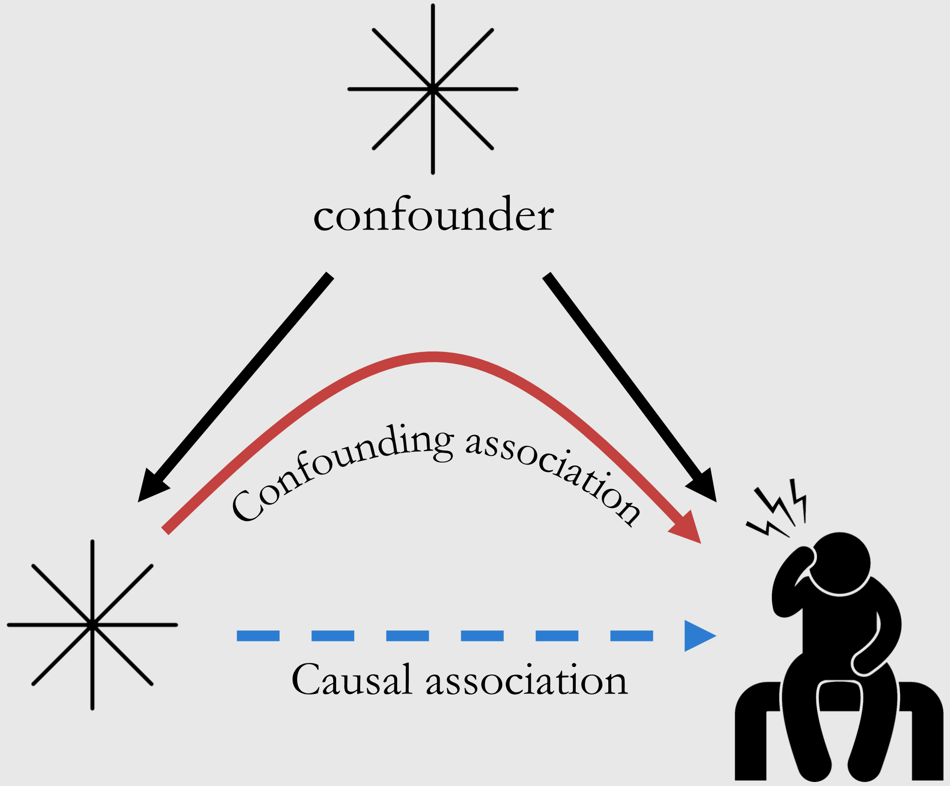

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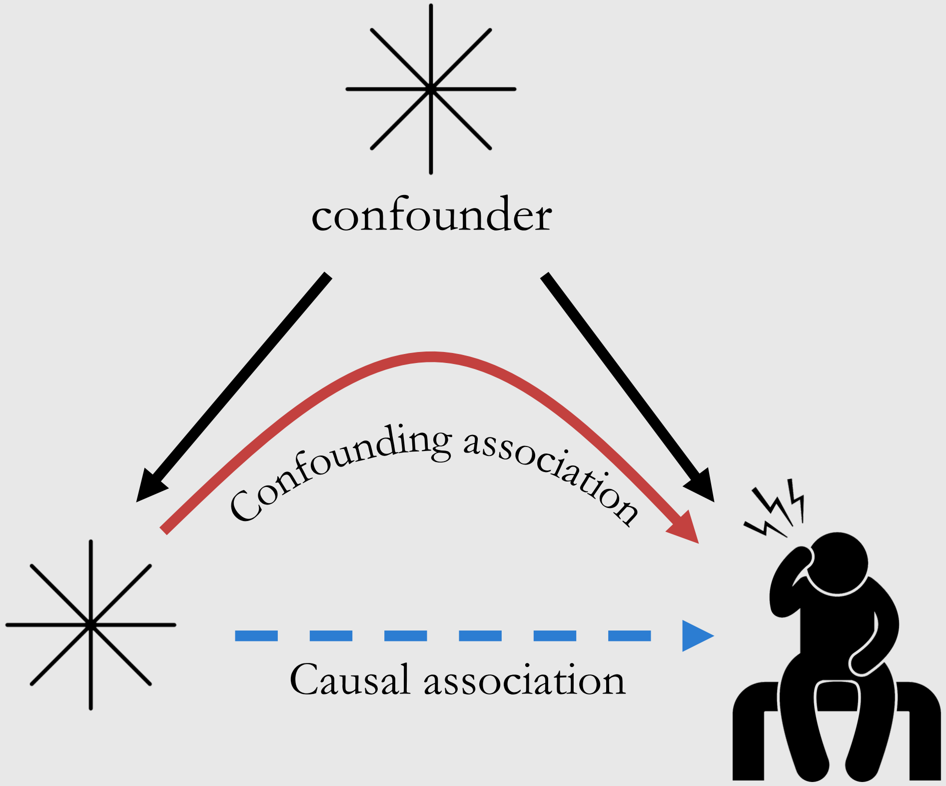

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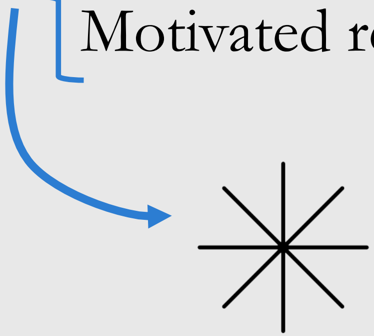

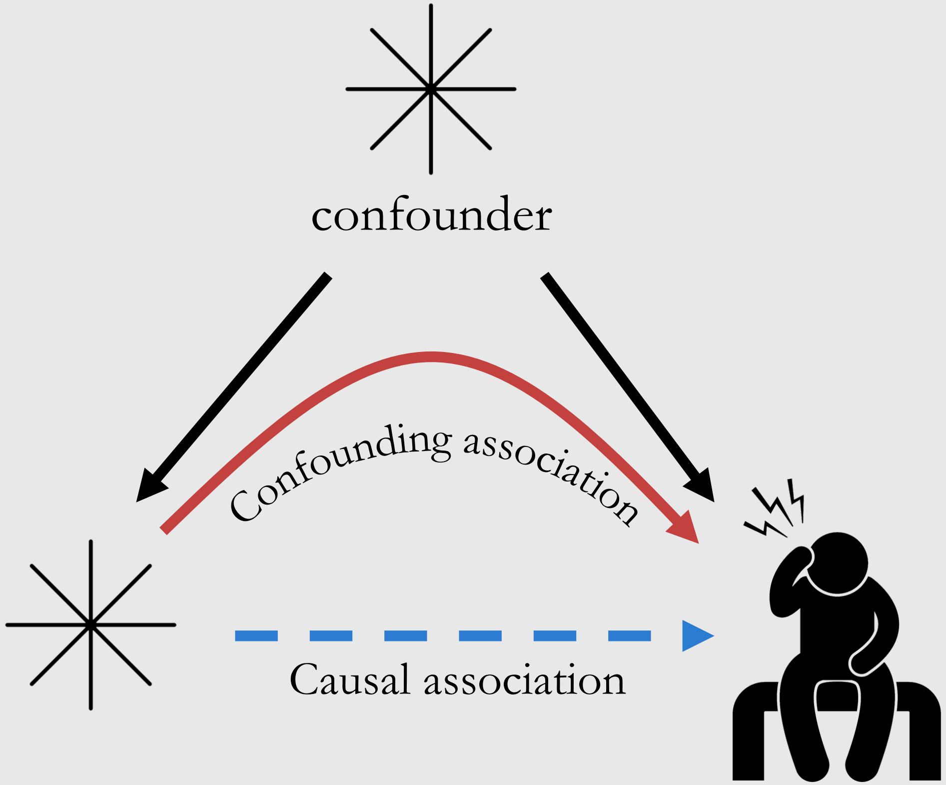

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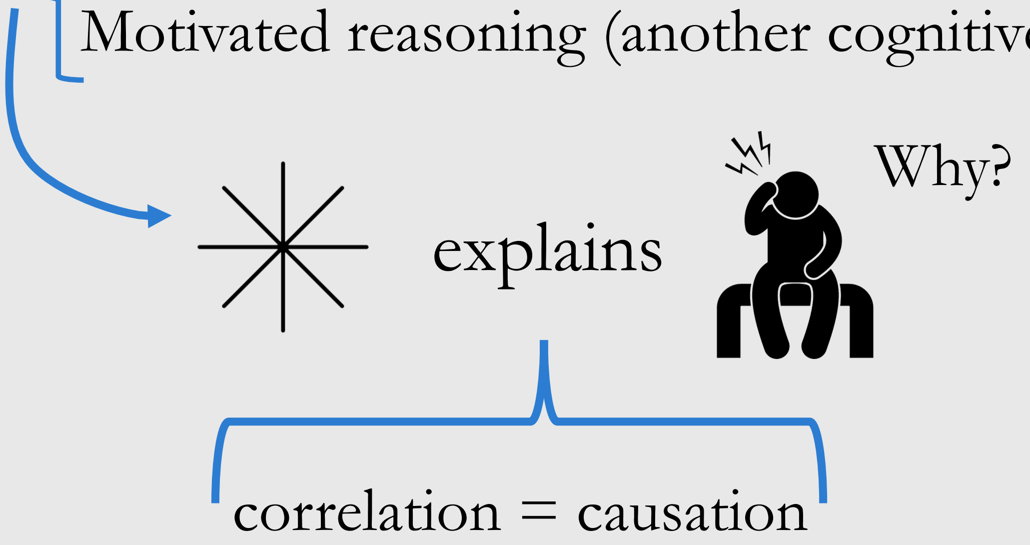

