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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- 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

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Simpson's paradox: COVID-27

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

Condition C: mild (0) or severe (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)

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

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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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Simpson's paradox: scenario 1 (treatment B)

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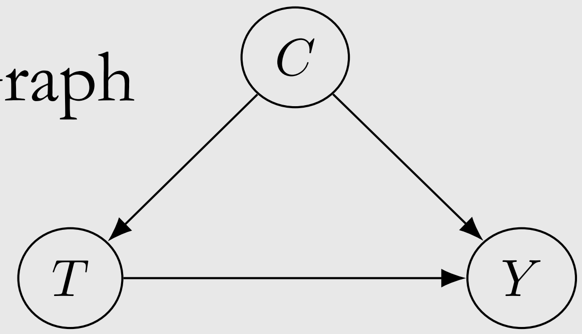
Causal Graph



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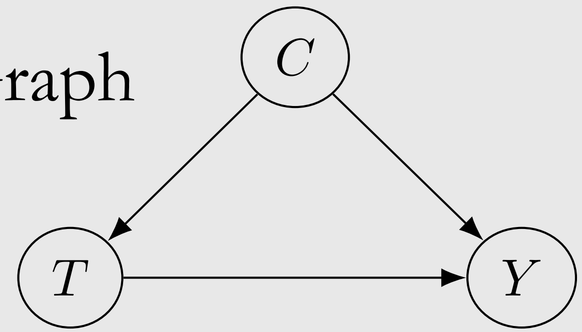

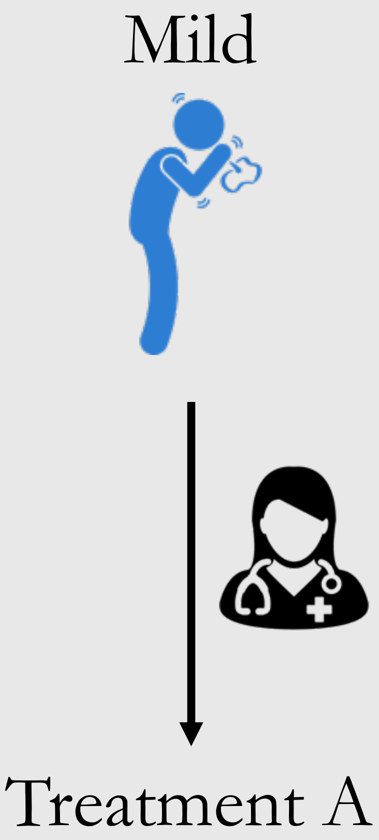

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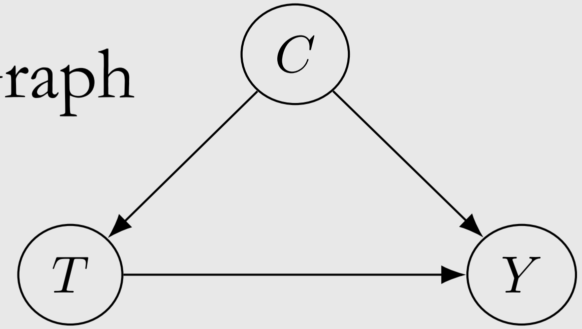

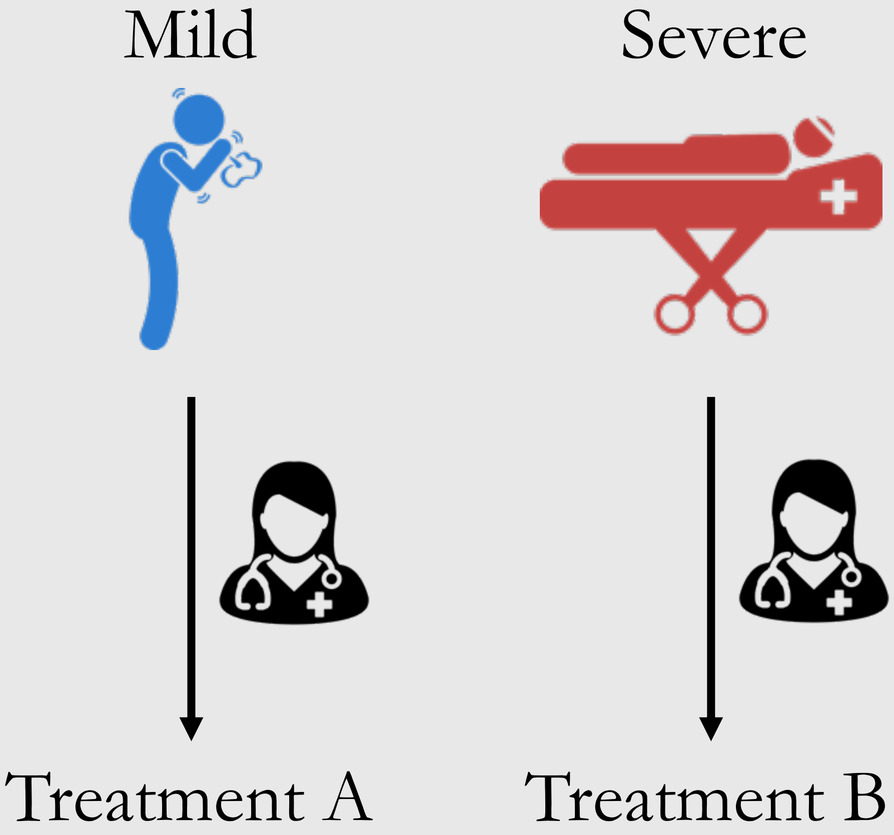

Simpson's paradox: scenario 2 (treatment A)

Condition

Treatment	Mild	Severe	Total
A	15% (210/1400)	30% (30/100)	**16%** (240/1500)
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Simpson's paradox: scenario 2 (treatment A)

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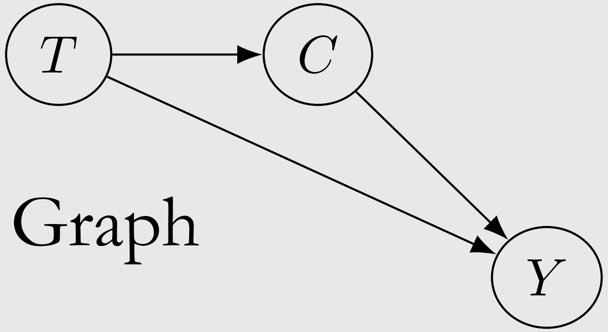

Causal Graph

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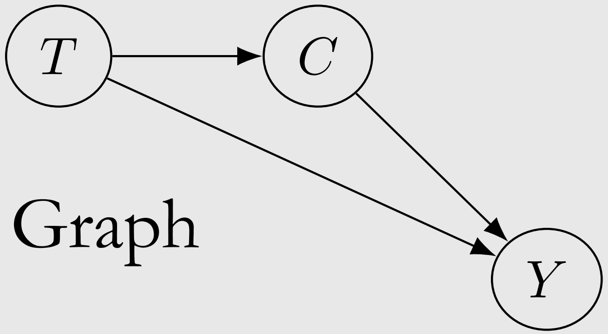

Causal Graph

Treatment B

$\downarrow$

Severe

Simpson's paradox: scenario 2 (treatment A)

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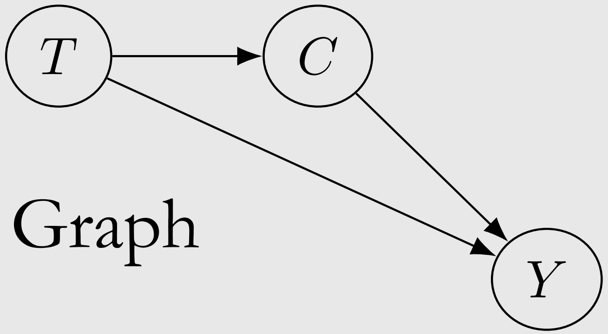
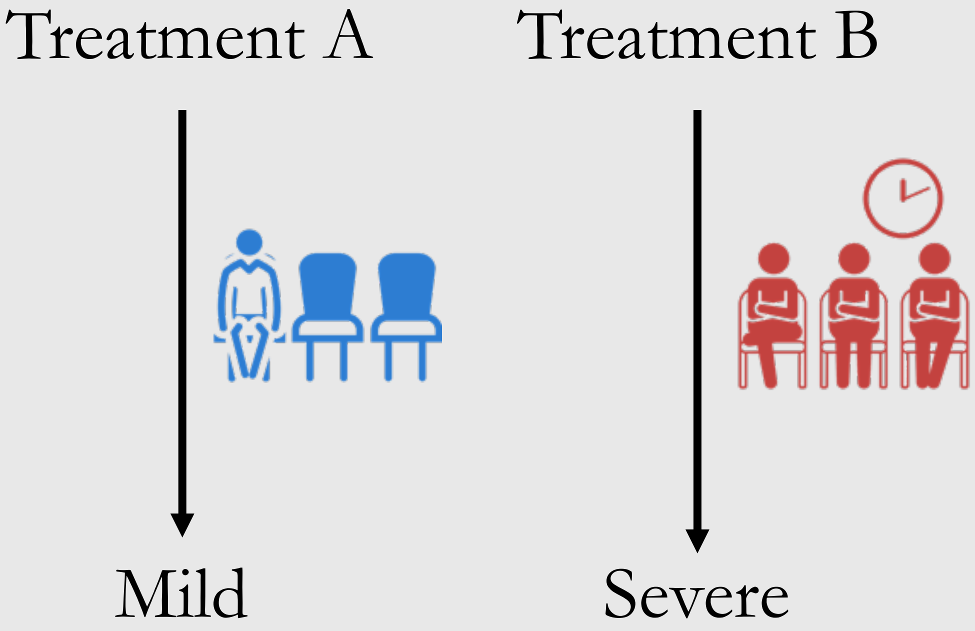


Causal Graph

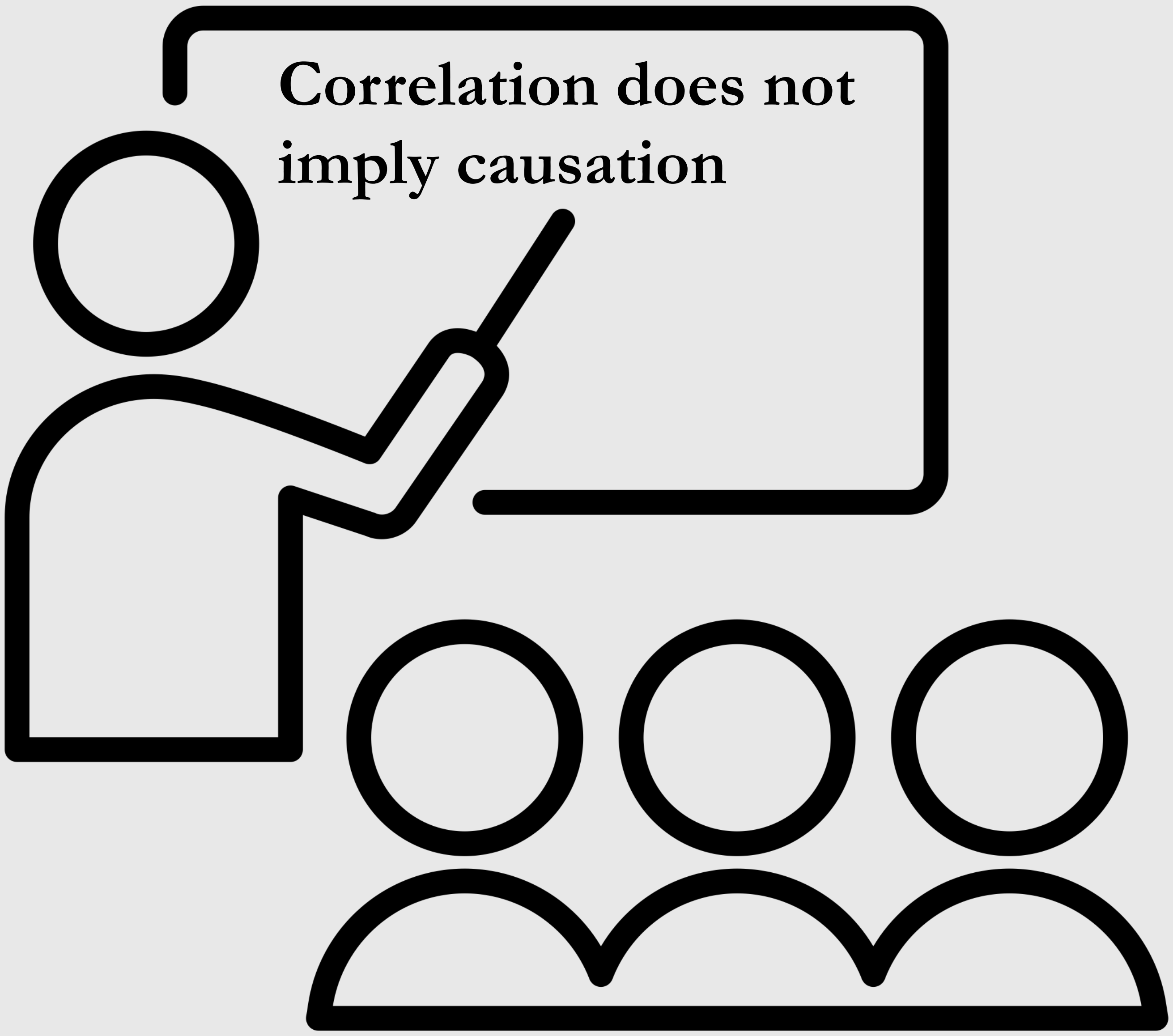


Motivating example: Simpson's paradox

Correlation does not imply causation

Then, what does imply causation?

Causation in observational studies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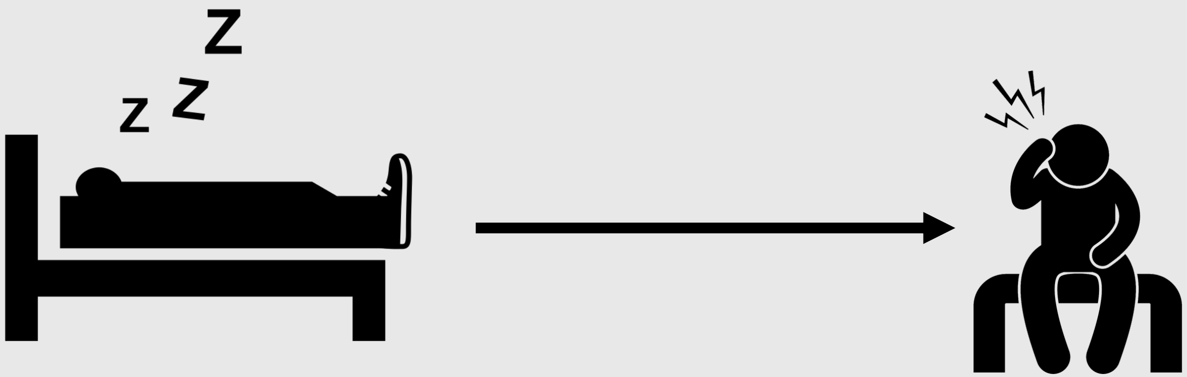
Sleeping with shoes on is strongly correlated with waking up with a headache



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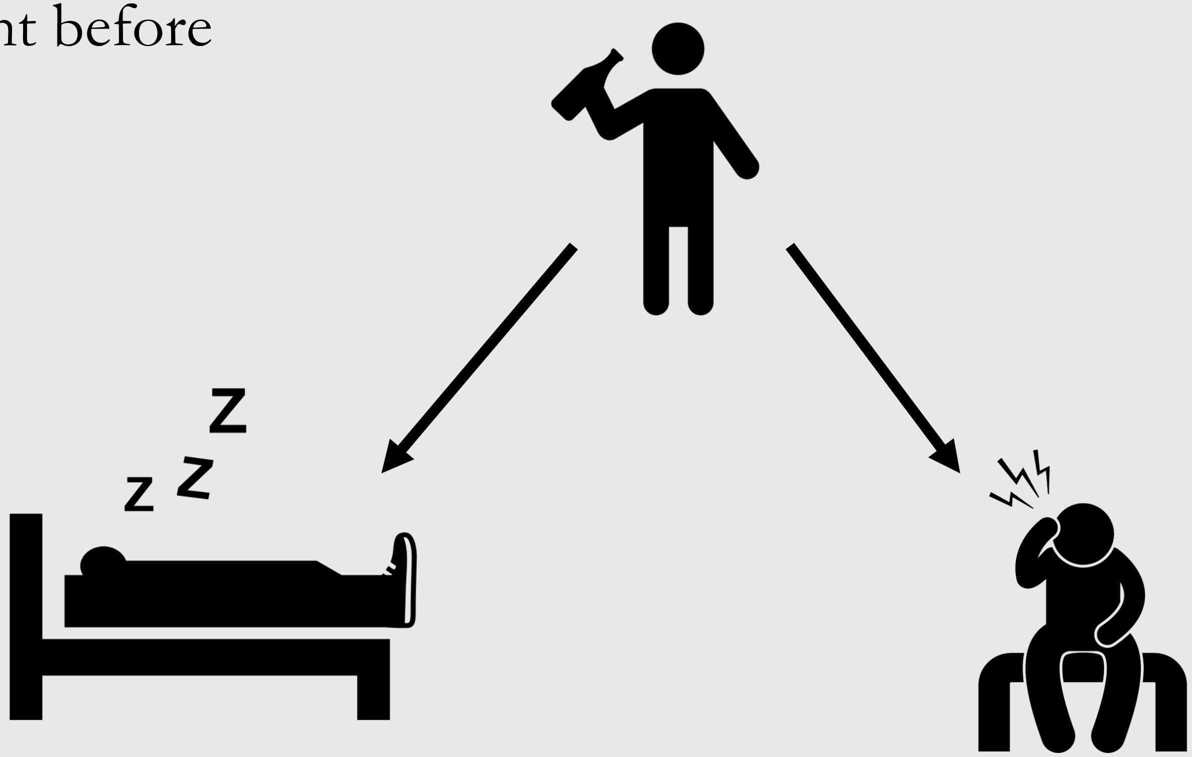
Common cause: drinking the night before



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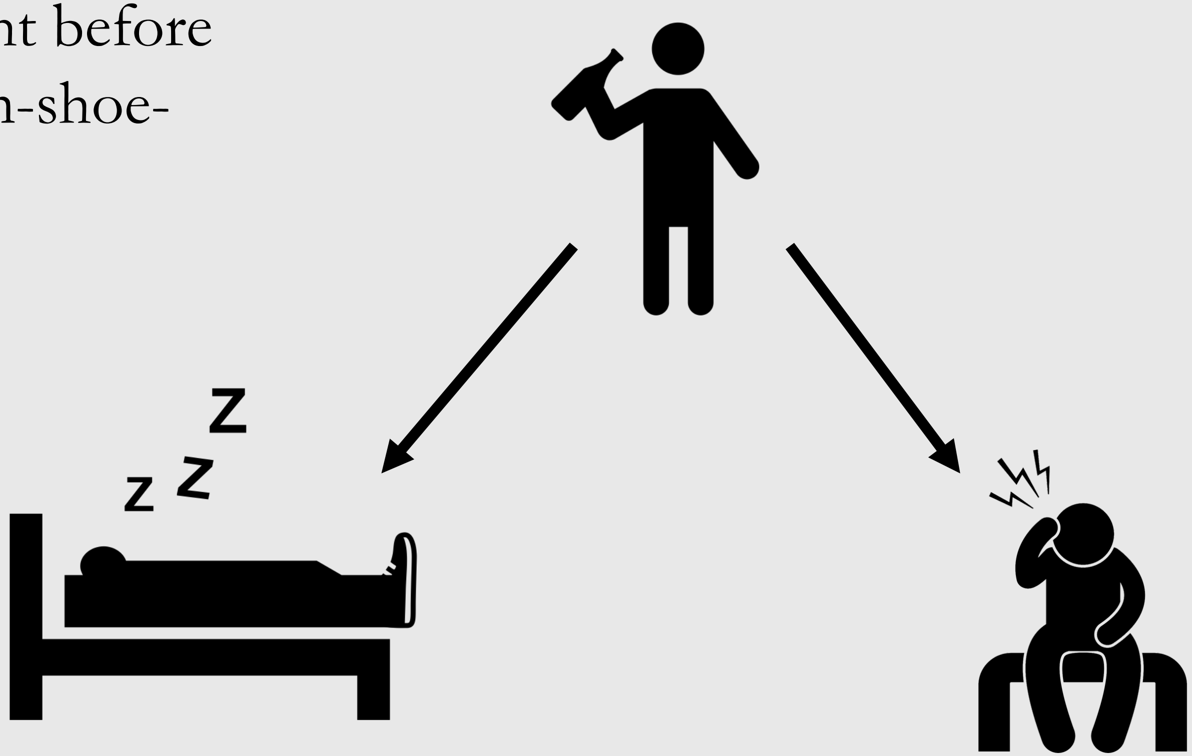
Common cause: drinking the night before