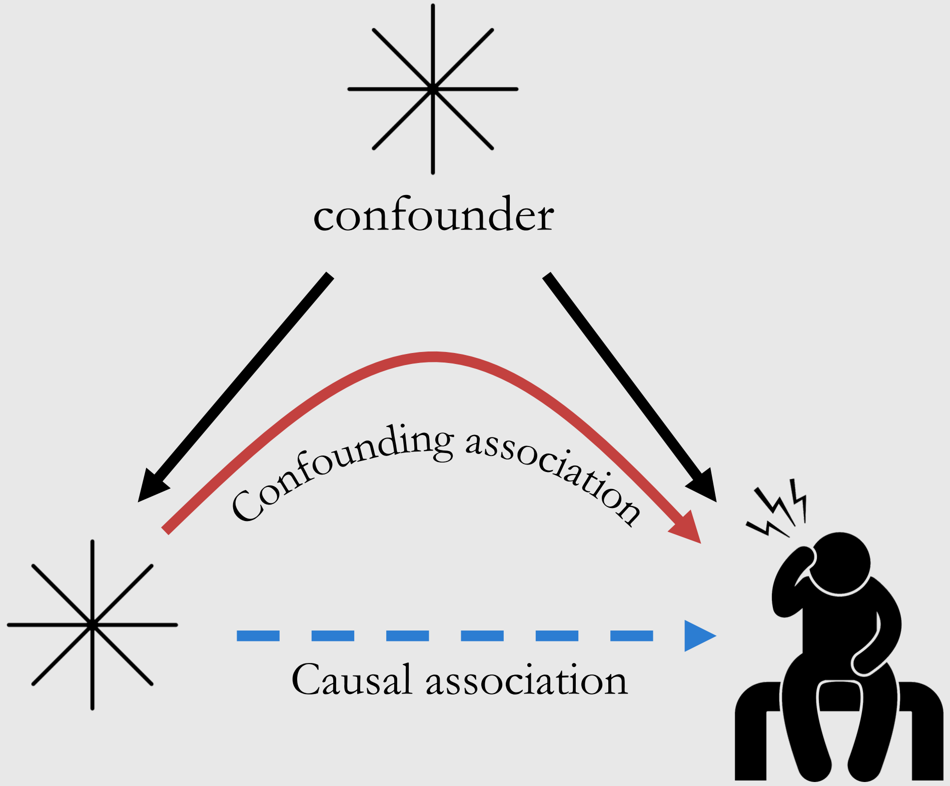

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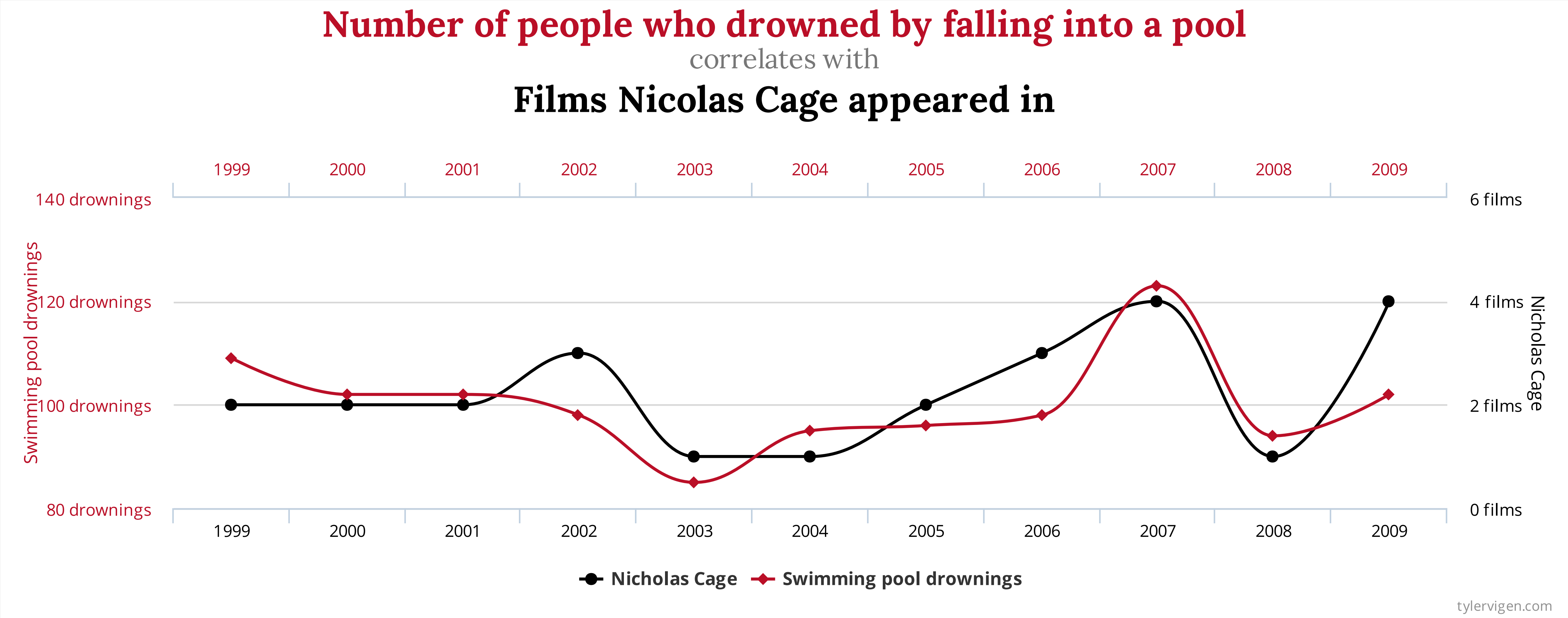
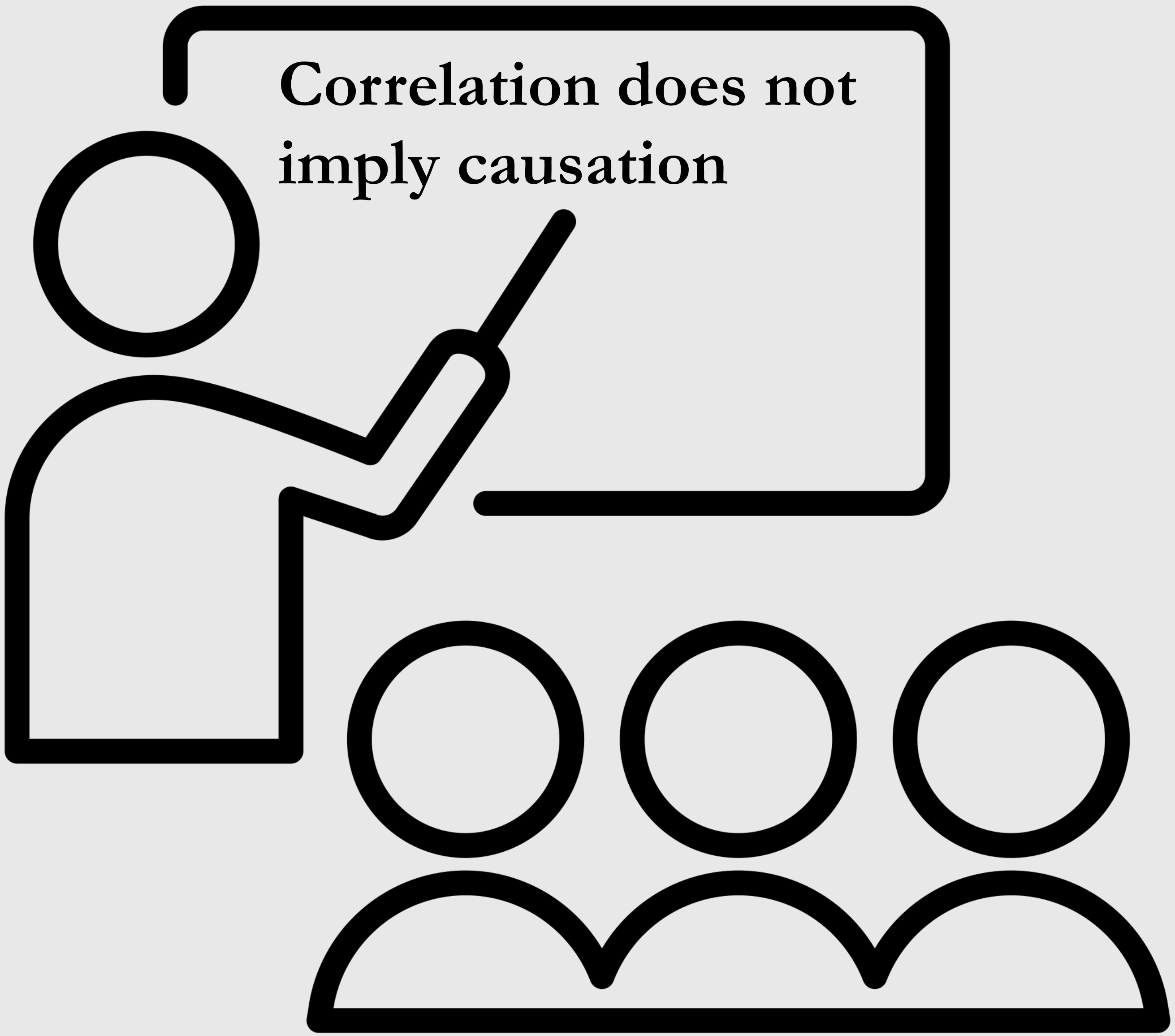
Nicolas Cage drives people to drown themselves



https://www.tylervigen.com/spurious-correlations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Causation in observational studies

Potential outcomes: intuition

Inferring the effect of treatment/policy on some outcome

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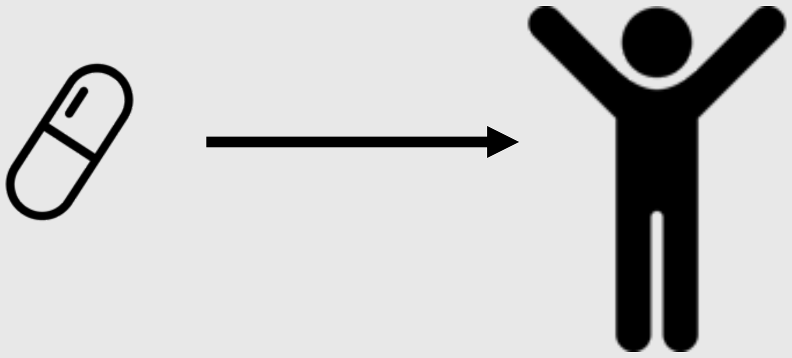
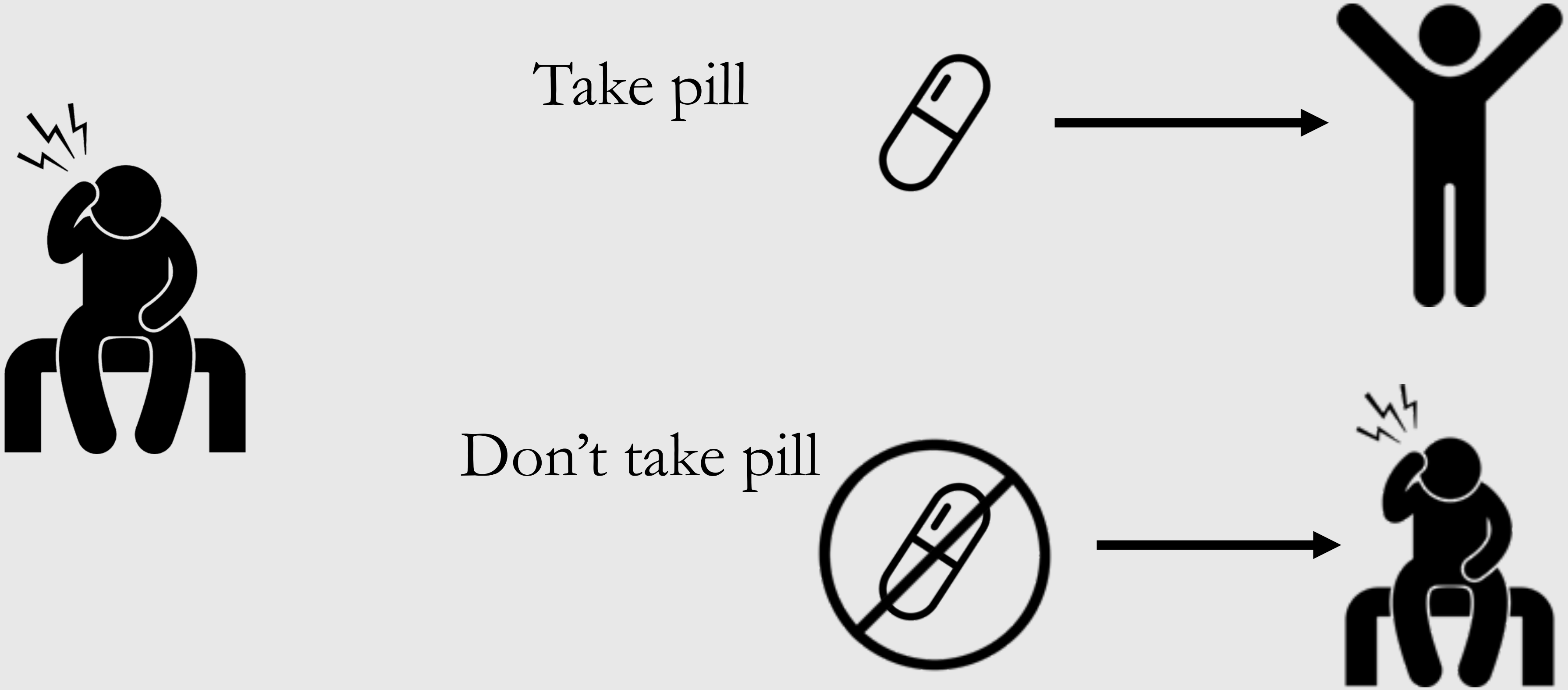
Inferring the effect of treatment/policy on some outcome

Take pill



Potential outcomes: intuition

Inferring the effect of treatment/policy on some outcome



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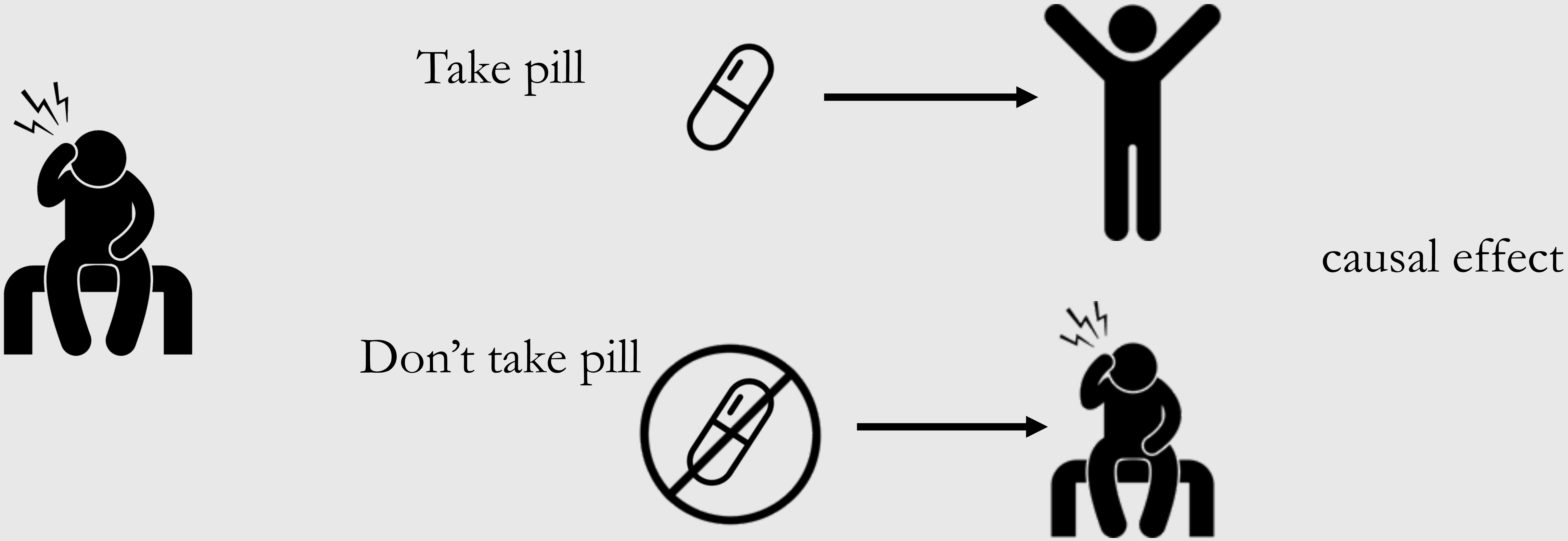