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



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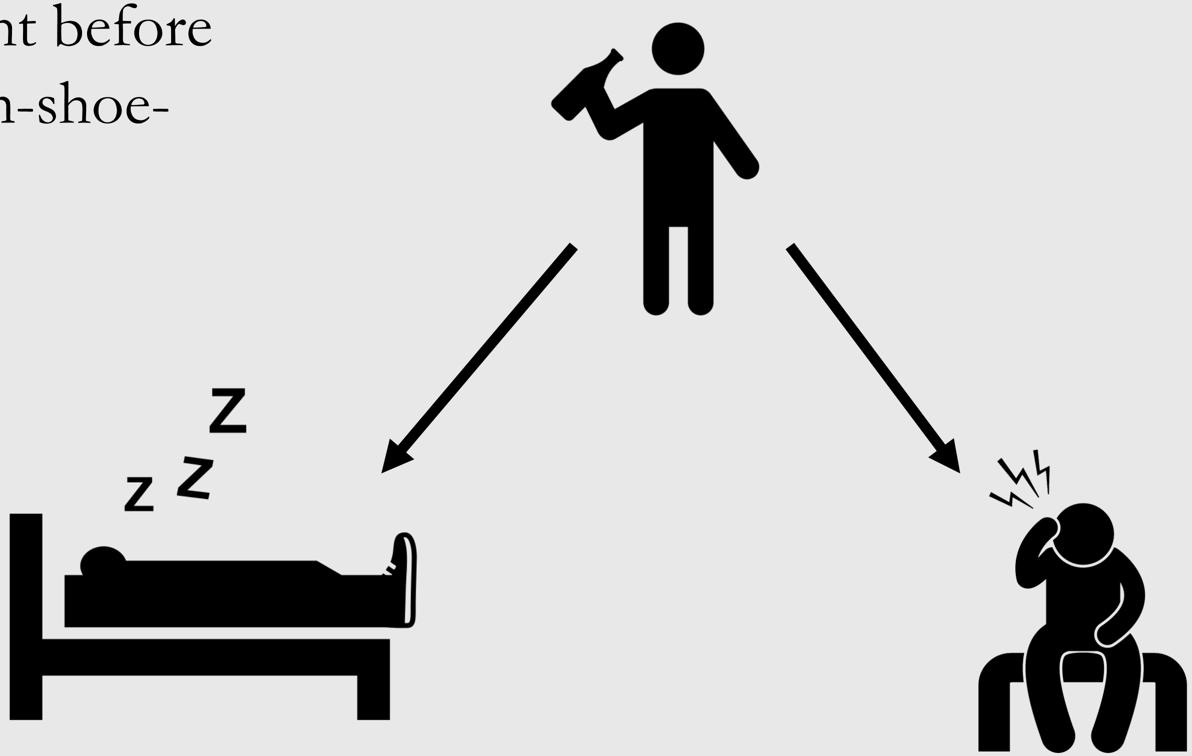

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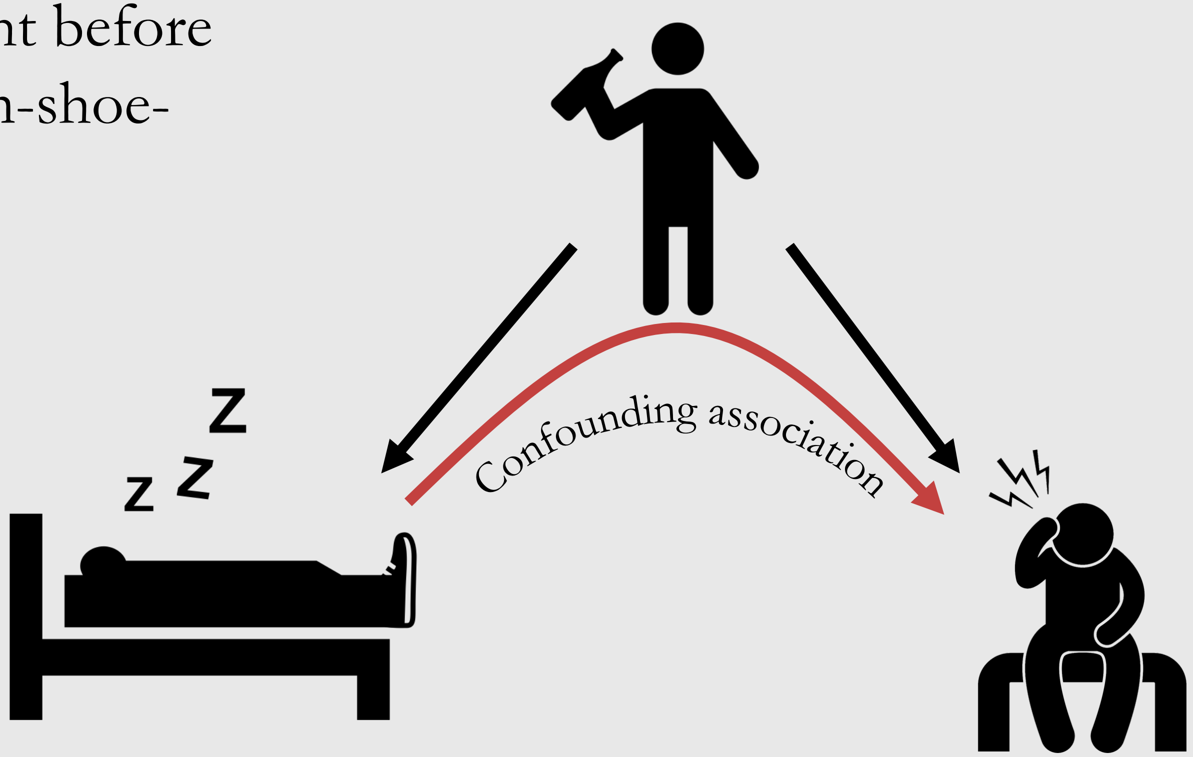

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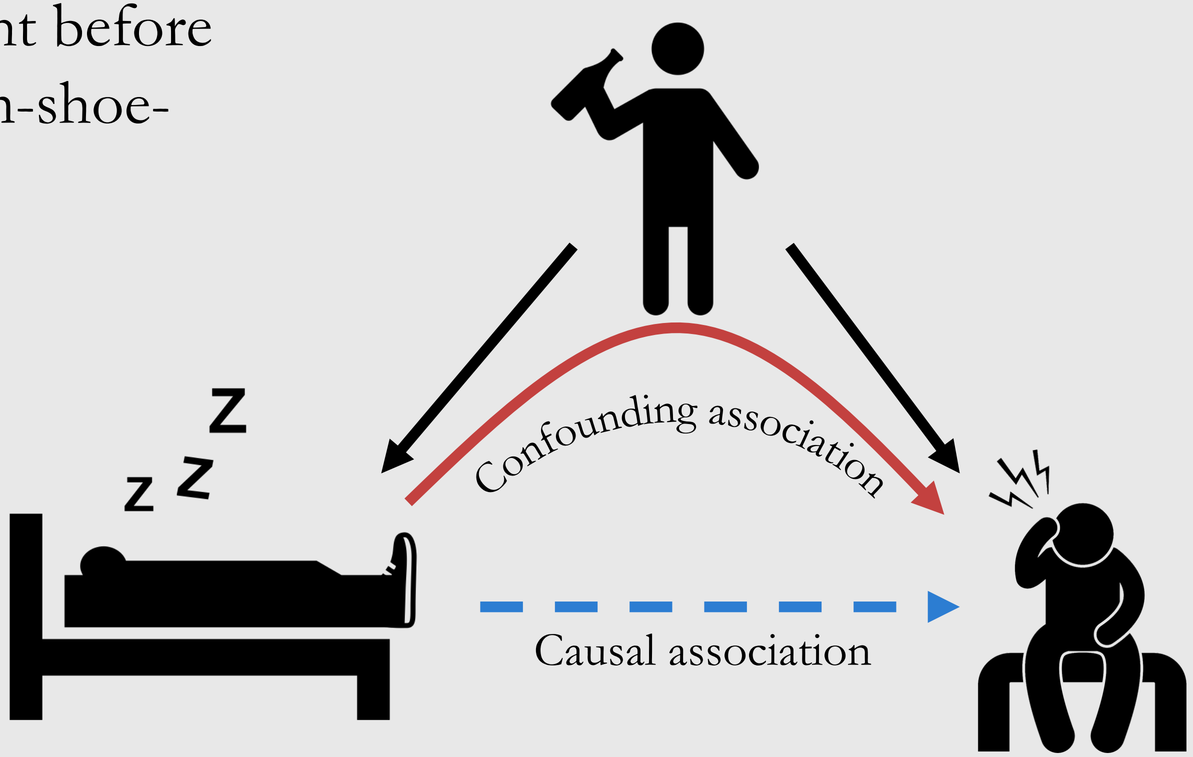

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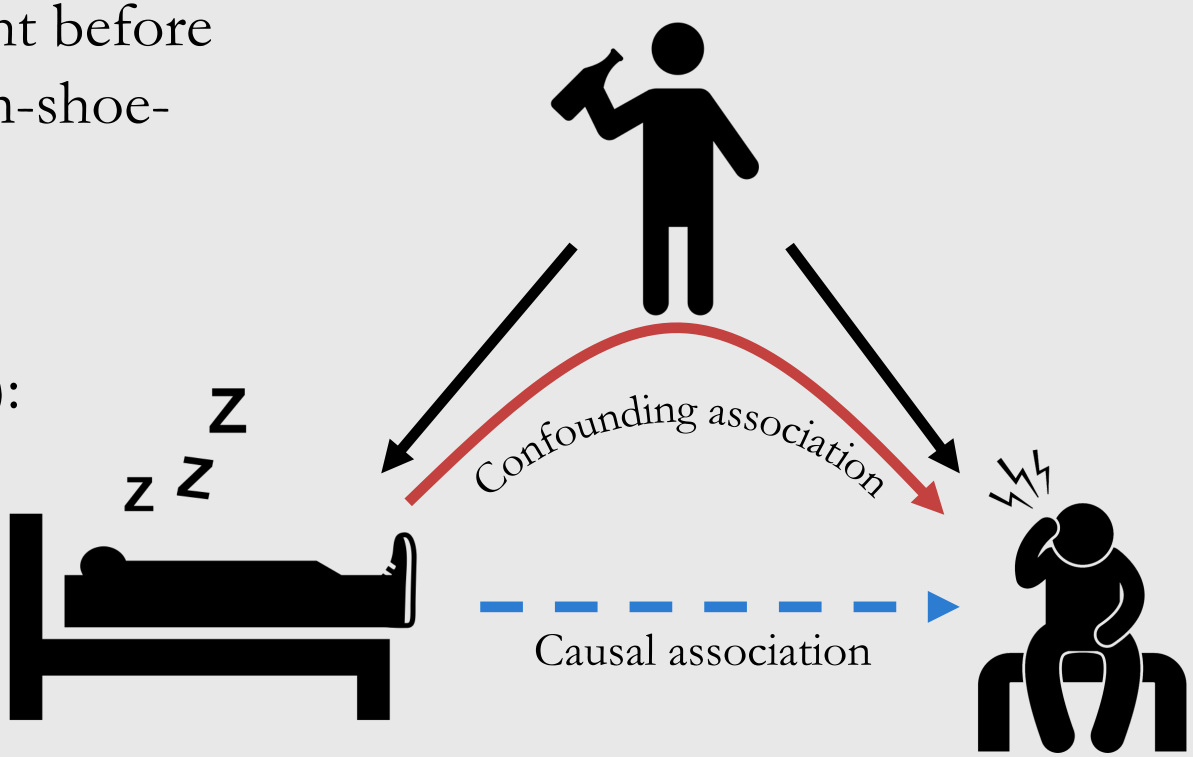
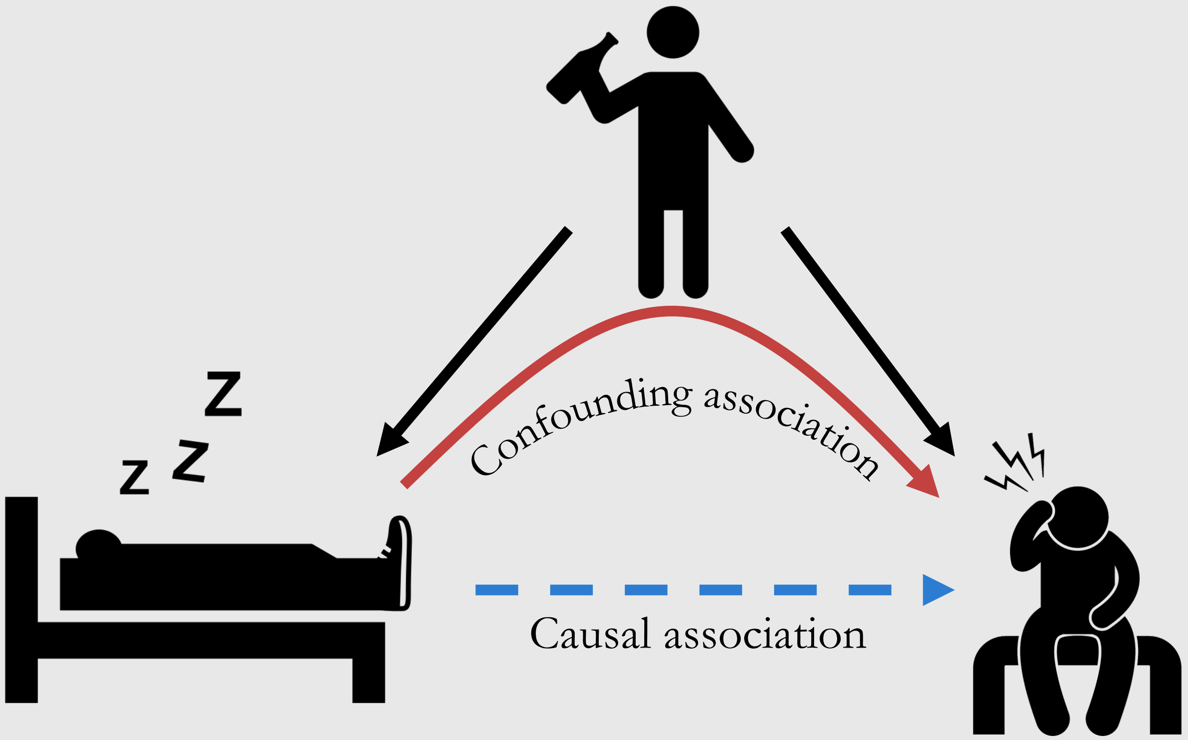
Total association (e.g. correlation): mixture of causal and confounding association



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



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

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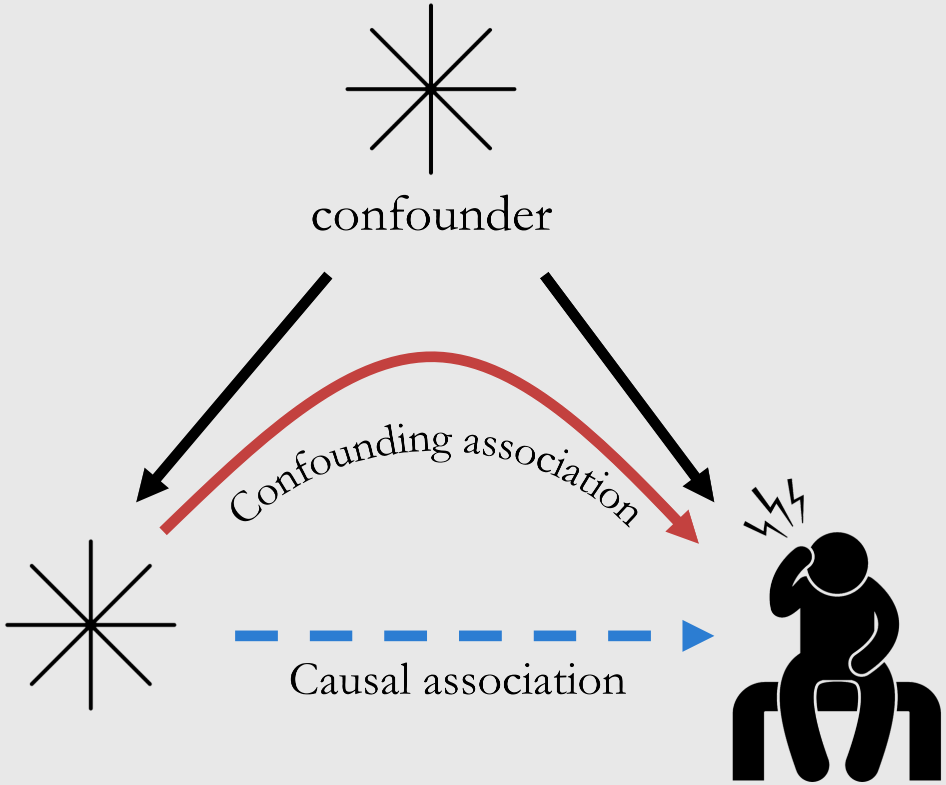

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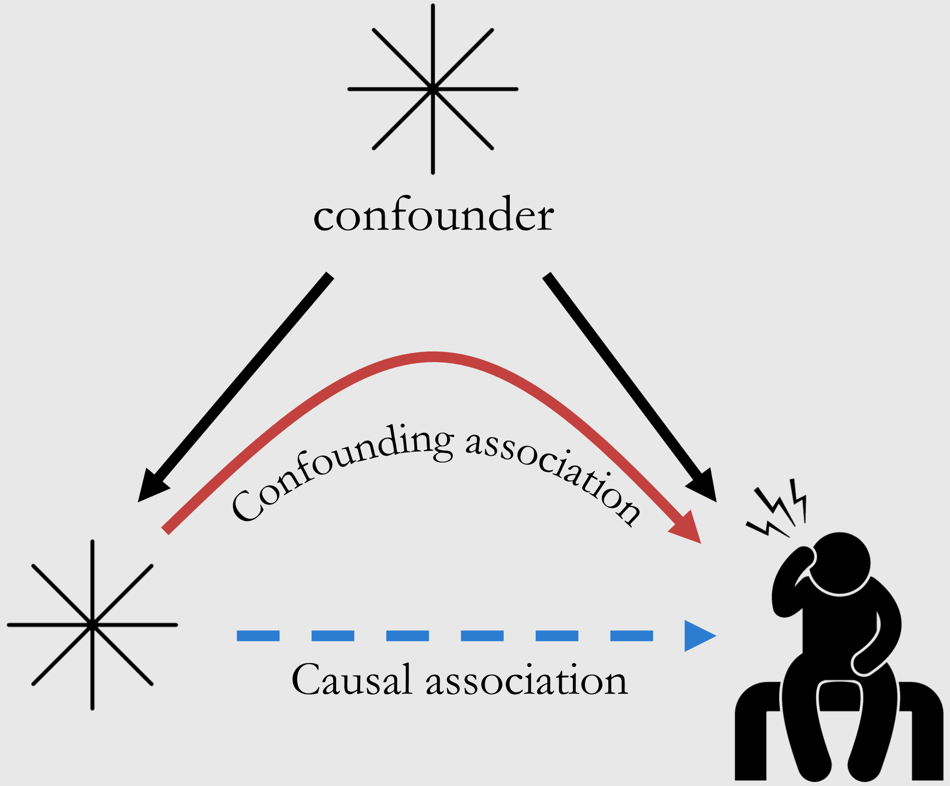

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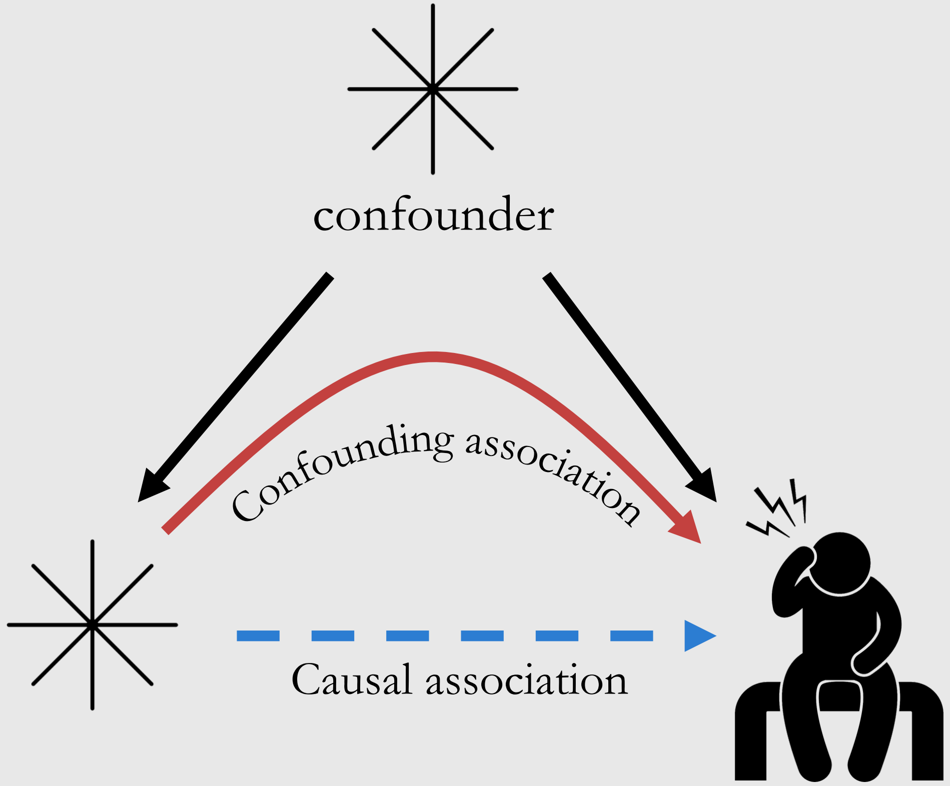