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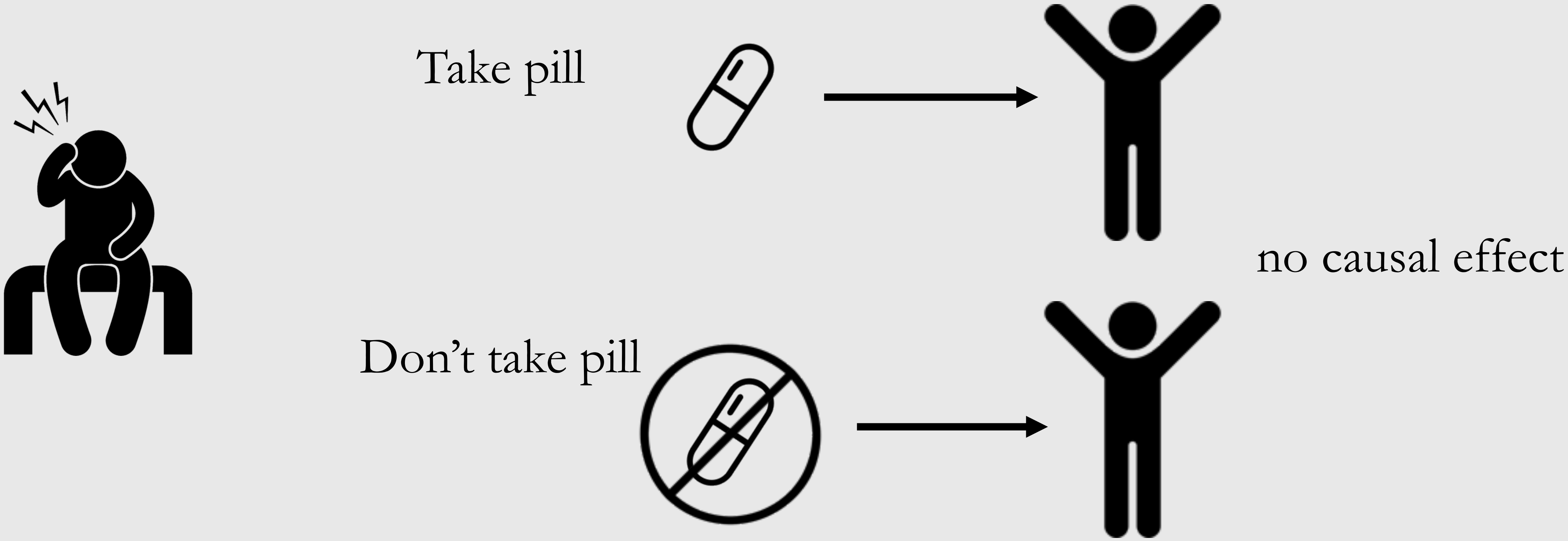
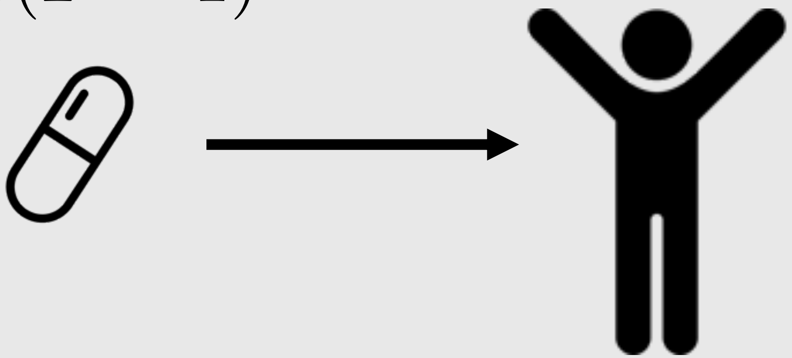
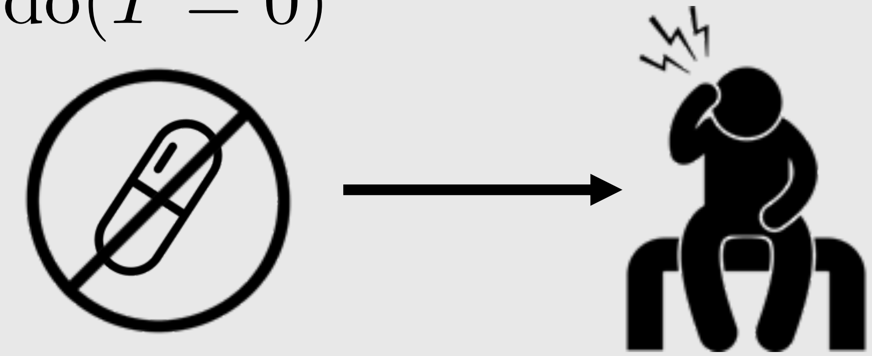


Potential outcomes: notation

$\text{do}(T = 1)$



$\text{do}(T = 0)$

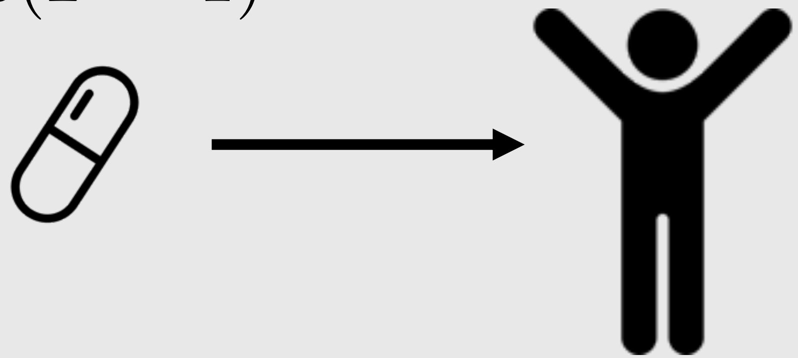


T : observed treatment
Y : observed outcome

Potential outcomes: notation

$\mathrm{do}(T = 1)$

$Y_i|_{\mathrm{do}(T=1)}$



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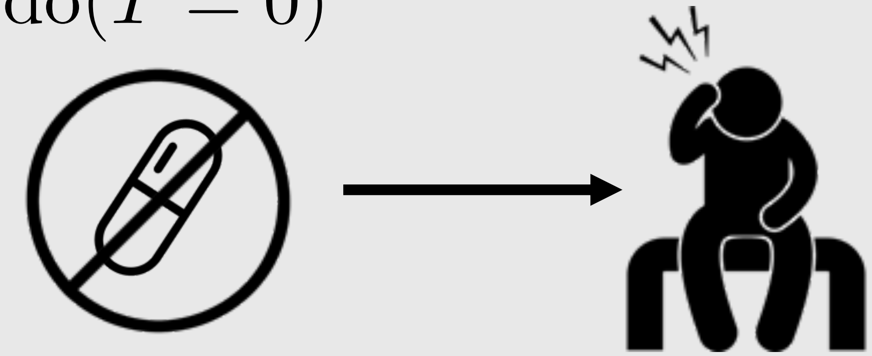

T : observed treatment
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i : used in subscript to denote a specific unit/individual

Potential outcomes: notation

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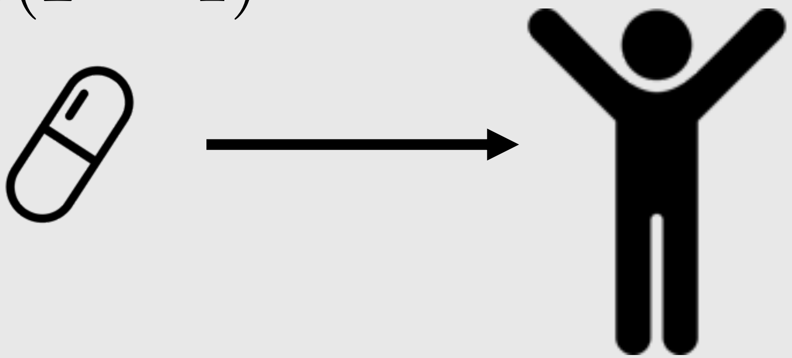

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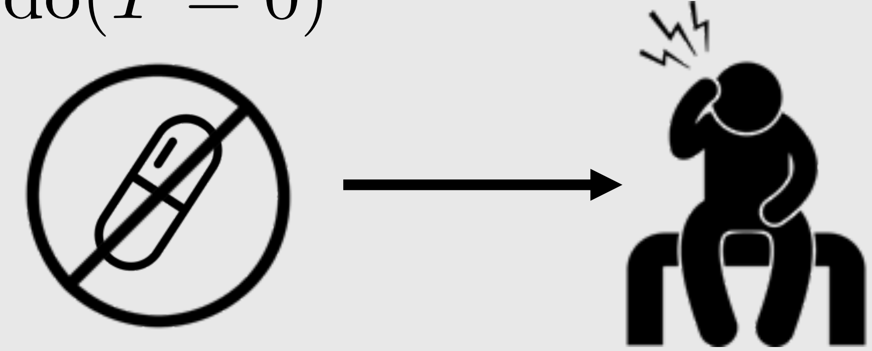

T	: observed treatment
Y	: observed outcome
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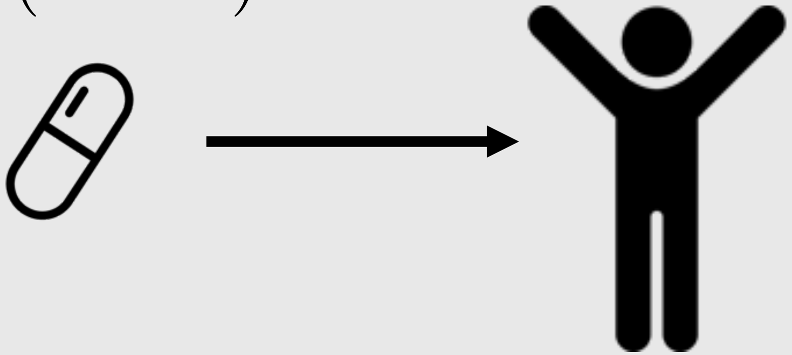
Potential outcomes: notation

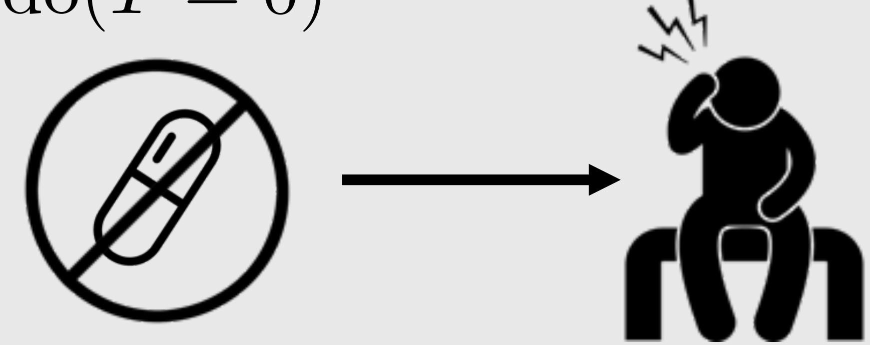
$\text{do}(T = 1)$

$Y_i|_{\text{do}(T=1)} \triangleq Y_i(1)$



$\text{do}(T = 0)$

$Y_i|_{\text{do}(T=0)}$



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$Y_i(1)$	: potential outcome under treatment

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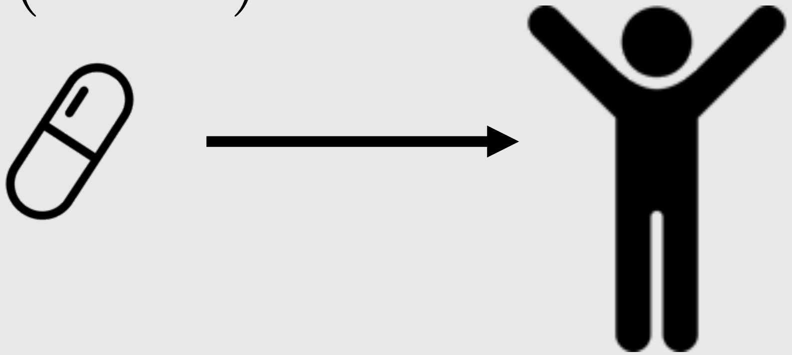
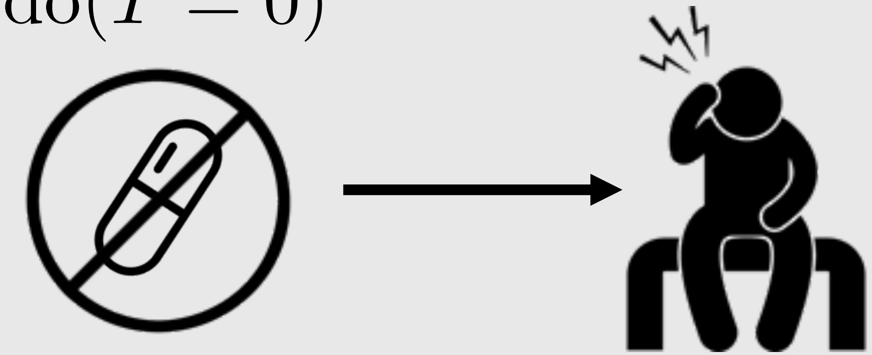