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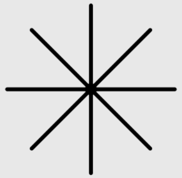
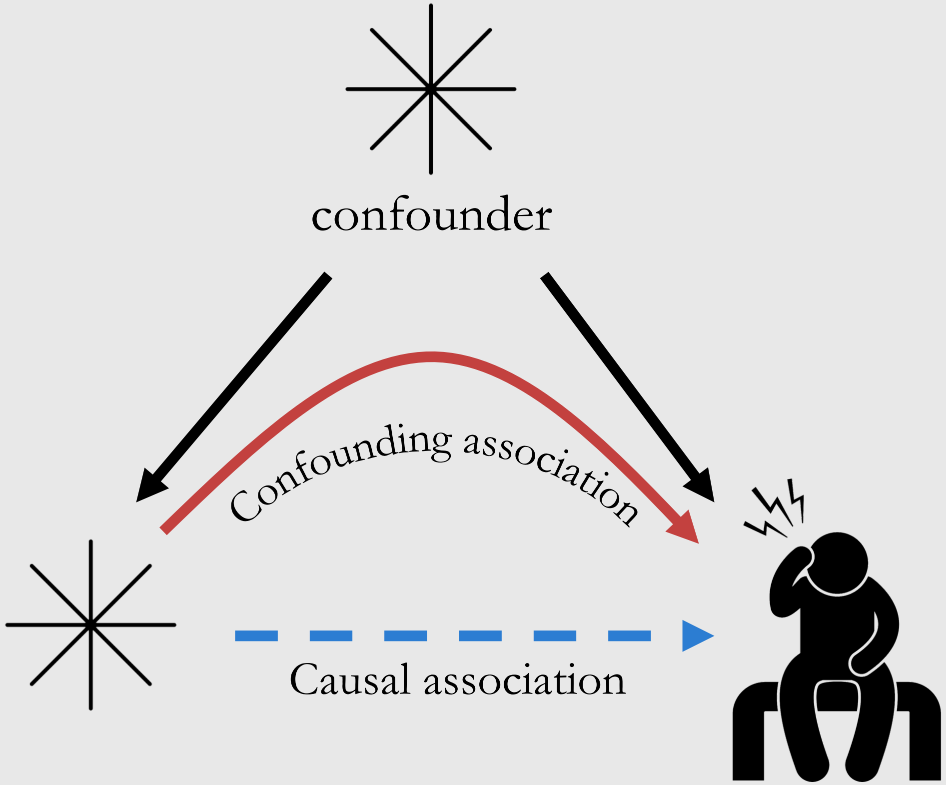


Why?



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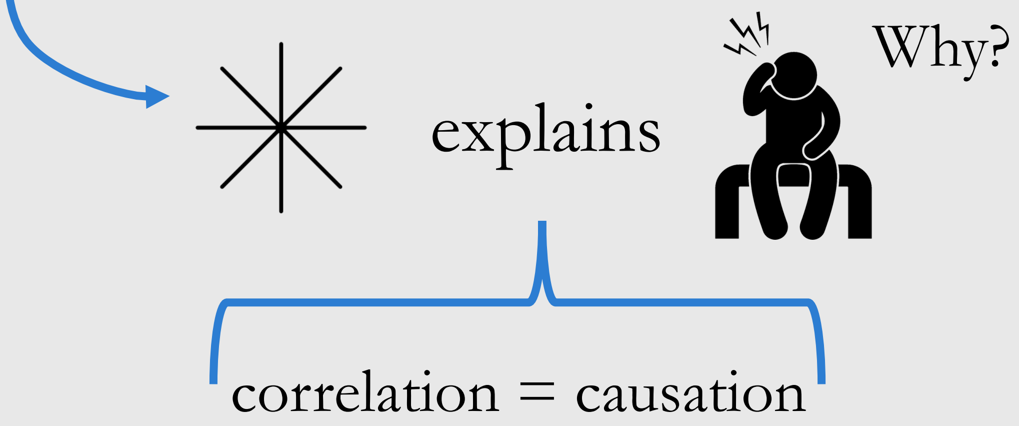