$\text{do}(T = 0)$

$Y_i|_{\text{do}(T=0)} \triangleq Y_i(0)$



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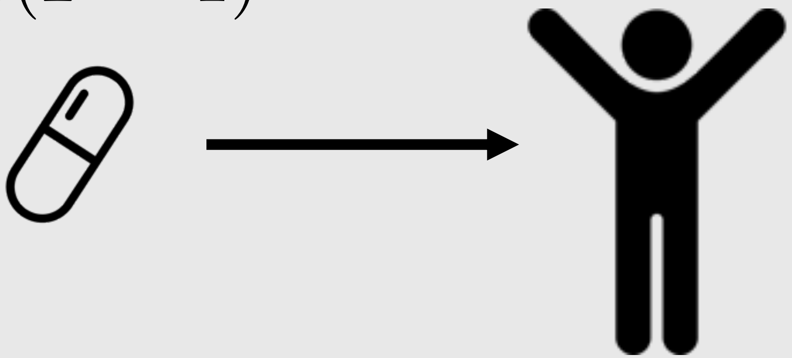
Y	: observed outcome
i	: used in subscript to denote a specific unit/individual
$Y_i(1)$	: potential outcome under treatment
$Y_i(0)$	: potential outcome under no treatment

Potential outcomes: notation

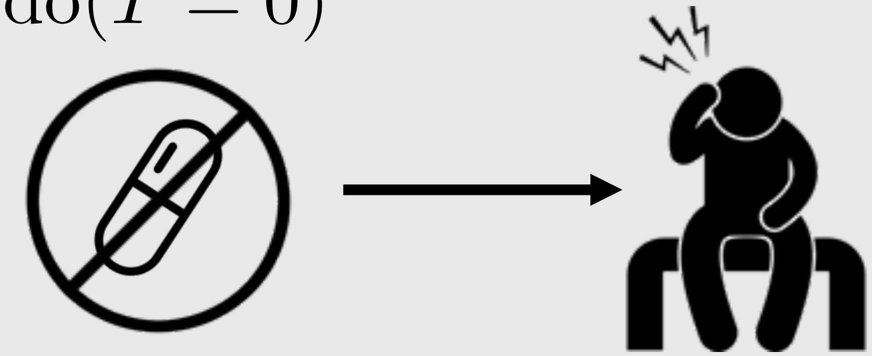
$$Y_i|_{do(T=1)} \triangleq Y_i(1)$$

$\text{do}(T = 1)$



$$Y_i|_{do(T=0)} \triangleq Y_i(0)$$

$\text{do}(T = 0)$



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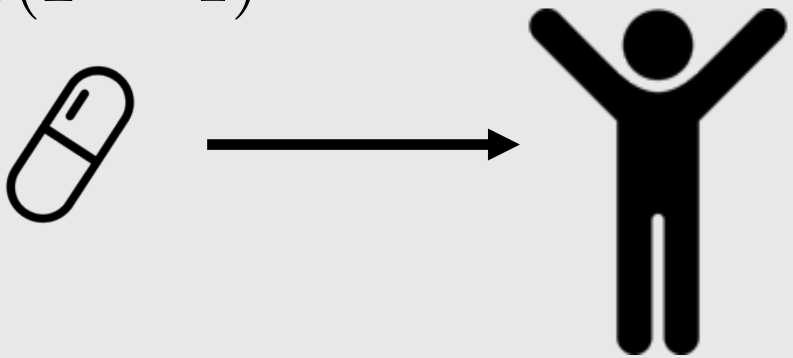
Causal effect

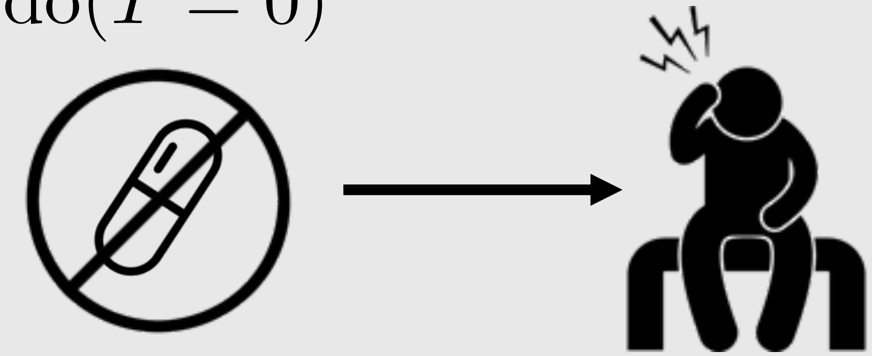
$$Y_i(1) - Y_i(0)$$

Fundamental problem of causal inference

$\mathrm{do}(T = 1)$ $\quad$ $Y_i(1) = 1$



$\mathrm{do}(T = 0)$ $\quad$ $Y_i(0) = 0$



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Causal effect

$$Y_i(1) - Y_i(0) = 1$$

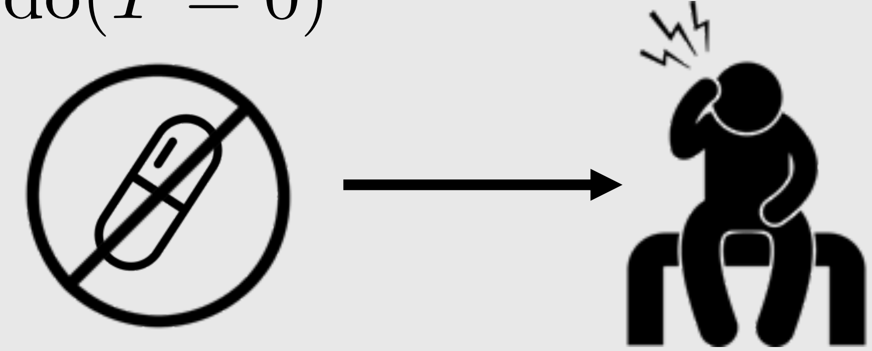
Fundamental problem of causal inference

Counterfactual

$\text{do}(T=1)$ $\quad Y_i(1) = 1$

Factual

$\text{do}(T=0)$ $\quad Y_i(0) = 0$



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Fundamental problem of causal inference

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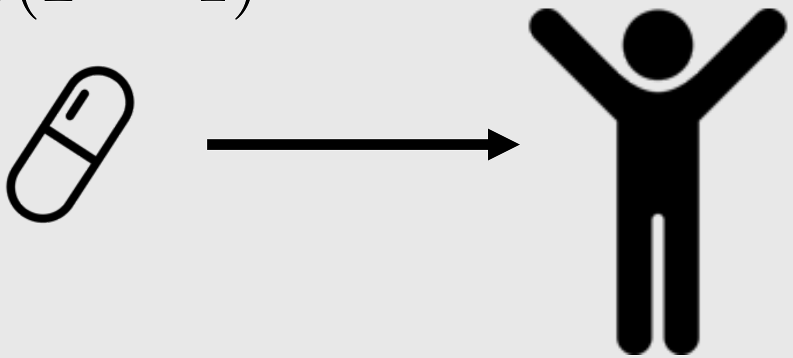

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Counterfactual

$\text{do}(T = 0)$

$Y_i(0) = 0$

Causal effect

$$Y_i(1) - Y_i(0) = 1$$

Average treatment effect (ATE)

Individual treatment effect (ITE): $Y_i(1) - Y_i(0)$

T	: observed treatment
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i	: used in subscript to denote a specific unit/individual
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Average treatment effect (ATE)

Individual treatment effect (ITE): $Y_i(1) - Y_i(0)$

Average treatment effect (ATE):

$$\mathbb{E}[Y_i(1) - Y_i(0)] = \mathbb{E}[Y(1)] - \mathbb{E}[Y(0)]$$

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$$\mathbb{E}[Y_i(1) - Y_i(0)] = \mathbb{E}[Y(1)] - \mathbb{E}[Y(0)]$$
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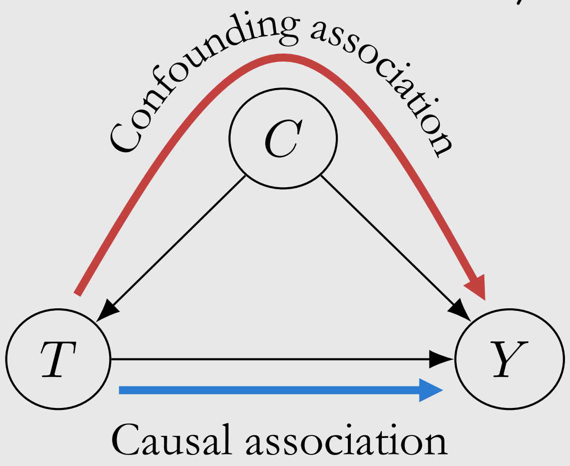

Recall: correlation does not imply causation

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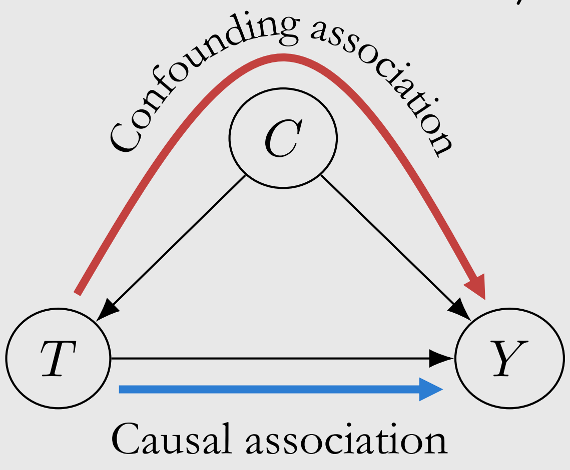

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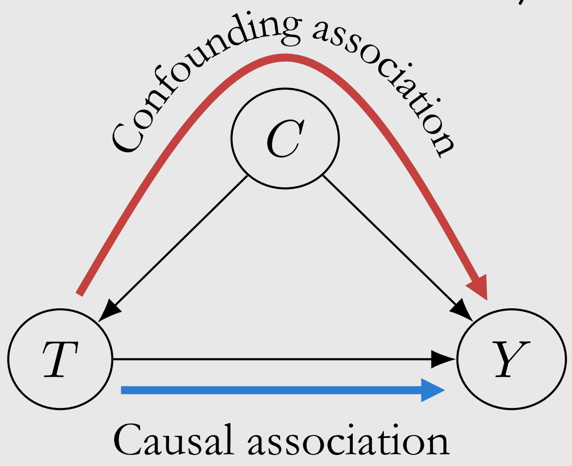
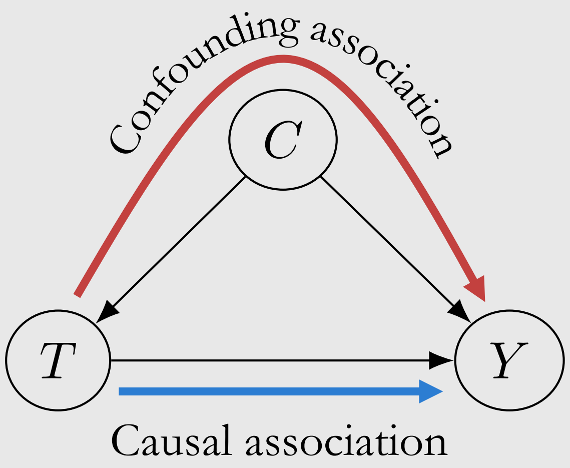


Recall: correlation does not imply causation

Randomized control trials (RCTs)

ATE when there is confounding:

$$\mathbb{E}[Y(1)] - \mathbb{E}[Y(0)] \neq \mathbb{E}[Y|T=1] - \mathbb{E}[Y|T=0]$$



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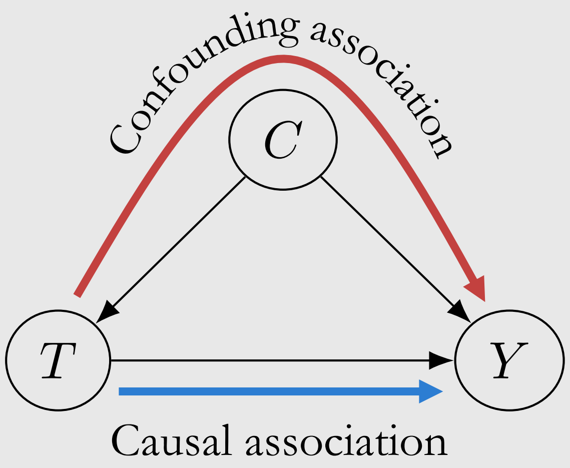

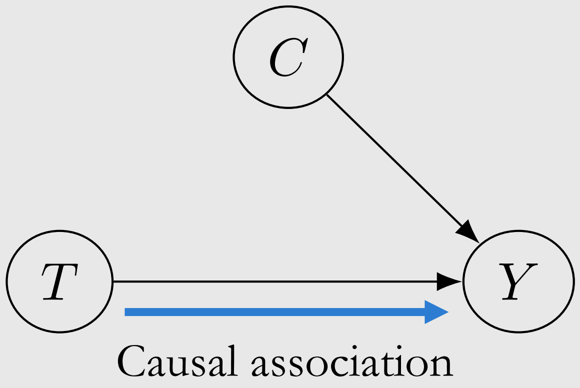

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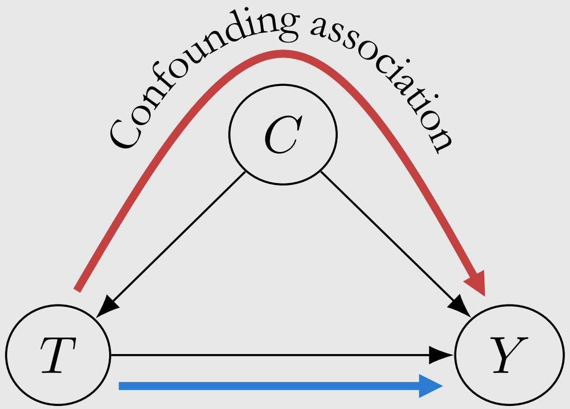

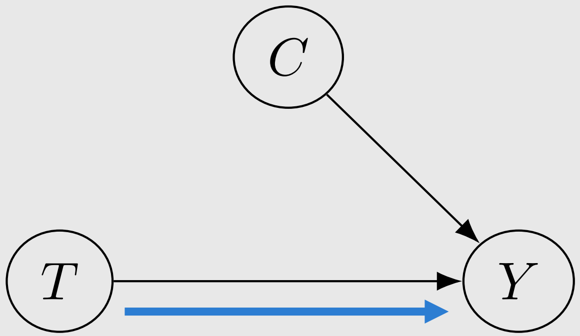

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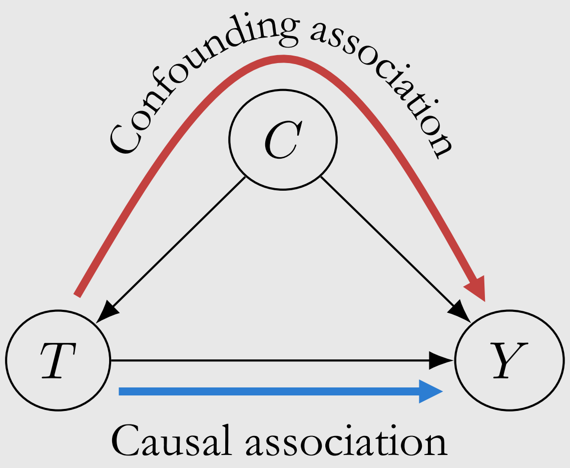
RCTs: experimenter randomizes subjects into treatment group or control group

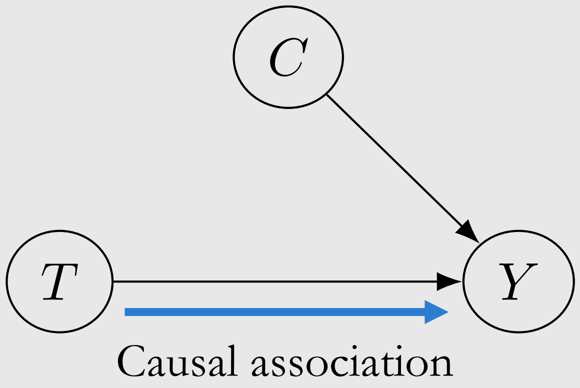
1. T cannot have any causal parents

Randomized control trials (RCTs)

ATE when there is confounding:

$$\mathbb{E}[Y(1)] - \mathbb{E}[Y(0)] \neq \mathbb{E}[Y|T=1] - \mathbb{E}[Y|T=0]$$





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RCTs: experimenter randomizes subjects into treatment group or control group

1. T cannot have any causal parents
2. Groups are comparable

Randomized control trials (RCTs)

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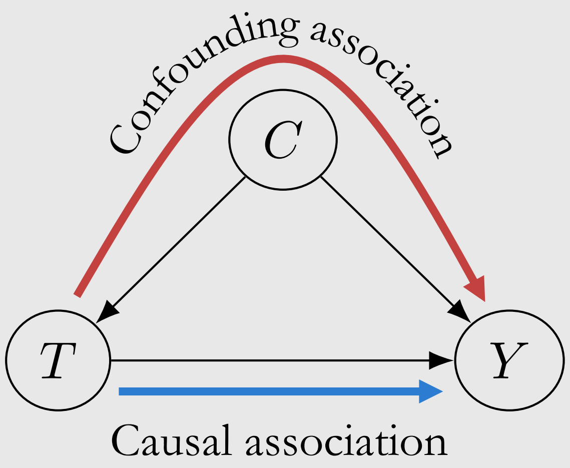
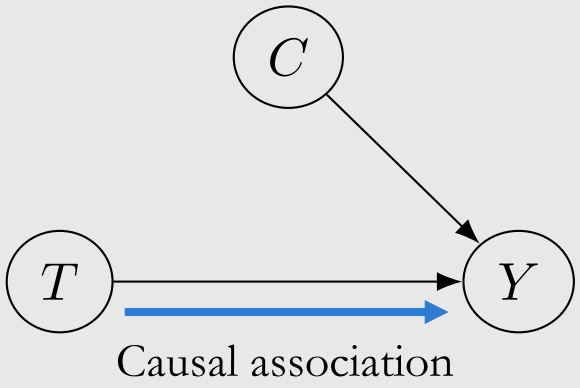
$$\mathbb{E}[Y(1)] - \mathbb{E}[Y(0)] \neq \mathbb{E}[Y|T=1] - \mathbb{E}[Y|T=0]$$





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RCTs: experimenter randomizes subjects into treatment group or control group

1. T cannot have any causal parents
2. Groups are comparable

ATE when there is **no** confounding (e.g. RCTs):

$$\mathbb{E}[Y(1)] - \mathbb{E}[Y(0)] = \mathbb{E}[Y|T=1] - \mathbb{E}[Y|T=0]$$

Motivating example: Simpson's paradox

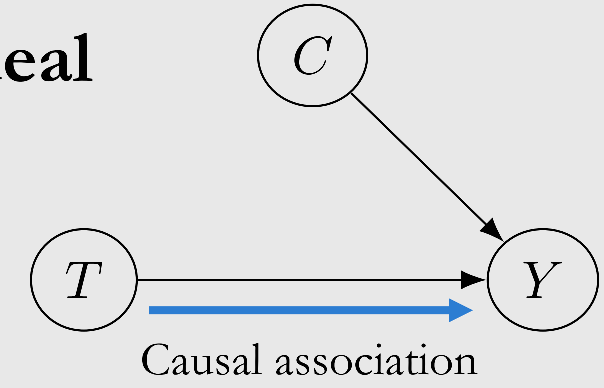
Correlation does not imply causation

Then, what does imply causation?

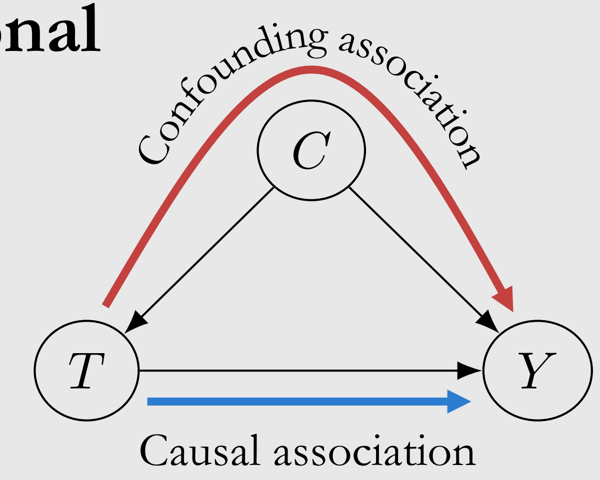
Causation in observational studies

Observational studies

Ideal

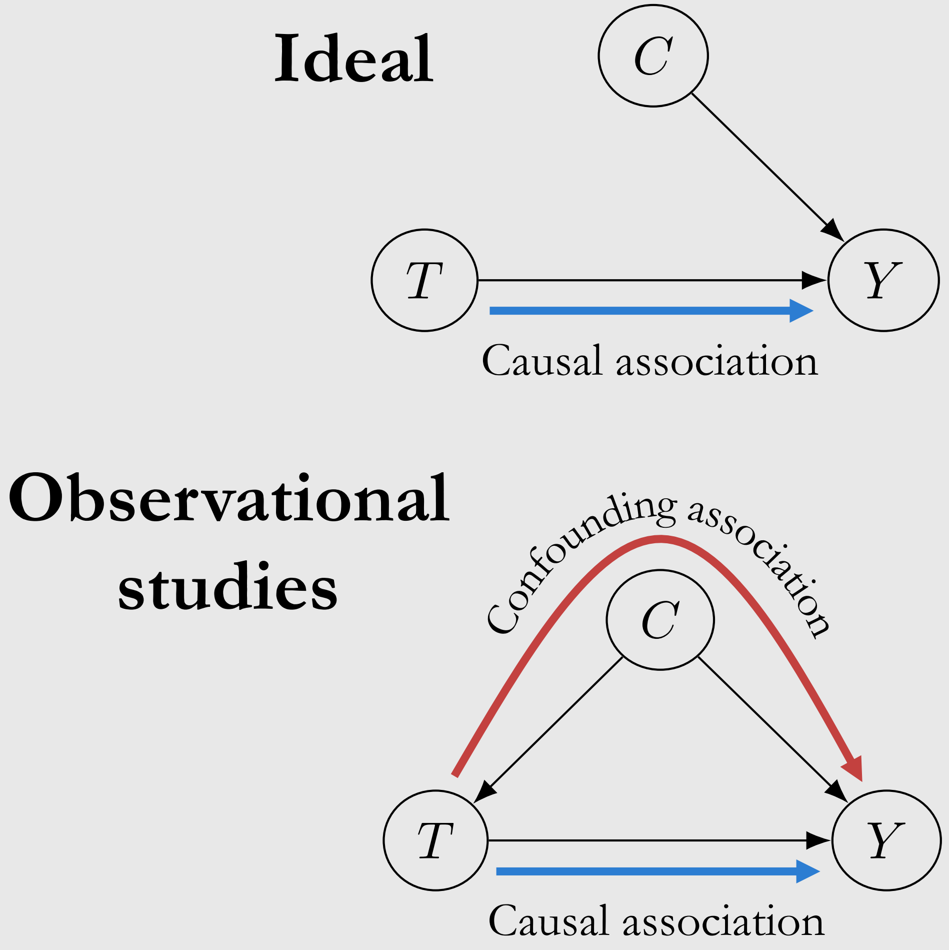


Observational studies



Observational studies

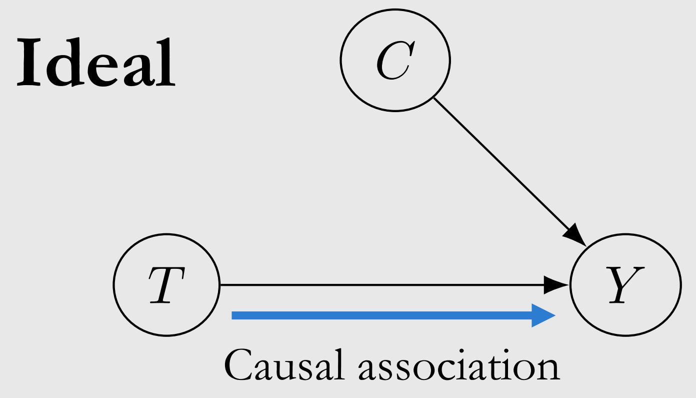
Can't always randomize treatment

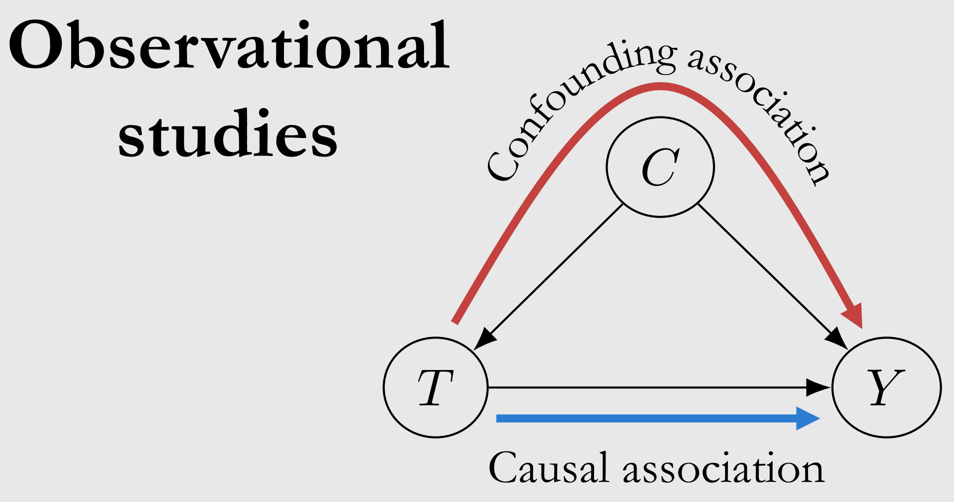


Observational studies

Can't always randomize treatment

- **Ethical reasons** (e.g. unethical to randomize people to smoke for measuring effect on lung cancer)