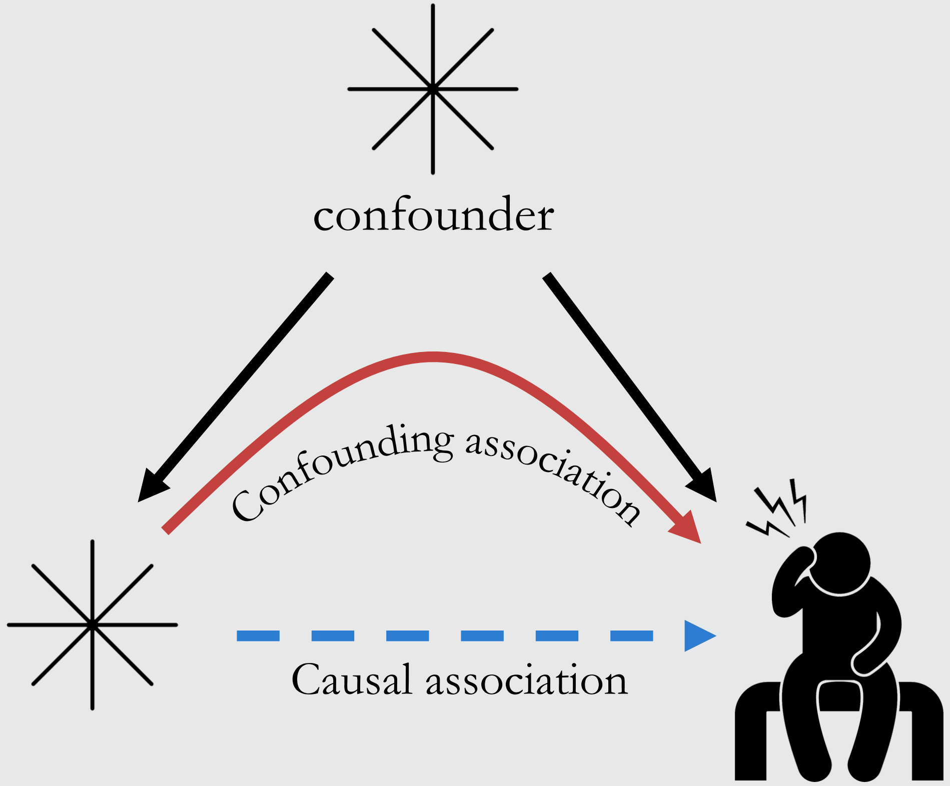

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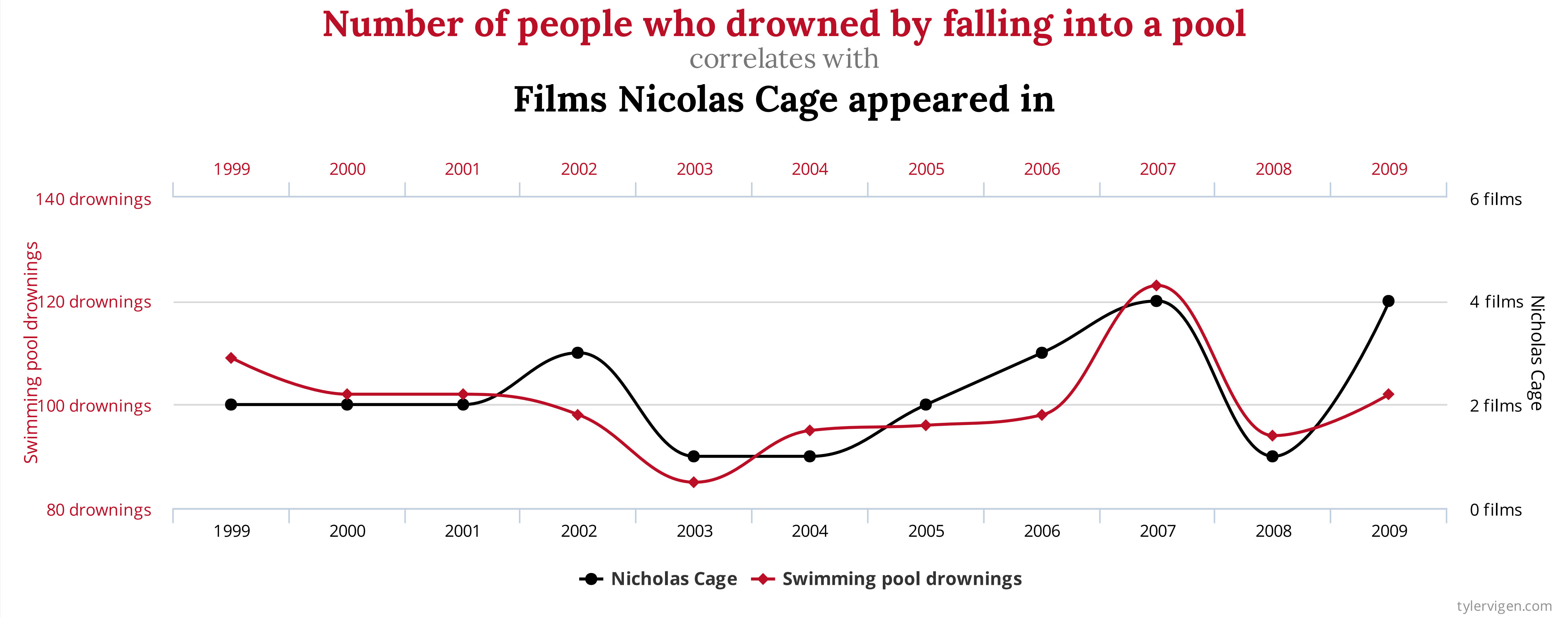
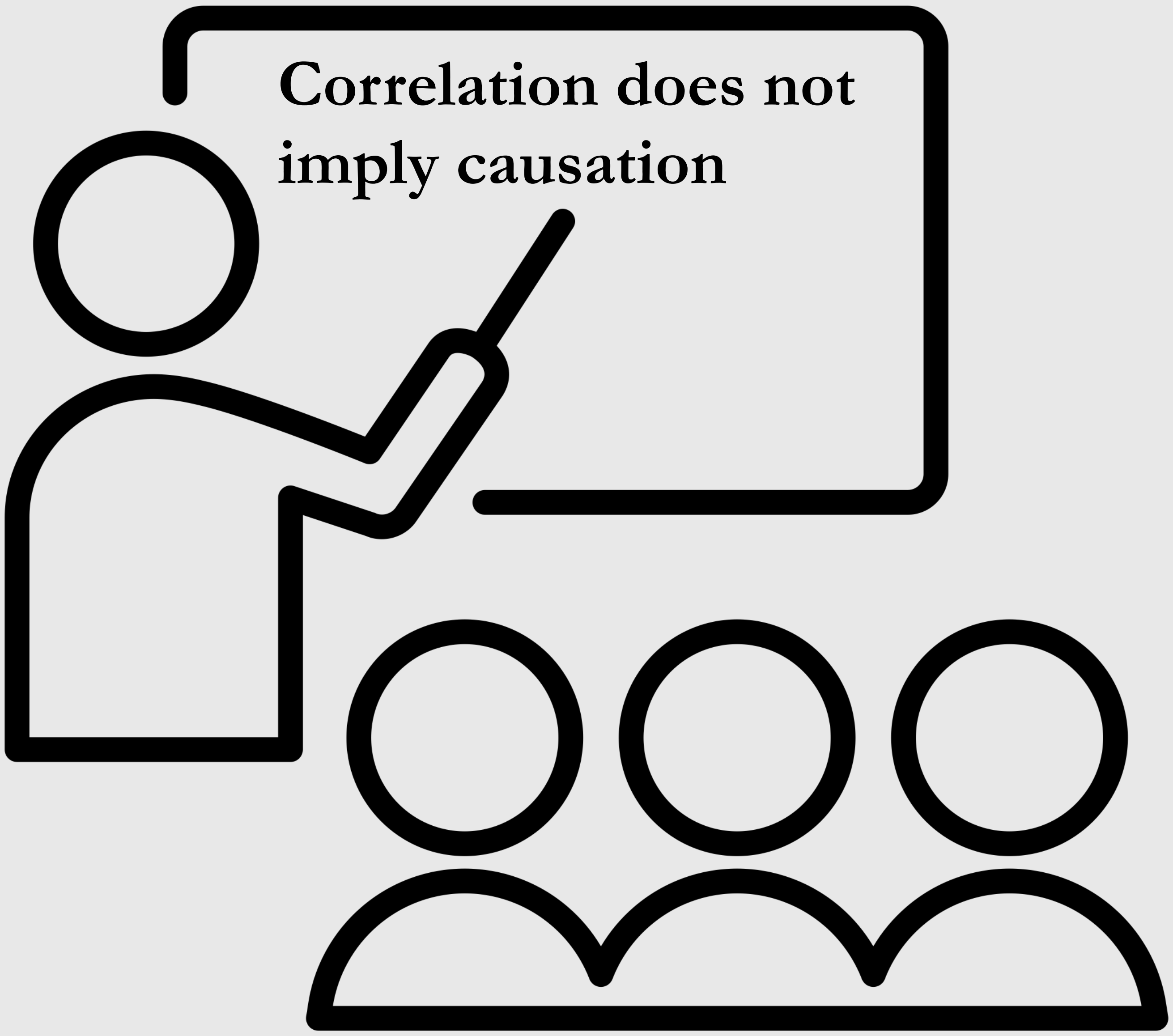
Nicolas Cage drives people to drown themselves



https://www.tylervigen.com/spurious-correlations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Inferring the effect of treatment/policy on some outcome

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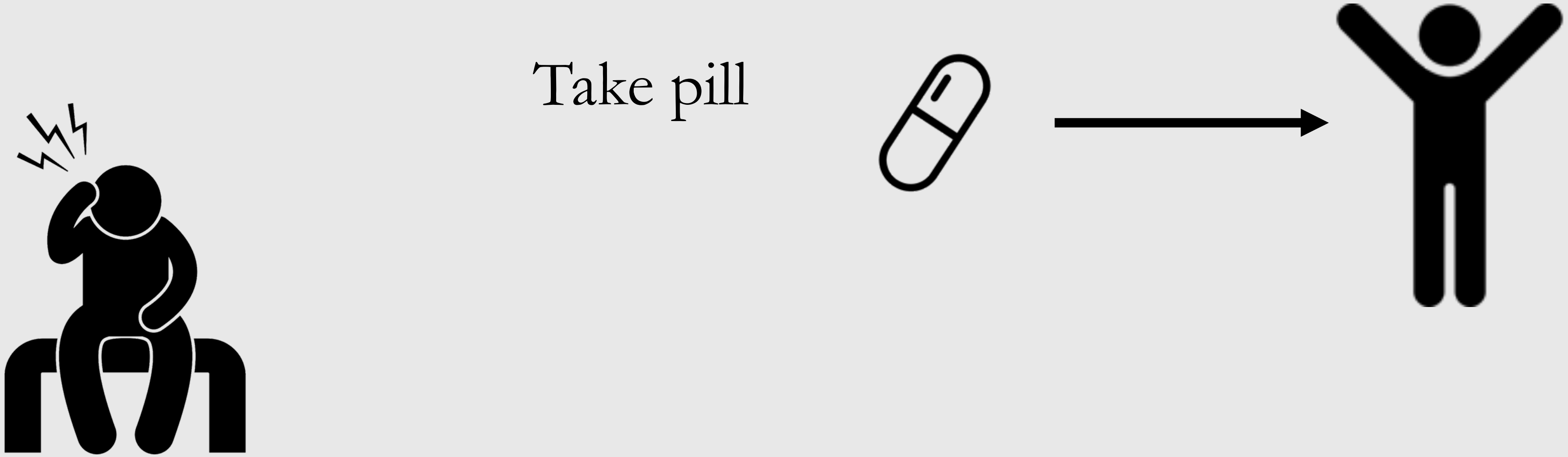
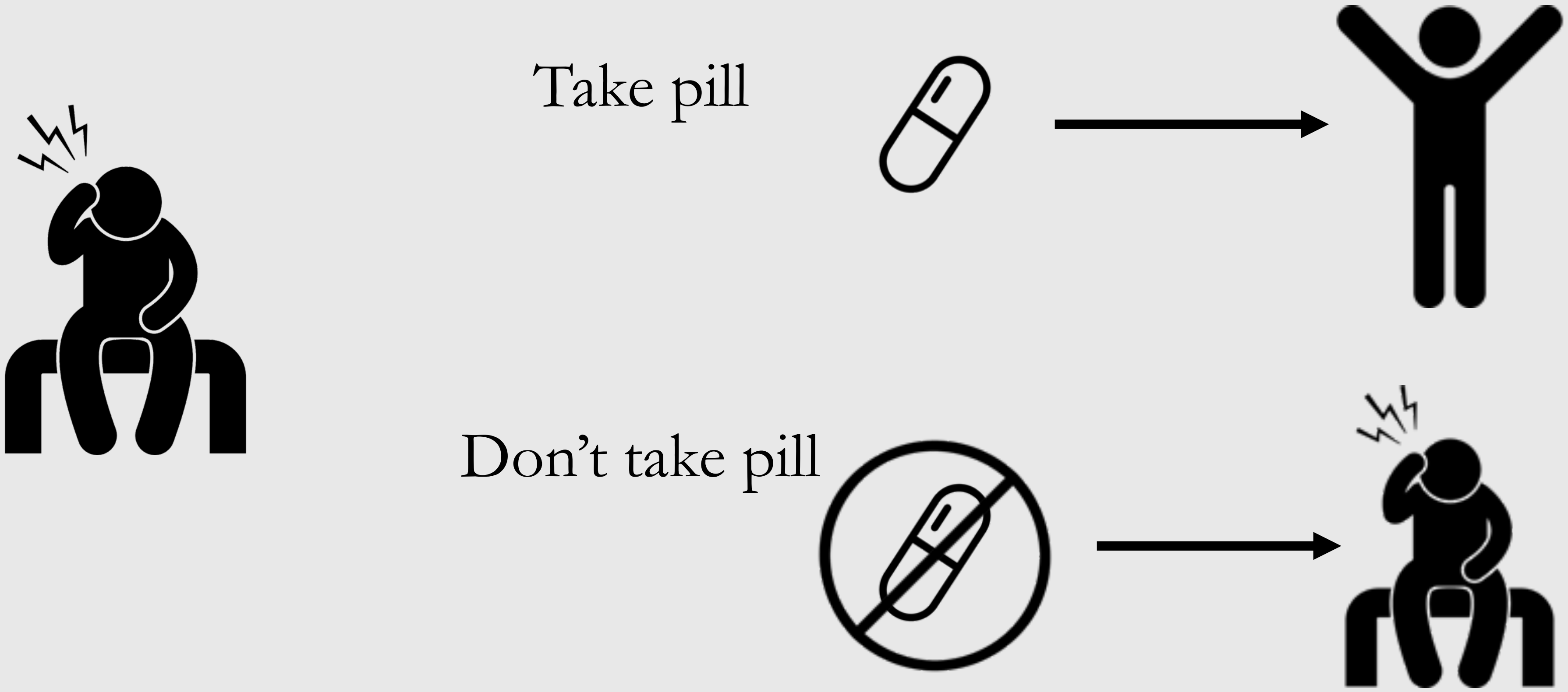