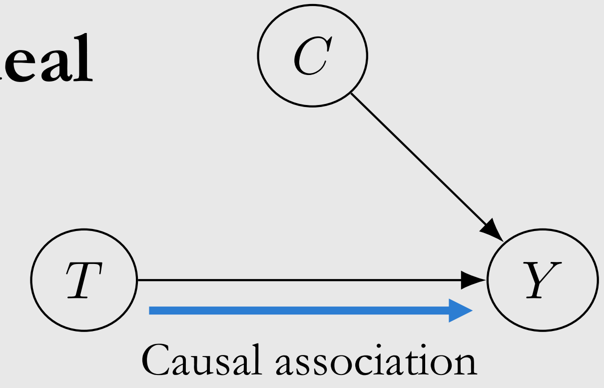


Observational studies

Can't always randomize treatment

- **Ethical reasons** (e.g. unethical to randomize people to smoke for measuring effect on lung cancer)
- **Infeasibility** (e.g. can't randomize countries into communist/capitalist systems to measure effect on GDP)

Ideal



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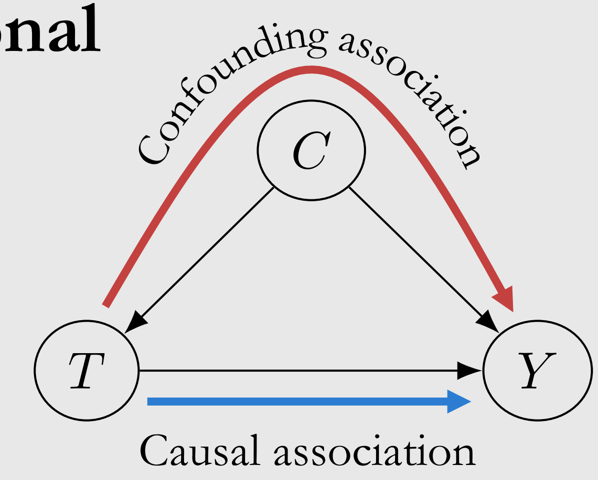
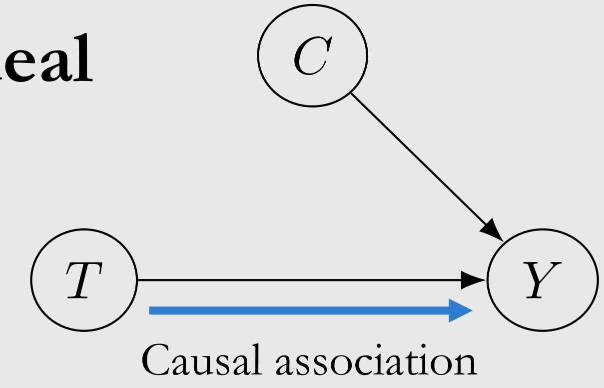


Observational studies

Can't always randomize treatment

- **Ethical reasons** (e.g. unethical to randomize people to smoke for measuring effect on lung cancer)
- **Infeasibility** (e.g. can't randomize countries into communist/capitalist systems to measure effect on GDP)
- **Impossibility** (e.g. can't change a living person's DNA at birth for measuring effect on breast cancer)

Ideal



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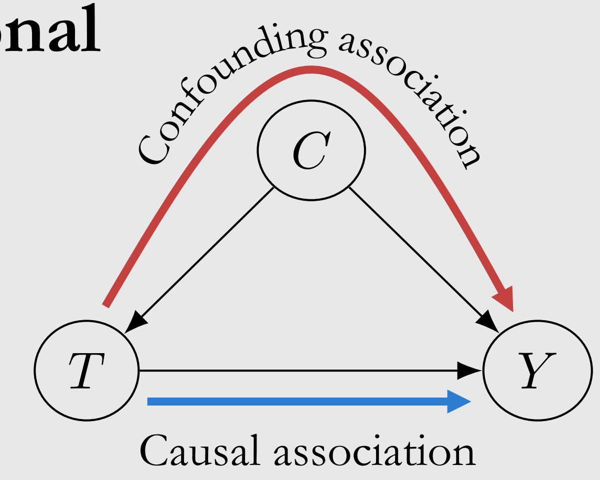
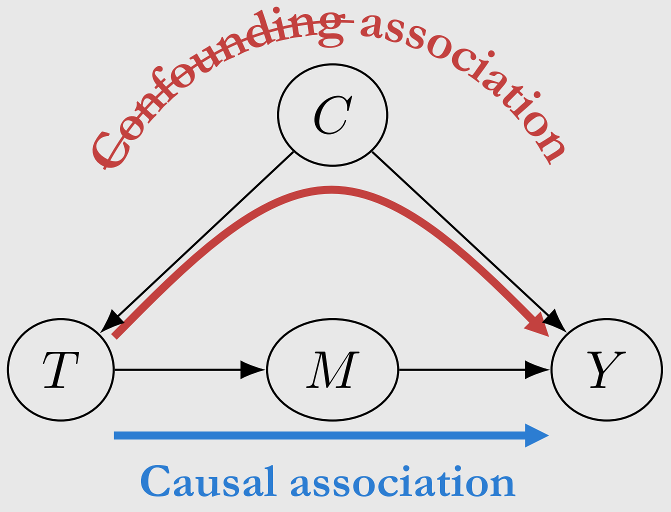


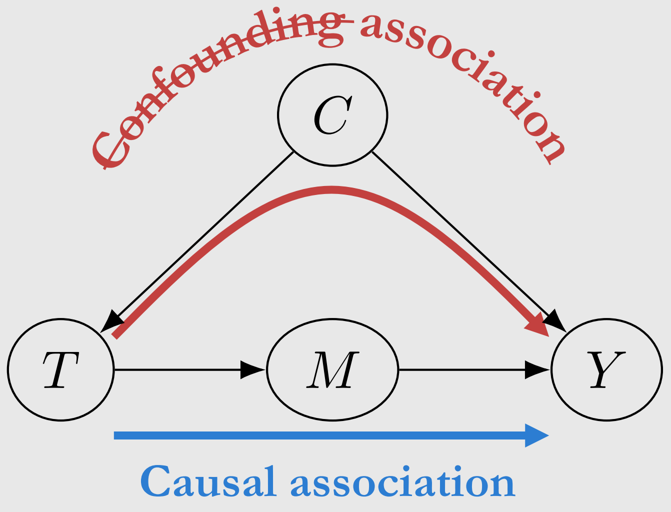
How do we measure causal effects in observational studies?

Solution: adjust/control for confounders



Solution: adjust/control for confounders

Adjust/control for the right variables W.

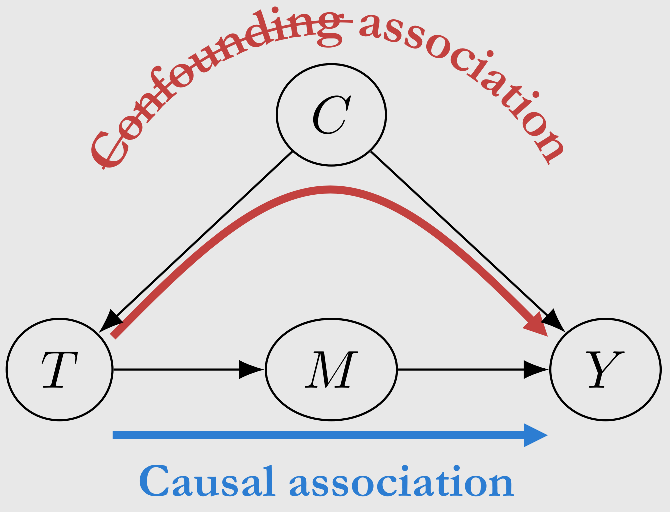


Solution: adjust/control for confounders

Adjust/control for the right variables W.

If W is a sufficient adjustment set, we have

$$\mathbb{E}[Y(t)|W = w] \triangleq \mathbb{E}[Y|\mathrm{do}(T = t), W = w] = \mathbb{E}[Y|t, w]$$



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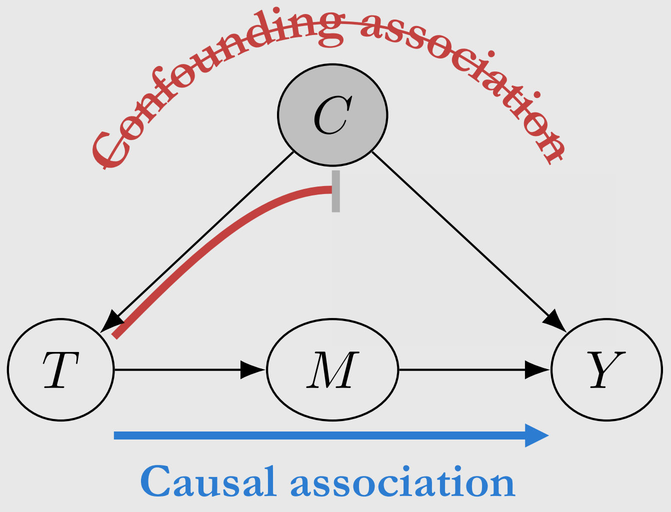

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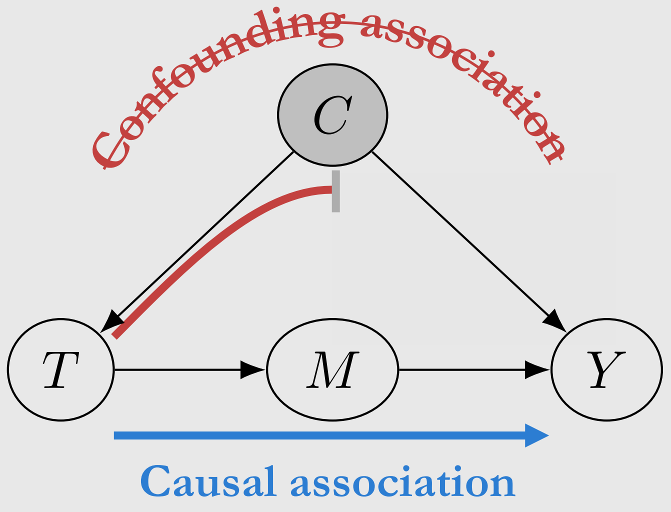
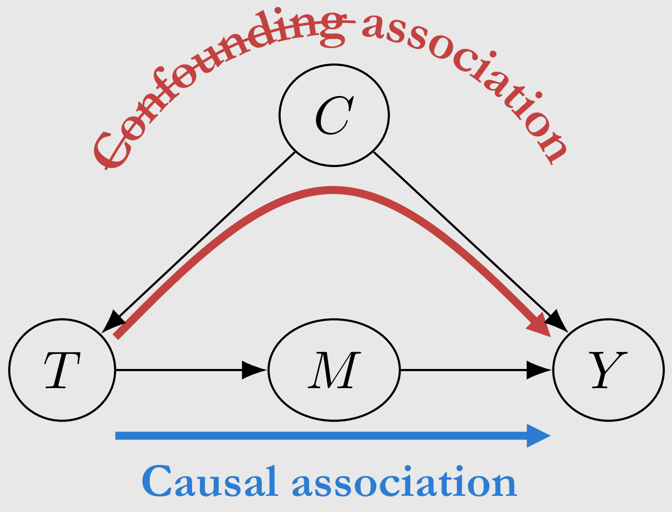
$$\mathbb{E}[Y(t)] \triangleq \mathbb{E}[Y|\text{do}(T = t)] = \mathbb{E}_W \mathbb{E}[Y|t, W]$$



Solution: backdoor adjustment

$$\mathbb{E}[Y|\text{do}(T=t)] = \mathbb{E}_W \mathbb{E}[Y|t, W]$$



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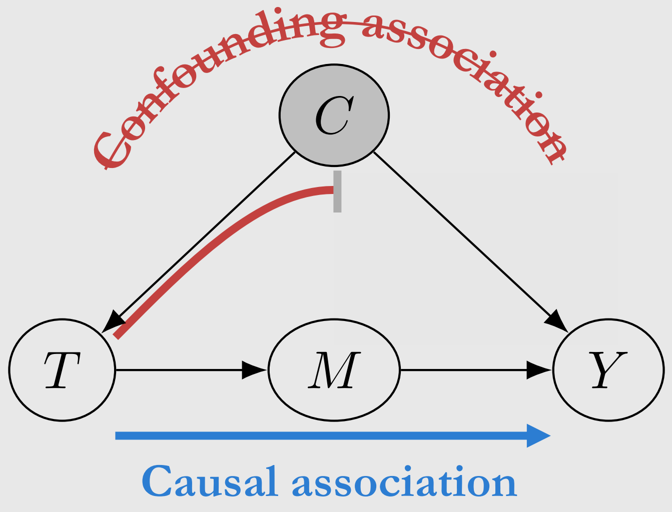

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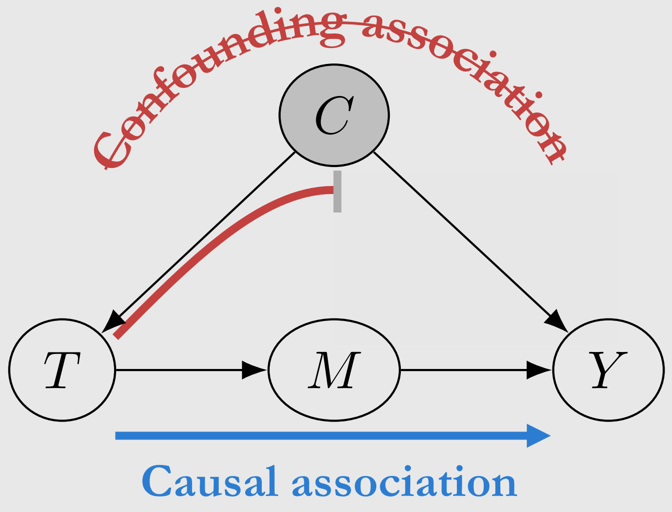
Shaded nodes are examples of sufficient adjustment sets W



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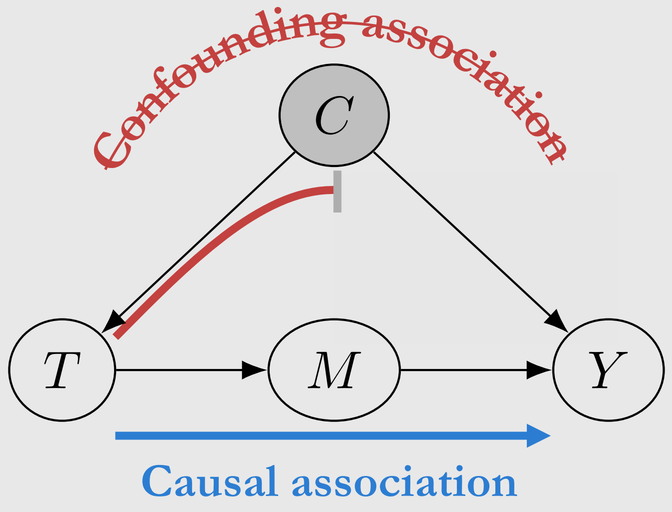

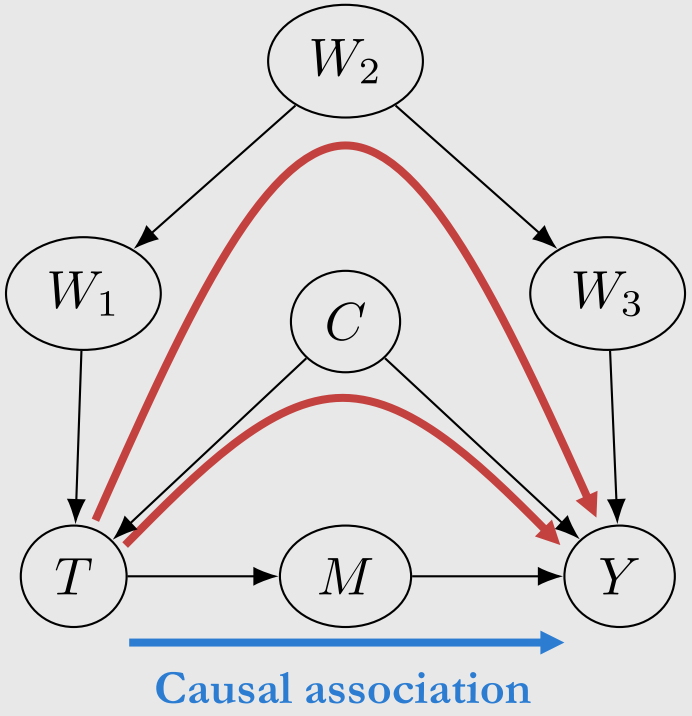

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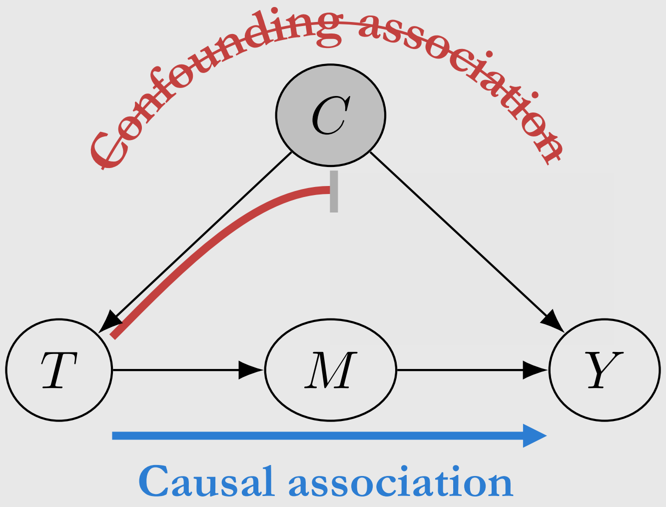

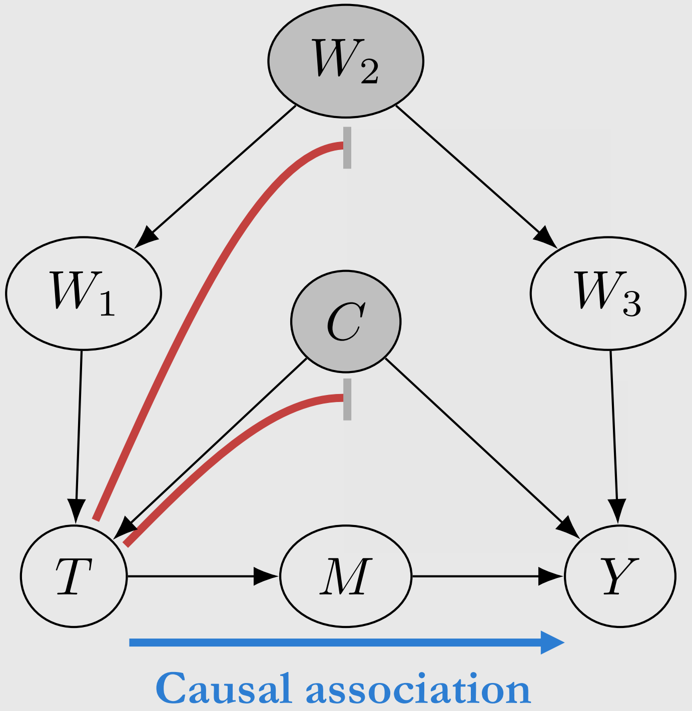

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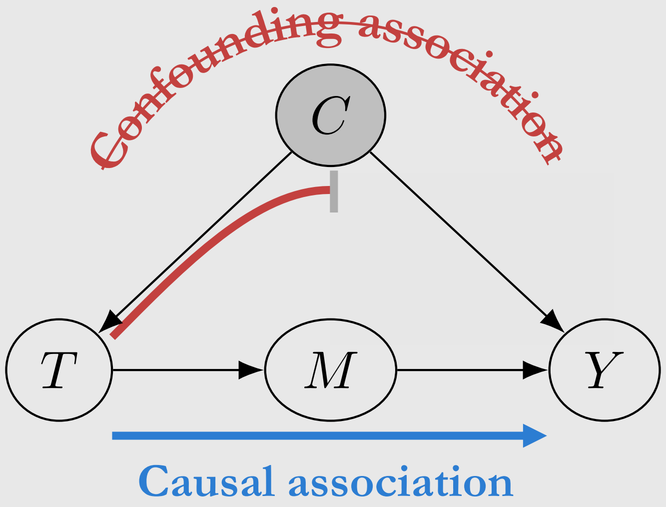

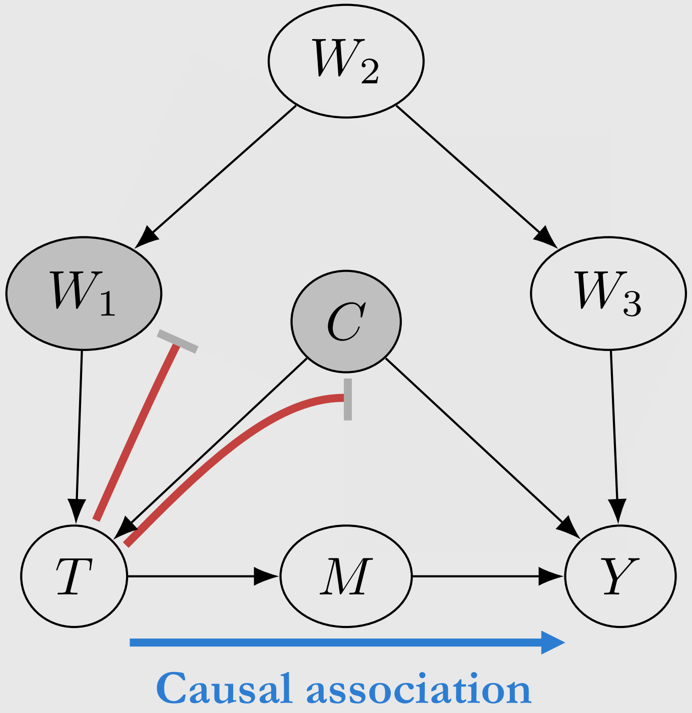

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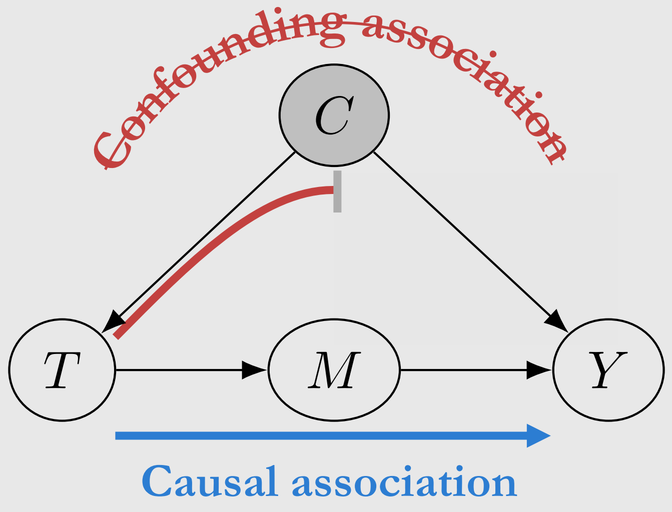