Potential outcomes: intuition

Inferring the effect of treatment/policy on some outcome



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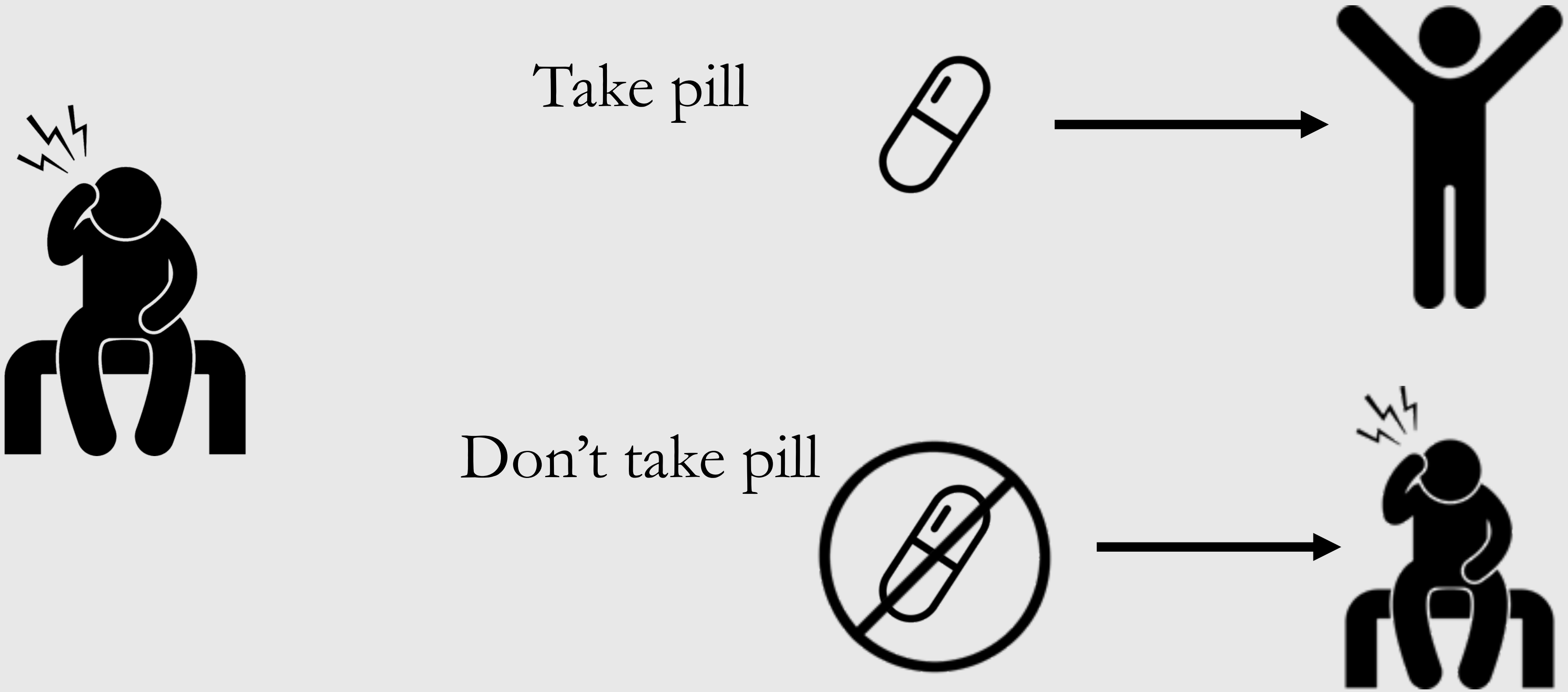

causal effect

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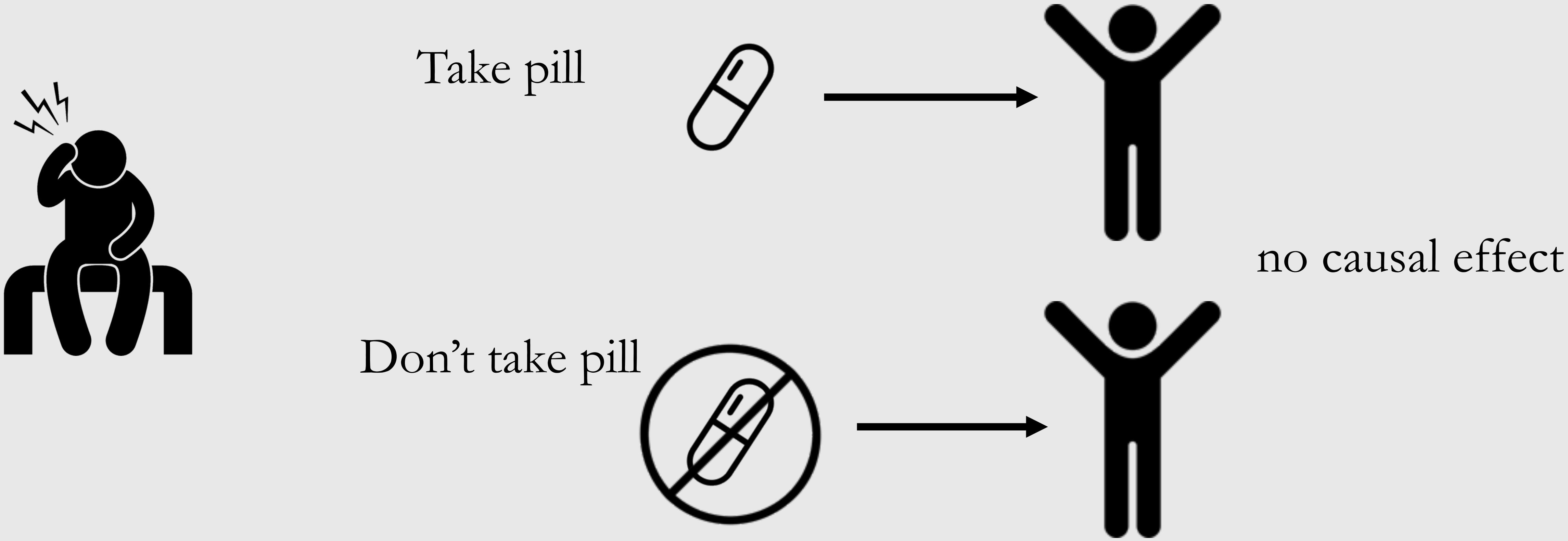
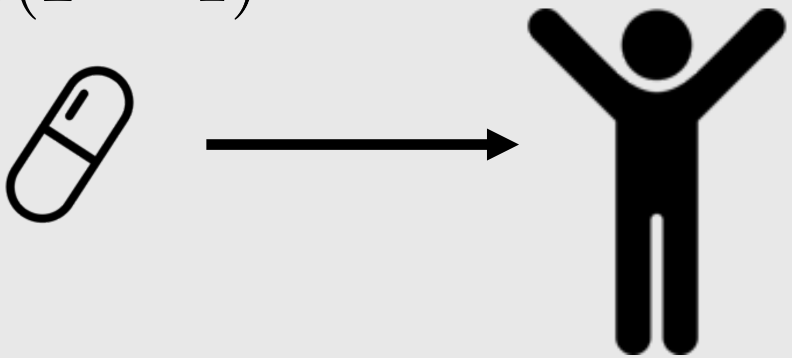
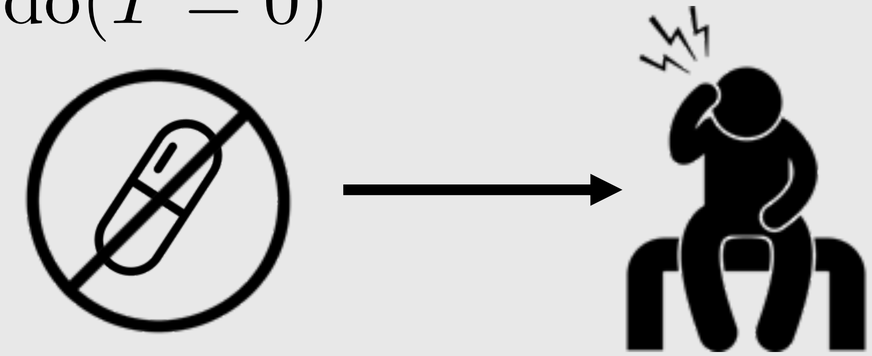


Potential outcomes: notation

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



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

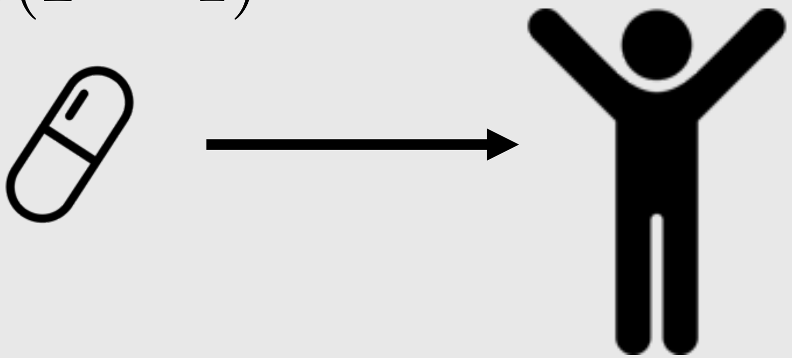


T : observed treatment
Y : observed outcome

Potential outcomes: notation

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

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



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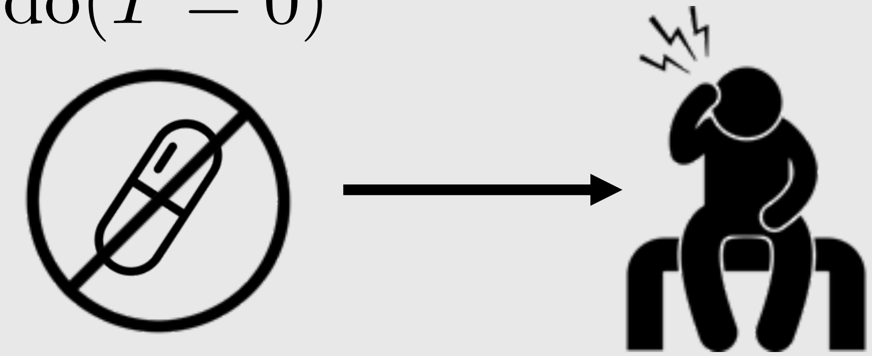

T	: observed treatment
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i	: used in subscript to denote a specific unit/individual

Potential outcomes: notation

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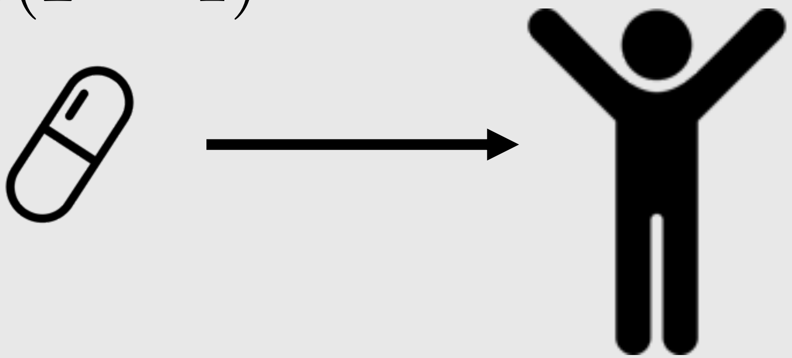