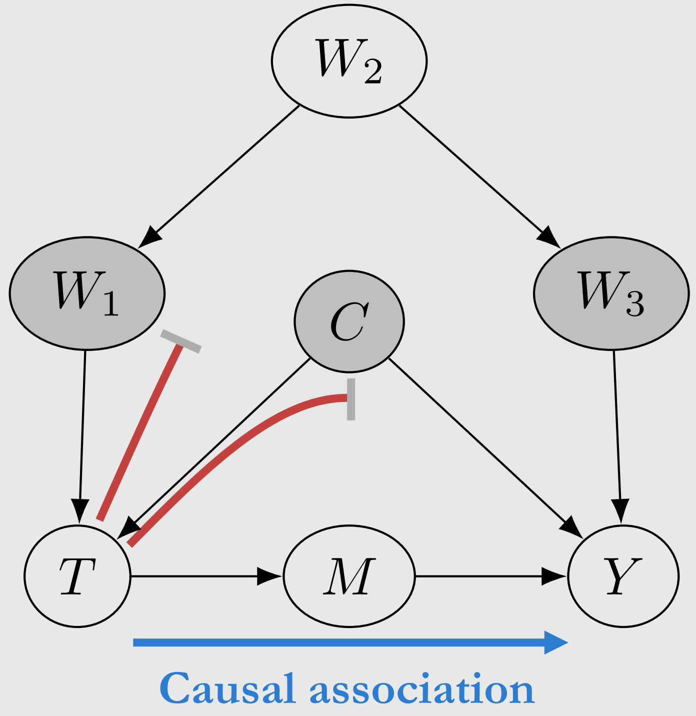

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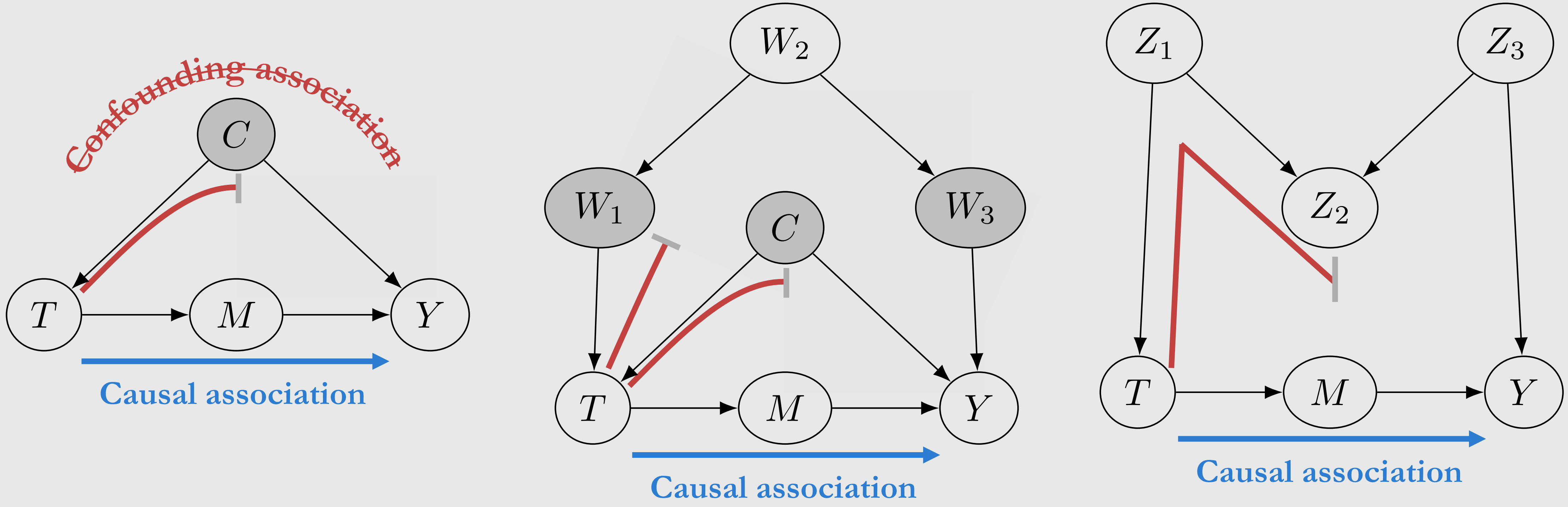
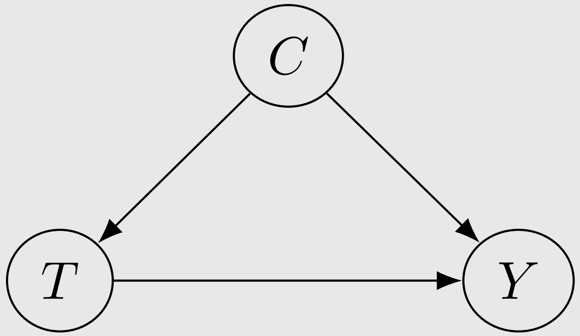


Application to the COVID-27 example

$$\mathbb{E}[Y|\text{do}(T=t)] = \mathbb{E}_C \mathbb{E}[Y|t, C]$$

Causal Graph



Condition

Treatment	Mild	Severe	Total
A	15% (210/1400)	30% (30/100)	**16%** (240/1500)
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	$\mathbb{E}[Y|t, C=0]$	$\mathbb{E}[Y|t, C=1]$	$\mathbb{E}[Y|t]$

Application to the COVID-27 example

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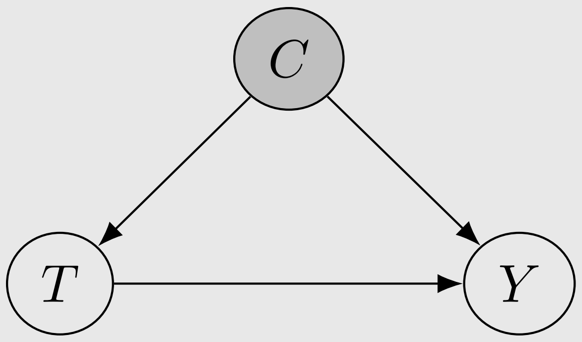

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Application to the COVID-27 example

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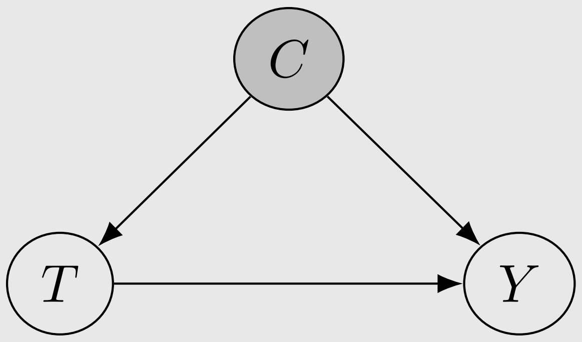

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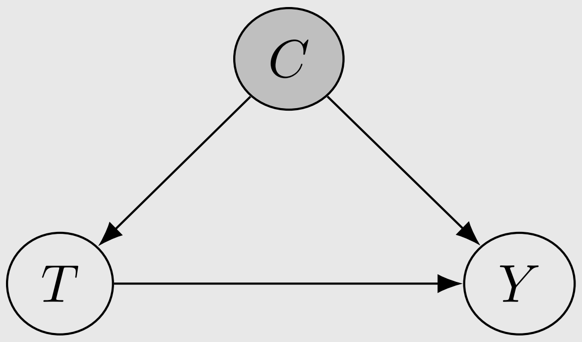

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Application to the COVID-27 example

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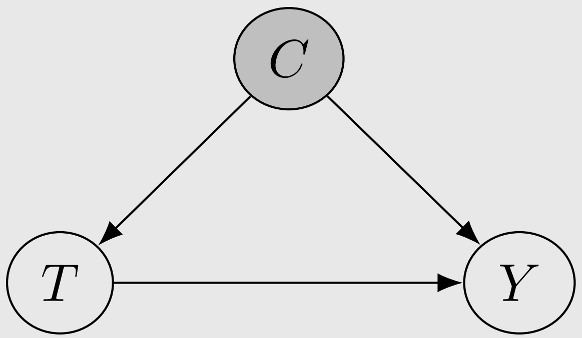

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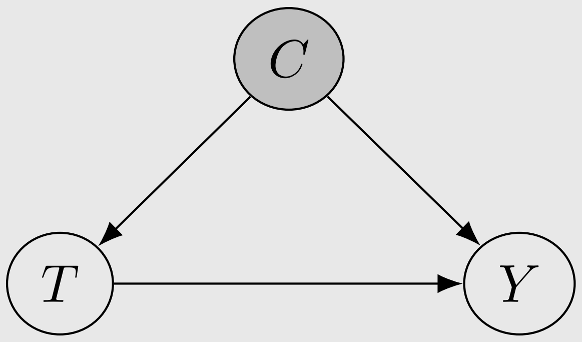

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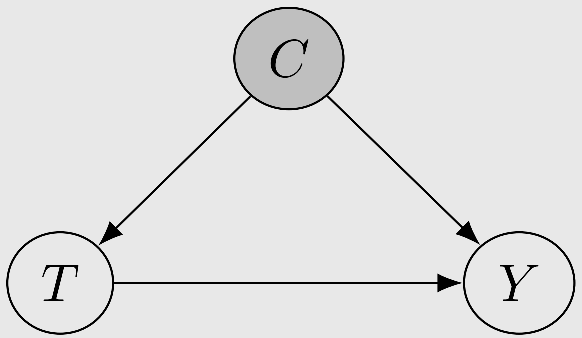

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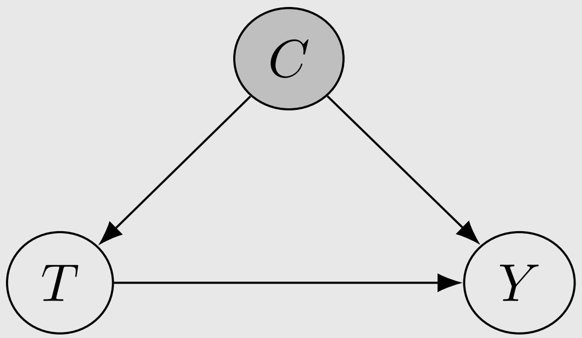

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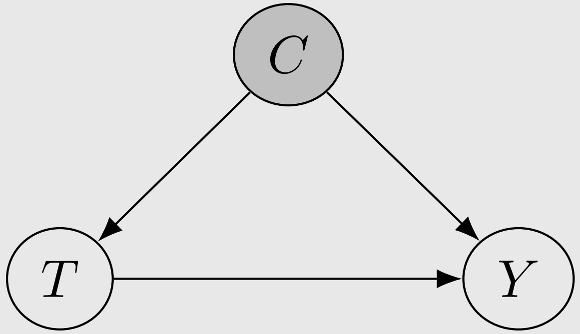

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Application to the COVID-27 example

Naive:

$$\frac{1400}{1500}(0.15) + \frac{100}{1500}(0.30) = 0.16$$

$$\frac{50}{550}(0.10) + \frac{500}{550}(0.20) = 0.19$$

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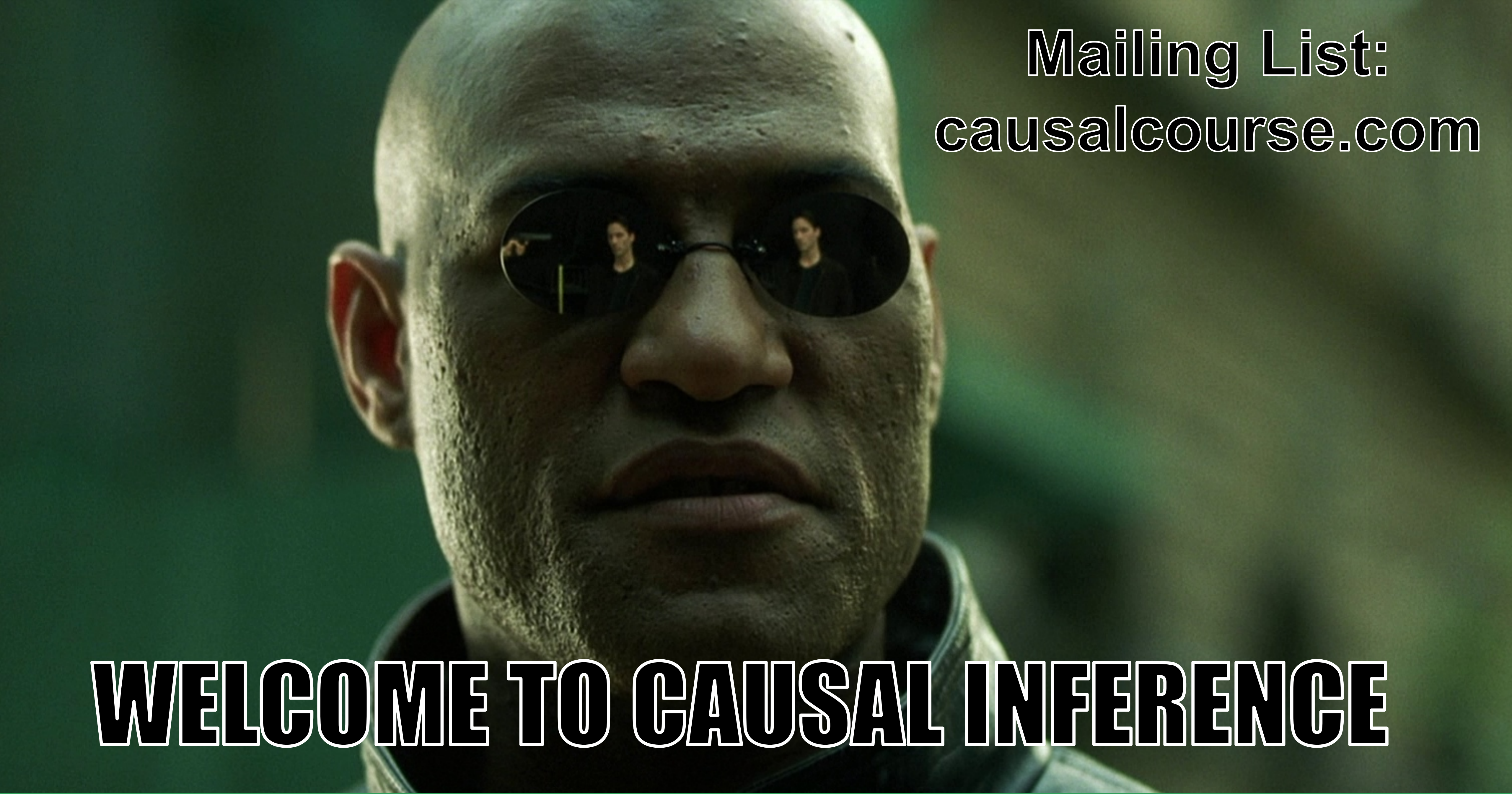
Mailing List:
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