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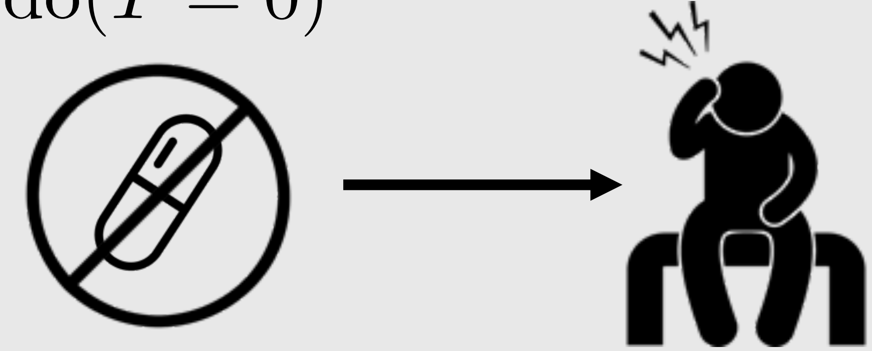

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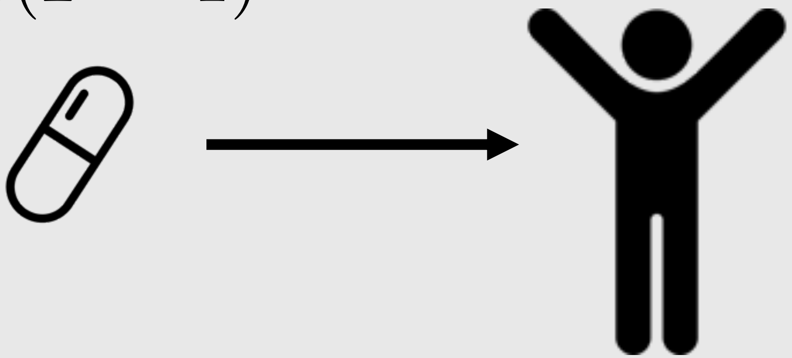
Potential outcomes: notation

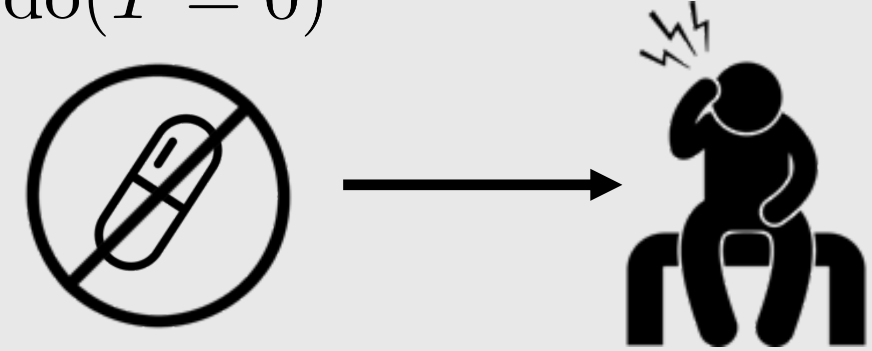
$\mathrm{do}(T = 1)$

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



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

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



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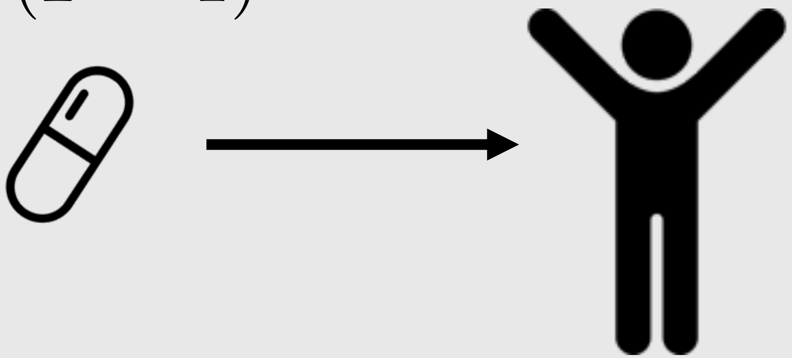
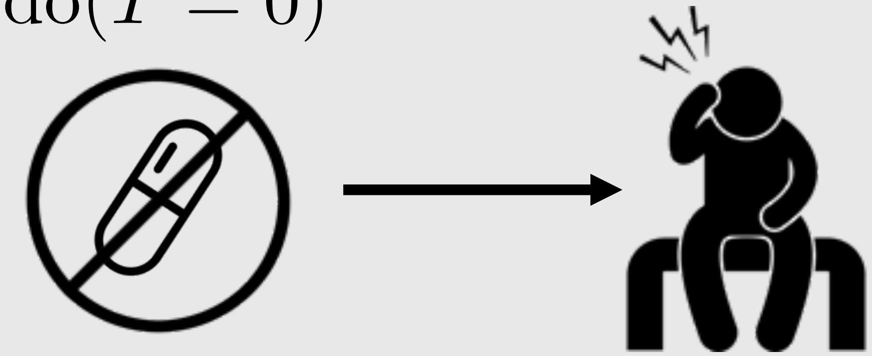


$\mathrm{do}(T = 0)$

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



T	: observed treatment
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

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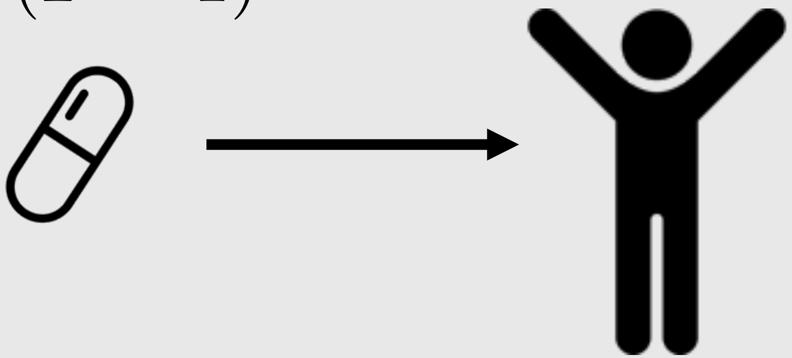
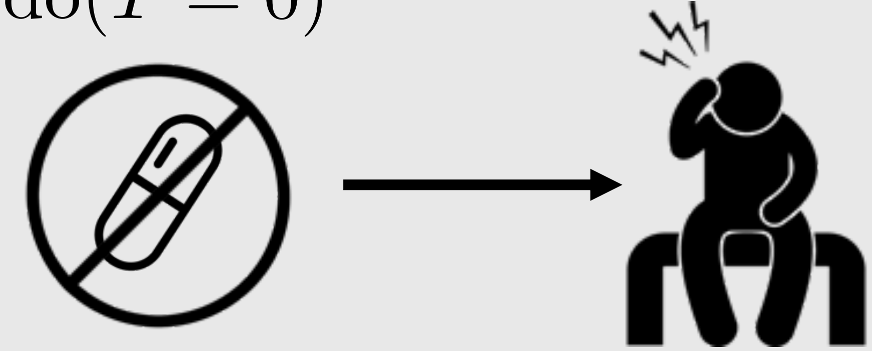
$Y_i|_{\mathrm{do}(T=1)} \triangleq Y_i(1)$



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

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



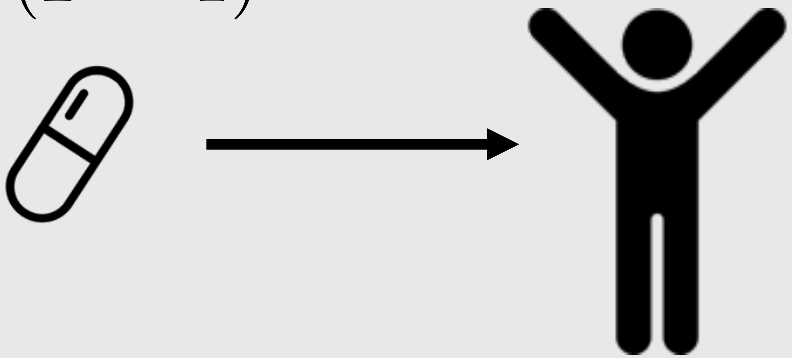
T : observed treatment
Y : observed outcome
i : used in subscript to denote a specific unit/individual
$Y_i(1)$: potential outcome under treatment
$Y_i(0)$: potential outcome under no treatment

Causal effect

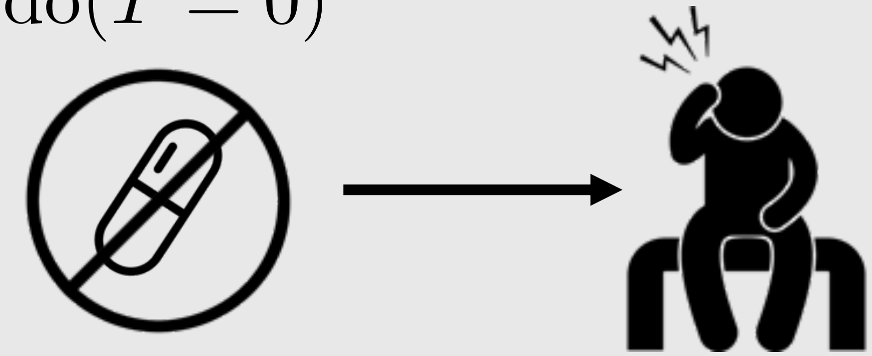
$Y_i(1) - Y_i(0)$

Fundamental problem of causal inference

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



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



T	: observed treatment
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

Causal effect

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

Fundamental problem of causal inference

Counterfactual

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

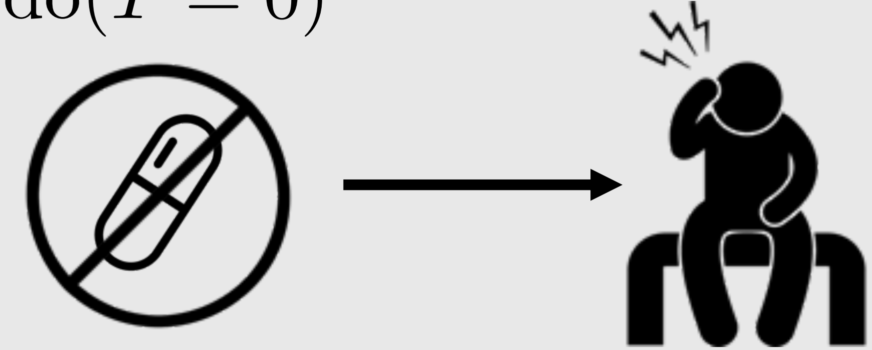
$Y_i(1) = 1$

T	: observed treatment
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

Factual

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

$Y_i(0) = 0$



Causal effect

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

Fundamental problem of causal inference

Factual

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

$Y_i(1) = 1$

T	: observed treatment
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

Counterfactual

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

$Y_i(0) = 0$

Causal effect

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